Unpredictable by design? How wage policy shapes hourly work

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Abstract

Workers in hourly service jobs experience shift cancellations, schedule adjustments, and unpredictable hours, often referred to as 'just-in-time' scheduling. Despite imposing significant costs on workers, little is known about the tradeoff between wages and schedule stability. I leverage the fact that most hourly service workers earn at or near the minimum wage to examine this question. Using daily administrative data from thousands of small businesses in the food and retail sectors across the US, I examine how large increases to state-level minimum wages impact the volatility of hourly workers' schedules. Following exogenous wage increases, schedule inaccuracy increases by roughly 45 minutes per week and the overall similarity of week-to-week schedules decreases by 20%. I utilize the granularity of the data to construct a machine learning model and demonstrate that the deviation of predicted hours increases substantially with the onset of a minimum wage. I utilize extreme weather days as shocks to consumer demand to demonstrate how schedules also become more responsive to a slow business day following the hike. This increase in volatility results in overall costs imposed on workers equivalent to 10-22% of the monetary gains from the wage increase per week.

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1 Introduction

It is well-established that the United States faces growing levels of income inequality, with wages at the lowest-end of the distribution stagnant for many years (Payne-Patterson and Maye 2023). This growing inequality has been accompanied by another, lesser-studied inequality: a disparity in the quality of work. Not only has the lowest quartile of wage rates dropped in real terms relative to 60 years ago, but these low-paid jobs are less likely to offer amenities such as paid leave, job security, or stable, predictable work schedules (Kelly 2025). This latter issue in particular is a growing threat to the financial stability of the millions of workers in the US participating in hourly shift work.

Over half of workers in the US are paid hourly. Many of these workers are subject to such 'just-in-time' scheduling, with shifts assigned or canceled at short notice, no guaranteed minimum number of hours per week, and a high level of variation in the number of hours and which days they are scheduled to work week-to-week (The Shift Project 2024). While this could be profit-maximizing for firms wishing to reduce payroll costs, this may take its toll on workers who bear the brunt of such volatility. However, we know very little about the determinants of schedule volatility and how public policy affects it.

Unpredictable schedules negatively impact worker health and productivity (Schneider and Harknett 2016; Ananat and Gassman-Pines 2021). These threatens workers' ability to budget for expenses in a given month or plan finances for the future, as instability in hours translates into instability in earnings(Bergman et al. 2023). Indeed, Mas and Pallais (2017) find that an average worker would be willing to give up 20% of their wages to avoid an employer-controlled schedule, showcasing the tradeoff that may exist between wages and volatile schedules. Workers also favor traditional 9-5 schedules, as this guarantees access to a set number of hours (and therefore income) per week, rather than a situation in which they work fewer hours than they would like.

Schedule volatility is most commonly found among low-income workers, highlighting the stark contrast in job quality between the top and bottom of the income distribution. In particular, these practices are most prevalent in the service sectors, which employs roughly 20% of the US labor force but contains 80% of the minimum wage workers, and in which just-in-time scheduling is commonly used (U.S. Bureau of Labor Statistics 2024; U.S. Bureau of Labor Statistics 2025b). The Shift Project (2024) finds that 66% of service-sector workers would prefer a more stable schedule. While there is an extensive literature and policy debate on what the optimal minimum wage should be for workers in these sectors to reduce wealth inequality, schedule volatility has been relatively understudied.

Despite schedule volatility being such a clear non-wage disamenity, there are still many unanswered questions concerning the causes and consequences of such practices. In this paper, I further our understanding of how schedule volatility and wages go hand-in-hand. I estimating the impacts of state-level minimum wage increases on the prevalence of just-in-time scheduling among service sector workers. With the majority of these workers earning at or near the minimum wage, these increases offer a useful avenue to explore schedule volatility among this class of workers.

Using highly granular proprietary payroll data, I test how minimum wage increases affect the provision of schedule stability, illustrate why firms may adjust along this margin in order to recuperate higher labor costs, and evaluate the overall costs imposed on workers from higher volatility. Minimum wage increases serve as the largest shifters to wage rates among workers in these sectors and their effects on employment have been extensively studied. However, measures of employment alone do not capture other margins of adjustment that firms may take following a hike, and consequently miss effects on the quality and dignity of employment following a minimum wage imposition. Volatility in particular is often missed, as it is difficult to capture without having a window into the scheduling practices of businesses. Leveraging daily, worker-level data, I am able to document patterns in schedule volatility and examine changes to these practices following an increase in the cost of labor.

To evaluate these dynamics, I rely on exogenous variation in timing of large state-level minimum wage increases across the US from 2017-2022, using these increases as shocks to the labor costs of firms. I focus on policy changes in 8 states to evaluate the effects on a wide range of employment and schedule volatility measures, derived from daily payroll and scheduling data for small businesses in the food and drink or retail industries. I then use extreme weather days as a shock to consumer demand to demonstrate why such scheduling volatility is profit-maximizing for firms, by showing how a minimum wage hike yields an increase in the cost of misallocating labor (i.e. over scheduling workers on what ends up being a 'slow' customer day). I finally calculate back-of-the-envelope costs to workers.

I first document characteristics of hourly work in the food and drink and retail sectors, and the degree to which these jobs are subject to volatile scheduling. Most workers are part-time, working fewer than 35 hours per week. It is consistently reported in surveys that many workers wish to work more hours than given (Schneider and Harknett 2019). The highest-paid and most-tenured workers typically work the most hours, consistent with common practices of rewarding the most experienced workers with the most desirable schedules. They typically experience more than one hour of difference between the hours they were scheduled to work and the hours they actually work per week, with the highest-paid workers typically working more than scheduled hours and the lowest-paid workers typically working fewer than scheduled hours. The similarity of schedules week-to-week changes varies drastically for workers as well. Although workers typically only work 3-4 days per week, which days they work change throughout the month, with most employees working at least 6 different week days throughout the month, making it difficult to predict what a typical week looks like. Predictability in the number of hours worked per week is low as well, with lower-paid and lowest-tenure workers having a higher coefficient of variation in their hours, despite working fewer hours overall. This variation in hours translates into variation in income, with take-home earnings fluctuating for workers month-to-month.

I then examine how increases in minimum wages impact these baseline levels of volatility. I find that a one standard deviation increase in the minimum wage results in an increase in the gap between scheduled and worked hours by roughly 45 minutes per week. Week to week similarity of hours drops by nearly 20%, as measured by the autocorrelation of weekly hours over the course of a given month. The standard deviation of week-to-week hours, meanwhile, increased roughly 100%, or an additional 4 hours per week of uncertainty in whether an employee will work or not. Taken together, this means that with higher pay comes more last-minute changes to schedules and less similarity between hours worked week-to-week. These are key issues that worker identify as making it more difficult for them to set up routines and regular budgets. Using county-level unemployment rate to proxy for health of the local economy, I see that working in a county with higher unemployment is correlated with relatively higher levels of volatility following a minimum wage hike. This matches with the notion that more competition for workers would drive up provision of non-wage amenities.

The rise in volatility is not accompanied by lower overall hours worked; hours worked per week per employee remains fairly constant in the months following the hike. This suggests that workers who had their pay increased to the new minimum wage did not see their hours reduced. However, the wage increase is paired with a modest increase in employee separation rates from affected firms. Likelihood of exit increases by about 5% following an increase. Again consistent with the common practice of rewarding more experienced workers, it is employees who have been with the companies for the least amount of time (and are the lowest paid) that drive this increase in exits. This indicates a pattern of using a ‘last-in, first-out’ management strategy.

The theory of compensating wage differentials suggests that firms will trade off wages and costly amenities in equilibrium. However, it is difficult to test this hypothesis due to the endogenous selection of workers to firms based on such amenities. To investigate this trade-off further, I utilize shocks to consumer demand brought on by negative weather conditions as exogenous shifters of the provision of schedule stability. Rather than using natural disasters or extended periods of extreme weather, I pinpoint single-day anomalies in temperature and precipitation relative to the norm for a given county and time of year. I then use these deviations to demonstrate the previously undocumented phenomenon of weather shocks negatively impacting the stability of worker schedules, decreasing hours worked and increasing the difference between scheduled and worked hours at extreme levels of temperature and rainfall. I then find that these schedule inaccuracies are exacerbated by an additional 10th to quarter of an hour following a minimum wage hike. This illustrates how firms may recuperate costs by pushing off risks of a slow business day onto workers following their gains in wages in order to compensate.

While the event study reveals how similarity changes in worker schedules week-to-week following a wage hike, we may also wish to determine how predictable a worker's schedule is. This is what enables them to plan to work additional jobs, arrange child or eldercare, or budget for their monthly expenses. To analyze predictability of schedules, I bring these findings together in a machine learning model, which mimics a worker attempting to predict their schedule based off firm characteristics and their past schedule. The model is highly dependent on a worker's schedule over the prior two weeks, as well as day-of-week and month characteristics. This model performs more poorly following a minimum wage hike, becoming 4.4% more inaccurate for those workers exposed to a large minimum wage hike than the control group.

Finally, I use back-of-the-envelope calculations to estimate that this increase in schedule volatility imposes a cost to workers, detracting from some gains arrived at through the minimum wage. These imposed costs can be interpreted as time costs, as they increase the amount of hours workers must spend uncertain about their schedules, and unable to plan for alternate uses. Pulling from the value of time literature, I assume a range of values of time, from 33 to 75% of average wage. The additional 45 minutes per week lost to schedule inaccuracy translates to a cost of \$1-2 per week, or 10-22% of the overall monetary gains per week from the minimum wage. Expanding the welfare cost to the increased week-to-week volatility, workers face an increased value of time cost of \$13-30 per week, a higher value than the total wage gain from the minimum wage hike (amounting to \$10 per week).

This work contributes to several areas of economic literature. Most closely, I add to the growing literature on schedule stability and worker welfare. Past literature has documented the value that workers place on reliable schedules (Mas and Pallais 2017; The Shift Project 2024), and the extent to which the lowest-income workers face the brunt of this volatility (Cai 2023). Lachowska et al. (2023) find that workers experience a large gap between their optimal hours and the hours dictated by their employers. Related work has measured how much workers value the ability to decide when and where they work, having the flexibility to choose their own hours rather than being at the whim of an employer (Chen et al. 2019; He et al. 2021).

Despite it being a clear non-wage disamenity for employees, this practice of just-in-time scheduling is common, and connects to broader business practices such as just-in-time inventory. Studies in operations management outline the ways in which firms aim to minimize inventory and efficiently matching needs along the supply chain at the most opportune times to reduce waste (Singhal and Raturi 1990; Yang et al. 2021). However, whereas inducing last-minute changes to inventory may result only in cost savings, the same has been shown not to be true when the same practices are used on workers.

Many studies have documented why it is that schedule volatility and last-minute adjustments are so harmful to employees. Ananat and Gassman-Pines (2021) shows that it harms worker mood and sleep quality, particularly for parents, while Aparicio Fenoll et al. (2025) finds negative consequences on the health of workers' children. On the other hand, several studies have found that increasing stability actually increases productivity of workers (Williams et al. 2018; Hashemian et al. 2020; Kaur et al. 2021), bringing into question why firms maintain such practices. Most of this work relies on survey data, and consequently has not been able to capture trends in predictability across large numbers of employees and firms. I complement this work by utilizing long-term, daily employer-employee linked payroll data which includes scheduled hours and hours worked to showcase volatility patterns across food and retail workers. I additionally am able to evaluate the degree to which these trends change when the cost of providing stability goes up. I furthermore provide insights into why firms may continue to engage in this practice, despite apparent losses to productivity, by illustrating what happens when shocks to consumer demand occur.

This work additionally adds to the expansive literature on minimum wages (Card and Krueger 1994; Dube and Lindner 2024). In particular, I closely follow the methodology of Cengiz et al. (2019a), using state-level minimum wage increases as plausibly exogenous shocks in order to study outcomes of interest. My findings that hours worked fail to go down and that exits are modest following a hike align with this body of work.

However, despite minimum wage workers being among the most susceptible to volatile work schedules, there is surprisingly little research documenting the relationship between the two. Clemens and Strain (2020) provides a theoretical framework for why an increase in the wage may lead to a decrease in worker welfare despite no drop in employment due to increases in schedule volatility. Yu et al. (2023) provides some initial empirical evidence on this topic, using data from one retail store to show increased volatility and increased unemployment following a hike in one state's minimum wage. In this project, I provide empirical evidence to support Clemens' framework, and am the first to my knowledge to show this phenomenon across businesses, industries, and several states over time. This allows me to examine patterns by different worker and labor market characteristics.

While there is limited research on minimum wages and schedule volatility, there are several recent papers on the minimum wage and other non-wage amenities. Firms have been shown to reduce amenities such as health insurance, workplace safety, and workplace dignity to compensate for higher wages (Davies et al. 2025; Clemens 2021; Meiselbach and Abraham 2023; Clemens, Kahn, et al. 2018; Dube, Naidu, et al. 2022). By utilizing weather shocks, this study has a unique advantage of being able to randomly shock the cost of the amenity in question, schedule stability. By doing so, this additionally complements recent literature demonstrating that higher disposable income is associated with improved capacity to adapt to weather shocks (Sarmiento et al. 2024), showing how weather and the minimum wage interact through the scheduling margin as well.

Lastly, I contribute to the body of literature focused on the climate impacts on labor markets. Many papers in this area have documented how extreme weather hampers overall hours worked, especially in the poorest areas (Graff Zivin et al. 2018; Rode et al. 2024; Behrer et al. 2021). Fewer have examined impacts of weather on other job characteristics. Park et al. (2021) show how workplace injuries increase with heat exposure, while Downey et al. (2023) documents how firms adjust labor demand in anticipation of seasonal rainfall volatility in the construction industry. This paper complements Downey et al. (2023) by showing how industries heavily-reliant on consumer demand similarly adjust labor in attempts to match weather-driven fluctuations. As such, this study provides an examination of the flip side of the coin to studies documenting how weather impacts consumer demand (Papp 2024; Roth Tran 2019). It connects these consumer effects to the resultant consequences for hourly workers whose shift work is highly dependent on consumer needs.

This study also informs several policy debates. The minimum wage is among the most common tools used for labor market regulation in the US. However, these results highlight how mandatory increases in wages may be coupled with decreases in non-wage amenities if not paired with additional policies aimed at their protection. In particular, it demonstrates how scheduling volatility is a major factor on which firms may be able to adjust to these new costs, despite it being highly undesirable for workers. Lastly, as policy-makers attempt to grapple with how climate change will impact vulnerable workers, these results indicate that more workers than just those employed by outdoor-exposed industries will be impacted by weather fluctuations. I document how consumer-facing industries see declines in hours worked on bad-weather days, leading to wage losses for hourly workers who are not paid unless they work for those hours. Not just hours are impacted however–the stability of schedules, a large non-wage amenity that workers value, is also brought down. Furthermore, when wages are increased without additional worker protection policies, workers become even more vulnerable to this weather-induced schedule volatility.

This paper is structured as follows. Section 2 provides background information on hourly work in the US and policies regarding scheduling and minimum wages. provide a theoretical framework for my study in Section 3 and outline my empirical strategy in Section 5. Section 6 details my results and my machine learning model and Section 7 translates select results into welfare costs to workers. Section 8 concludes.

2 Background

In the United States, over half of workers are paid hourly (BLS 2022), suggesting that if their employer is unable to operate or is not in need of their labor on a given day, the employee will not be paid. While many workers who fall under the hourly category of work are employed in full-time, regularly scheduled jobs, many others are subject to irregular or unpredictable schedules set in place by their employers, referred to as 'just-in-time' scheduling. This means that employees are frequently assigned to work shifts with extremely short notice or are subject to last-minute shift cancellations and adjustments. Using data from the American Time Use Survey, Guyot and Reeves (2020) estimates that 2 in 5 workers over the age of 15 know their work schedules less than one month in advance, with 1 in 5 knowing less than a week in advance. Additionally, most workers are not guaranteed a minimum number of hours per week. As such, workers can be sent home without working scheduled hours if business slows to less than expected. At the same time, many experience having to be on-call for shifts they may or may not be paid for, leaving them unable to schedule other work in case they are needed for a shift at their primary place of employment. Finnigan (2018) finds that schedule volatility has increased since the Great Recession, and argues that this is due to businesses passing the risk of decreased consumer demand off onto workers more frequently. Raising equity concerns, non-white workers and low-income workers are significantly more likely to experience these workplace patterns, leading to concerns of inequality, as volatile hours entails less predictable take-home income, with the brunt of this burden largely faced by the lowest-income and least educated workers (Cai 2023).

This unpredictability in work schedules has severe consequences for employees along several dimensions. If households are already under financial stress, these patterns can exacerbate the challenge of being able to keep up with expenses and plan for future expenditures, threatening financial security (Schneider and Harknett 2016). Ananat and Gassman-Pines (2021) shows that volatility has similarly negative consequences for sleep quality and mental well-being. Unpredictability in hours also can threaten low-income households' access to programs such as the Supplemental Nutrition Assistance Program (SNAP) that have work requirements recipients must meet. If an employee is not able to target a certain number of hours at their place of work per month, their eligibility for benefits is put at risk (Ananat, Gassman-Pines, and Howard 2025). Past individual-level consequences, however, it has been shown that this may have employer-level effects, with more volatility associated with increased turnover and decreased productivity (Bergman et al. 2023; Kesavan et al. 2022).

Some states have instituted 'reporting-time pay' laws, mandating that in situations where workers are required to show up to work but are then no longer needed and dismissed, they will still be paid for a certain number of hours, meant to compensate for their commute. Currently, only California, Connecticut, the District of Columbia, Massachusetts, New Hampshire, New Jersey, New York, Oregon (for minors), and Rhode Island have instituted such laws, but most limit compliance to large companies employing more than 200 workers. Most states do not impose any regulations at all on just-in-time scheduling practices, allowing firms to push risk of fluctuating demand for their businesses off on workers. This is particularly severe in the food and retail sectors, which are highly dependent on consumer demand. These sectors employ nearly 20% of the population, but 80% of minimum wage workers.

As such, minimum wage laws are very relevant in this context, impacting the workers that are most likely to be exposed to just-in-time scheduling. While the federal minimum wage has not increased from \$7.25 per hour for this class of non-exempt workers since 2009, 30 states as well as the District of Columbia have imposed their own minimum wage increases, exceeding this federal standard. Several have pinned their wage increases to match inflation rates, or otherwise go up by a certain amount every year. The federal tipped minimum wage stands at \$2.13 per hour, and many states have likewise introduced tipped minimum wages above this number. In these cases, if an employee's wages combined with their earned tips do not meet the state minimum wage, employers are required to pay them the difference to make up for this. Unlike the scheduling laws discussed above, these minimum wage laws apply to all workers employed within a given state without exception. Several cities have instituted minimum wages even above their states' minimum. In these cases, it is more common to include exemptions for small businesses or specific industries.

As noted above, extreme weather events are a particular shock to labor demand, and states differ in how they handle extreme temperature days, with the vast majority not legally enforcing any restrictions on allowed hours under extreme heat. Only five states, Washington, Oregon, California, Colorado, and Minnesota, have adopted occupational heat standards, requiring states to halt work if temperatures reach above a certain threshold deemed unsafe for workers, but these laws again mainly apply to outdoor or large workplaces. Past these provisions, there are no existing regulations in place for how businesses need to manage labor under increasingly severe climate stressors.

3 Theoretical framework

Here, I outline a simple theoretical model describing how minimum wage increases could increase worker schedule volatility in the presence of idiosyncratic productivity. I build off the model presented in Clemens and Strain (2020), which presents a theoretical framework for how a firm may increase a productive disamenity, like schedule volatility, following a minimum wage hike, in order to compensate, and result in lower overall surplus. I add to this model by instead considering volatility as an endogenous response to the risk of a low-productivity day, and therefore weakening the need for labor.

Firms and workers make labor decisions over 2 periods. At $T = 1$, a firm assigns a worker h_e expected hours for $T = 2$ given their expected productivity level $\bar{a}$, given the information available to them at time $T = 1$. On day $T = 2$, the firm realizes their true productivity level, $a + \epsilon$, with $\epsilon > 0$ indicating higher productivity than expected, $\epsilon < 0$ indicating lower productivity than expected, and $\epsilon = 0$ indicating productivity exactly as projected. $\mathbb{E}[\epsilon] = 0$. The firm, upon realizing this shock ϵ, assigns the worker actual hours worked h_2.

A worker has a distaste for working a different number of hours than previously assigned, as it is costly logistically or financially for them to adjust their schedules. This distaste can be represented by: $\gamma(h_2 - h_e)^2$, where γ is a value greater than 0 and represents how much a worker dislikes this change to their schedule. The value is squared, as the worker dislikes the difference in either direction; they must adjust their schedule whether they are asked to work more than initially planned or less.

Given that they have a reservation utility U_r and receives wage rate w, the worker will only choose to work if:

$$wh_2 - \gamma(h_2 - h_e)^2 \geq U_r \tag{1}$$

The firm's profits at $T = 2$ depend on a standard quadratic production function, dependent on the hours actually worked and the productivity shock: $f(h_2) = (\bar{a} + \epsilon)h_2 - bh_2^2$, with $\bar{a} > 0$ and $b > 0$. They receive price p for their output, and pay wage w.

Period 1:

In period 1, the firm must set expected hours h_e based on the assumption that $\mathbb{E}[\epsilon] = 0$, and that therefore there is no unpredictability. They therefore solve:

$$\begin{aligned} &\text{Max } \pi = p(\bar{a}h_e - bh_e^2) - wh_e \\ &\text{s.t. } wh_e \geq U_r \end{aligned} \tag{2}$$

Substituting in the participation constraint and solving yields the optimal solution $h_e^* = \frac{\bar{a}}{2b}$.

Period 2:

At time $T = 2$, ϵ is realized and the firms must set actual hours h_2. Their decision is therefore to maximize profits subject to the worker's participation constraint, which includes their distaste of deviations from the expected:

$$\begin{aligned} \text{Max } \pi &= p((\bar{a}+\epsilon)h_2 - bh_2^2) - wh_2 \\ \text{s.t. } & wh_2 - \gamma(h_2 - h_e)^2 \geq U_r \end{aligned} \tag{3}$$

Rearranging to solve for w, we get that:

$$w = \frac{U_r + \gamma(h_2 - h_e)^2}{h_2} \tag{4}$$

Substituting this back into the equation and setting the derivative equal to 0 and optimizing with respect to h_2 yields:

$$\frac{d\pi}{dh_2} = p(\bar{a} + \epsilon - 2bh_2) - 2\gamma h_2 + 2\gamma h_e = 0 \tag{5}$$

The optimal hours a firm assigns a worker is represented by:

$$h_2^* = \frac{p(\bar{a}+\epsilon) + 2\gamma h_e}{2(\gamma + pb)} \tag{6}$$

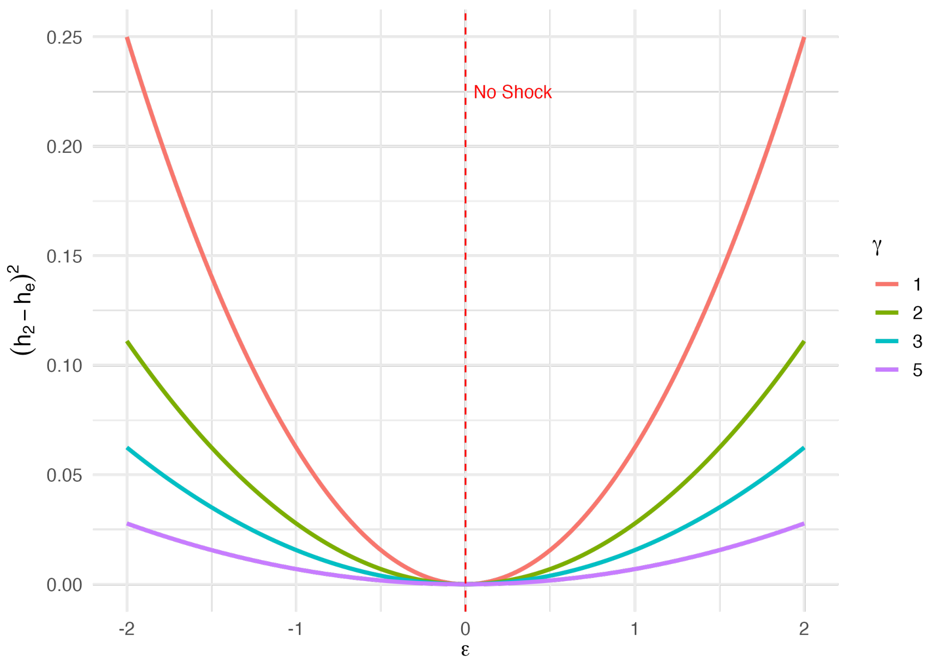
We recall that the optimal solution for h_e is given by: $\frac{\bar{a}}{2b}$. Plugging this in, we find the optimal solution for h_2 written as:

$$h_2^* = \frac{p(\bar{a}+\epsilon) + \gamma\frac{\bar{a}}{b}}{2(\gamma + pb)} \tag{7}$$

When assigning the hours for the shift on the day-of, the firm must take into account several parameters. The numerator increases with a more positive productivity shock, and with the coefficient $\bar{a}$. The denominator, however, captures marginal costs of setting higher hours through the disutility term γ.

To understand what this solution implies for volatility, we can examine the comparative statics, particularly how schedule deviations change with the productivity shocks. We can first solve for $(h_2^* - h_e)$ as a function of ϵ. This allows us to interpret how $(h_2^* - h_e)$, the difference between scheduled and worked hours, changes with productivity shocks. Solving

Figure 1: Schedule Unpredictability vs Productivity Shock



for this, we get:

$$(h_2^* - h_e) = \frac{p(\bar{a} + \epsilon) + \gamma \frac{\bar{a}}{b}}{2(\gamma + pb)} - \frac{\bar{a}}{2b} = \frac{p\epsilon}{2(\gamma + pb)} \tag{8}$$

Now, we can see that when $\epsilon = 0$, $(h_2^* - h_e) = 0$, as there is no productivity shock and therefore hours were projected correctly. When $\epsilon > 0$, $h_2^* > h_e$, and firms increase worker hours above previously expected levels. When $\epsilon < 0$, $h_2^* < h_e$, and firms cut hours below the previously scheduled amount. When the worker's distaste for schedule deviations, γ, increases, the distance between the scheduled and worked hours goes down. However, increased prices p incentivize firms to widen the distance between scheduled and worked hours. Total schedule unpredictability can be represented by:

$$(h_2^* - h_e)^2 = \frac{p^2 \epsilon^2}{4(\gamma + pb)^2} \tag{9}$$

Figure 1 depicts this relationship between the value of the productivity shock and the extent to which the schedule will deviate from the planned schedule for different values of γ.

Minimum wage increase

So far, this analysis has assumed that the firm may adjust wages optimally depending on a worker's reservation utility, the worker's distaste for schedule adjustments, the expected hours worked, and the actual hours worked, represented by equation 4. We can now consider the case in which a legally binding minium wage is imposed on firms. Under these conditions, the firm's maximization problem becomes:

$$\begin{gathered}\text{Max } \pi = p((\bar{a}+\epsilon)h_2 - bh_2^2) - w_{min}h_2 \\ \text{s.t. } w_{min}h_2 - \gamma(h_2-h_e)^2 \geq U_r\end{gathered} \tag{10}$$

If the w_{min} is below the wage already set by the firm, then the optimal solution remains the same. However, if the minimum wage is higher than the existing optimal wage, then this wage will no longer be available. Instead, firms will need to set:

$$w_{min} = \frac{U_r + \gamma(h_2-h_e)^2}{h_2} > w^* \tag{11}$$

In order to reach this new level, for all values of h_2, they will need to increase the value of $(h_2 - h_e)^2$ in order to make up for their increased costs. Following the imposition of a minimum wage, the overall unpredictability of schedules will be increased; firms will increase the practice of pushing off the risk of productivity shocks on to workers in order to compensate for the higher cost of labor. This pattern is depicted in Figure 2. Under a minimum wage, both the levels of volatility and the rates at which this unpredictability increases in the presence of a productivity shock increase.

Other insights

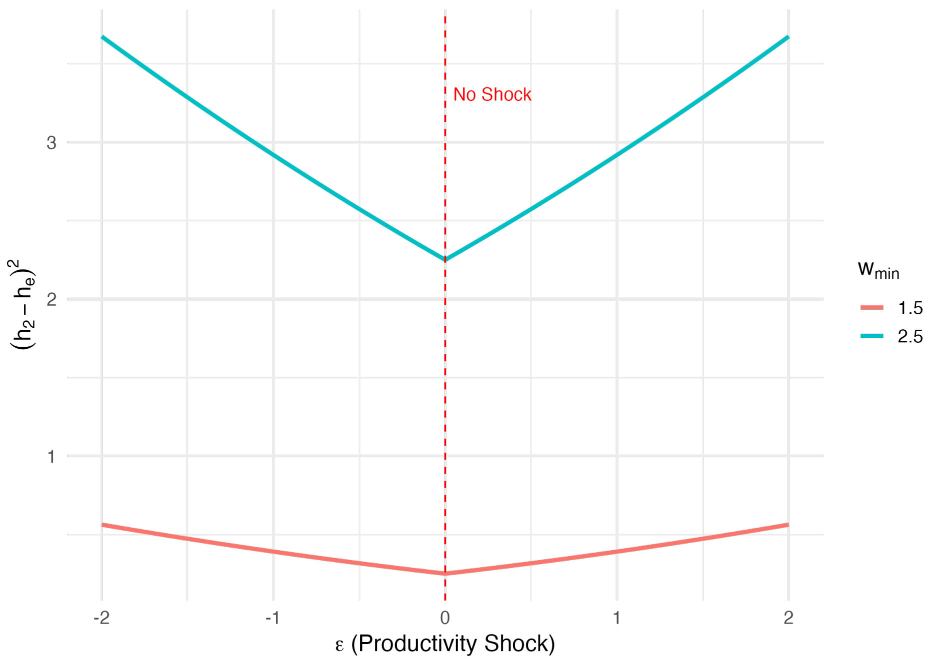
We can also learn from this exercise what the implications could be for two different labor markets, one with high levels of slack and one with low. In a labor market with high slack, we would expect an employee's reservation utility, $U_{r,low}$ to be relatively low, as there is more competition from other workers relative to the number of job openings. The opposite would hold in a labor market with low slack, leading reservation utilities to be higher: $U_{r,high}$.

Following a minimum wage hike, then, we could expect volatility to increase relatively more in the high slack context. In this setting, we would see that:

$$w_{min} = \frac{U_{r,high} + \gamma(h_2-h_e)^2}{h_2} = \frac{U_{r,low} + \gamma(h_2-h_e)^2}{h_2} \tag{12}$$

For equality to hold, $(h_2 - h_e)^2$ much be greater magnitude in the low high slack labor

Figure 2: Schedule Unpredictability under Different Minimum Wages



market, resulting in increased unpredictability.

3.1 Empirical testing

In this study, I test for the theoretical predictions of this model by using the highly granular administrative data that allows for observation of scheduled hours as of one day in advance of a shift and worked hours on the day of a shift. I first combine this with minimum wage increases at the state level to first test for changes in the *levels* of volatility following the increased cost of labor to firms. I examine the difference between hours worked and scheduled as well as what this entails for overall baseline similarity of schedules week-to-week.

Then, I test for changes in the rate of change of volatility in response to shocks to productivity following a minimum wage hike. To do so, I utilize extreme weather days: days with high levels of precipitation or colder or hotter temperatures than normal for a given season. I demonstrate how these days act as shocks to schedule stability, increasing the unpredictability of schedules for workers. I then test whether following a minimum wage hike, workers in the treated group see this increase in unpredictability at a higher rate, resulting in the increasing responsiveness to shocks that the model predicts.

4 Data and descriptives of hourly work

4.1 Homebase data

I take advantage of a large and rarely-before-used database of daily, employee payroll data provided by the company Homebase. Homebase offers scheduling, employee time-sheet tracking, and payroll management tools to small businesses through a web-based platform. On this platform, managers or business owners can assign workers' shifts, track their attendance, and conduct payroll operations. Workers at Homebase client businesses use the Homebase application to clock in and out of work. They can also use the tool to request time off, or request shift swaps or coverage from other employees.[1]

Homebase aggregates the information they receive from their thousands of business clients through their platform into a daily dataset, with data spanning from 2016 to present. This dataset includes unique worker IDs, overarching company IDs, and establishment IDs along with zip code of location and industry. For each day that an employee works, their employment level (manager or general worker), hourly wage rate, total hours worked per day, and total wages earned per day are provided. In addition, the number of hours scheduled to work as of one day prior are also given, allowing for the creation of a variable indicating the difference between the hours the worker was scheduled to work and how much they actually worked on the given day. Homebase also provides dates the worker began working at the given establishment and the date they were marked as no longer working there, which I use to calculate tenure. When those variables are not available, I assume an employee has exited when the employee stops appearing in the dataset for at least 2 months. It is not rare for an employee to not appear on a work schedule for several weeks; as employees are part-time, they are not guaranteed shifts, and could be scheduled many hours some weeks while others none at all. However, if they are absent from any schedule for greater than 2 months without a reappearance, I count them as separating from the company.

I restrict my sample similarly to the categories of workplaces in Homebase that Kurmann et al. (2021) consider to be a representative sample. The Homebase data is dominated by the 'Food and Drink' and 'Retail' sectors, and as these house the majority of minimum-wage workers and are the most susceptible to volatile hourly scheduling, I restrict my study to only these sectors. I focus on businesses employing between 5 and 50 individuals per week, which is the large majority of businesses that use Homebase. This enables me to observe small businesses that still have enough workers to face scheduling decisions. My sample includes data from the beginning of 2016 through the end of 2022, and I additionally restrict the

[1]Images of the user interface of the Homebase application are provided in the appendix (Figure A1).

sample to establishments present in both January and December (all throughout the year) to avoid seasonal workplaces or workplaces that used the tool for less than a year. Data is available from all 50 states, but is skewed towards the west coast, Texas, and Florida. To account for fluctuations in Homebase's client base, I use a balanced panel of establishments for all analyses. While a minimum wage hike could lead to some businesses shutting down or relocating, that is beyond the scope of this study, which is largely focused on how businesses adjust along non-wage margins. As such, I restrict to businesses who are present before and after the hike, allowing me to observe effects on workers.

Table 1 displays summary statistics within these two industries. Although similar in their propensity to hire part-time, hourly workers, these industries differ in the number of workers they typically employ and the wages they pay. As such, I include industry fixed effects throughout this study. Food and drink establishments account for the majority of the data, with Homebase servicing over 26,000 locations and nearly 750,000 employees over the sample period. Almost 8,500 retail establishments use Homebase over this sample period, employing roughly 120,000 workers. The included businesses in both industries are typically small; most only have one establishment per company. Food and drink establishments typically employ around 30 workers per week while retail establishments employ around 15 workers per week. These workers are mainly part-time, logging an average of less than 35 hours per week over 3-4 days, meaning that they are largely not eligible for overtime pay. Average hourly wages range from roughly $11-$13 per hour.

Table 1: Homebase Summary Statistics (2016–2022)

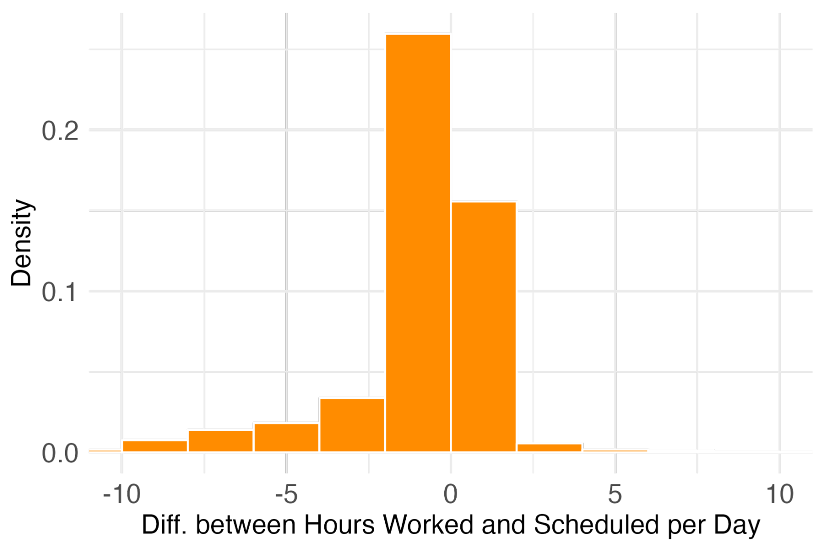
Metric	Food & Drink	Retail
Total Locations	26,109	8,410
Total Employees	742,463	122,177
Employees per Location	30	15
Hours Worked per Week	23.1	24.7
Hours Worked per Day	6.59	6.97
Scheduled Hours per Week	25.5	27.6
Days Worked	3.41	3.43
Abs. Diff. Hours Worked vs Scheduled	1.28	1.37
Weekly Wage ($)	267	332
Hourly Wage ($)	11.2	13.0

Notes: This table summarizes employee-level data for Food & Drink and Retail establishments using Homebase between 2016–2022. Hours, wages, and schedules are averages across employees. The difference between hours worked and scheduled is the absolute difference in hours between what an employee was scheduled to work as of one day prior to their shift and the actual number of hours they worked on the day of their shift.

Workers at these small retail and food businesses face considerable schedule volatility while on the job. On average, the difference per day between how much a worker was scheduled to work and how much they actually worked is around 1.3 hours. This accounts for scheduling errors in either direction; either workers are asked to work more than their initially planned hours for a day, or they work fewer hours than planned for. Both offer scheduling challenges to workers; although many in these jobs want more hours in order to earn more, it could be difficult to plan for things such as childcare or household care if working extra time at the last minute (Schneider and Harknett 2019). On the other hand, working fewer hours than expecting means less take-home income than expected with possible difficulty finding substitute work at short notice.

Figure 3 displays this distribution of differences in scheduling inaccuracy. The majority of scheduling errors skew negative, with employees working fewer hours than scheduled. Another source of uncertainty arises for workers attempting to predict which days of the week they will work. Although workers typically work only 3-4 days per week, which days they work are far from certain. Figure 4 shows that most employees work on 6 different days of the week throughout the course of a month, often working 7 different days. This again presents challenges to workers who may wish to establish regular routines.

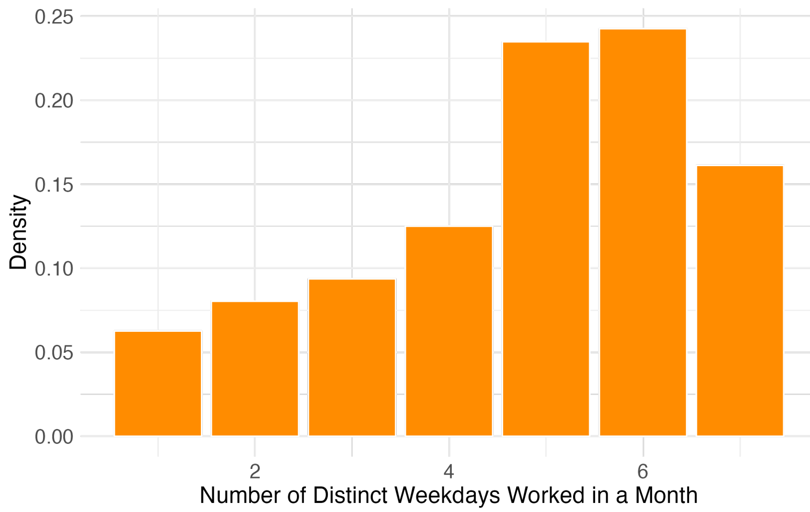
Figure 3: Difference between scheduled and worked hours



Notes: This figure shows the distribution of the difference between the day-ahead scheduled hours and the resulting worked hours. Most deviations are small, but skew negative: employees are typically more likely to be scheduled for more hours than they actually work. As these differences are between the day-ahead schedule and the day-of hours worked, this captures last-minute shift changes.

This irregular nature of this shift work has implications for the predictability of worker income as well. While salaried workers can usually predict their monthly take home income quite accurately, the same can often not be said for hourly workers, whose income solely relies

Figure 4: Different weekdays worked per month

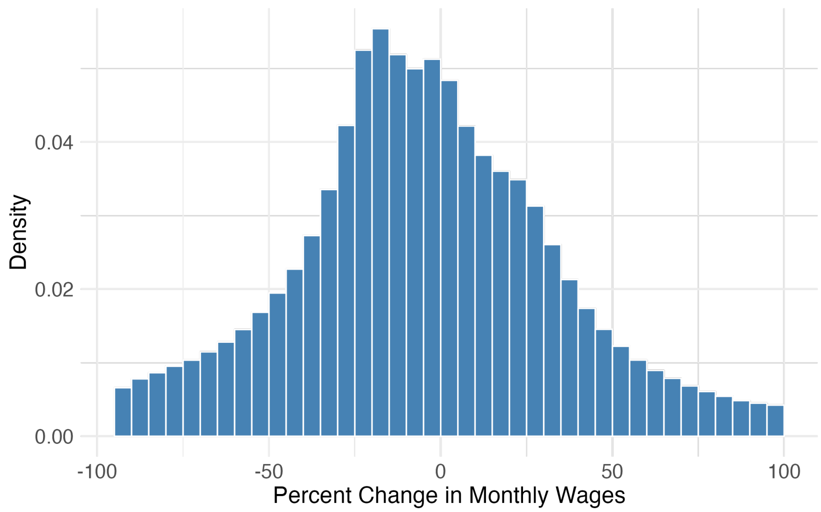


Notes: This figure captures the number of unique days of the week an employee works in a given month. Despite typically only working 3-4 days per week, an employee may work a different distribution of days every week. For example, one week, they may work Tuesday, Thursday, and Friday, while the next they may work Tuesday, Wednesday, and Saturday. This shows that most employees work 5 or 6 different days of the week throughout the month, potentially making it difficult to create regular routines around always working specific days of the week.

on the precise number of hours they work. When these hours are volatile, it becomes more challenging to predict resulting take-home income. Figure 5 shows that a significant number of workers face drastic swings in their incomes month-to-month.

Both hours worked and baseline volatility vary significantly across employees, and are highly correlated with their wage rates and how long they've been at their job. Typically, workers with the longest tenure work the most hours and earn the highest hourly wage rate. This is consistent with workers in these industries regularly reporting wanting more hours than usually given, and the common practice of rewarding more tenured or experienced workers with better hours and more shift opportunities (Lu et al. 2022). More shifts would be a positive for many workers, and a premium afforded to the longest-serving employees. Table 2 shows that as workers stay at an establishment for longer periods of time, their hourly wage increases as do their hours worked per week. However, their volatility does not, as the coefficient of variation in hours worked per week declines with employee tenure. Similar patterns can be seen when observing workers earning above or below the median wage for their given state and industry. Figure 6 depicts how higher earners typically work more hours per week, while figure 7 shows the coefficient of variation consistently higher for the group of lower earners. In addition, figure 8 shows that the higher-paid workers typically work more hours relative to their initially scheduled hours, while lower-paid workers typically work fewer hours than scheduled.

Figure 5: Percent change in income month-to-month



Notes: This figure depicts the distribution of percent changes to an employee's income month-to-month. Most employees experience some variation in their income level, which can make budgeting for monthly expenses or qualifying for government programs with work requirements difficult.

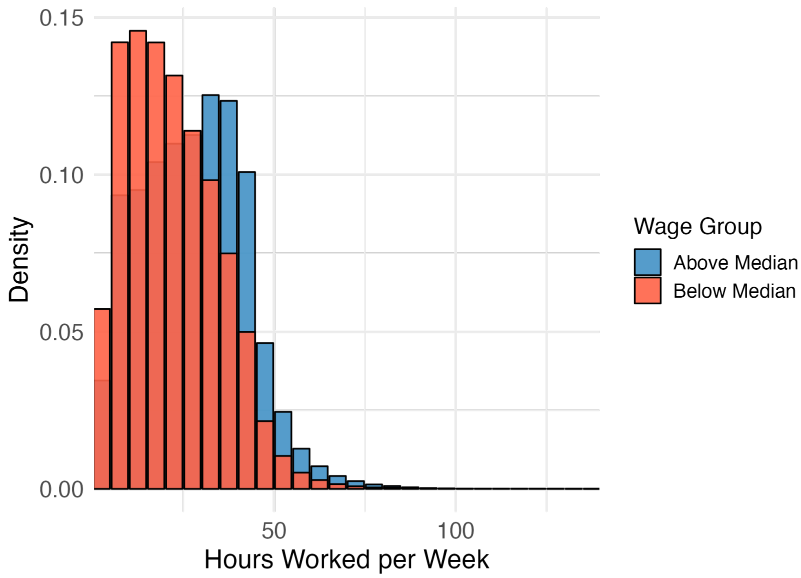
This indicates that schedule predictability moves with wages and tenure, rather than the most volatile workers experiencing higher compensation to make up for this disamenity.

Table 2: Selected Summary Statistics by Tenure (months)

Metric	0-3	3-6	6-12	12+
Hours Worked per Week	20.480	22.120	23.250	25.290
Hourly Wage	10.820	11.060	11.310	11.900
Abs. Diff. Hours Worked vs Scheduled per Week	1.390	1.280	1.250	1.270
Coefficient of Variation of Hours Worked per Week	0.667	0.642	0.627	0.597

Notes: This table summarizes employee-level data by tenure at an establishment in months. Highest-tenure workers tend to earn the highest wages and work the most number of hours per week. Least tenured workers have higher differences between the number of hours they were scheduled to work as of one day prior to a shift and the hours they actually worked on the day of that shift. They also have higher coefficients of variation in weekly hours worked.

Figure 6: Hours worked per week by wage group



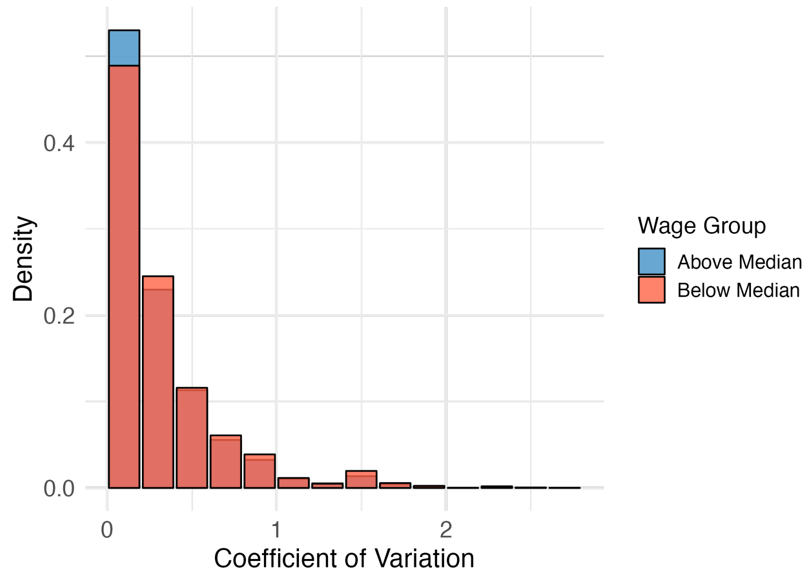
Notes: Employees who earn above the median wage at their place of employment typically also work more hours per week, with many working above the threshold for part-time employment (35 hours per week).

4.2 Minimum wage data

I pair this rich set of data on worker wages, hours, and volatility by industry and tenure with state-level minimum wage data. I rely on Vaghul and Zipperer (2022) for data on minimum wages, a database describing historical state and sub-state minimum wage increases from 1974 through 2022. To determine which increases to study, I follow the methodology outlined in Cengiz et al. (2019a). As mentioned previously, although the federal minimum wage remains at $7.25 per, over half of states have imposed their own minimum wages. Several states introduced or increased these state-level minimum wages over my sample period, serving as possible candidates for examination of the effects of increases. However, several of these increases were small (below $1 per hour), pegged to inflation, or following several consecutive years of steady large minimum wage increases, making them unable to be used as shocks to the labor market.

Therefore, in order to focus on solely large, unique increases, I narrow my scope to study just increases at the state level occurring between 2017 and 2022 that increased the minimum wage by more than $1. I further restrict valid increases to those that were not preceded by such large increases in at least the two years prior. If two such increases occurred in the same state over the time period, I use only the first hike as a shock. This leaves 8 shocks in as many

Figure 7: CV of hours worked per week by wage group



Notes: Despite employees earning above the median wage typically working more hours per week, their hours tend to be more stable. This figure depicts the coefficient of variation of weekly hours worked for those above and below the median wage at their place of business. This implies that when adjusting for total hours worked, the deviation of hours is higher for the lowest-paid workers at an establishment.

Figure 8: Difference between scheduled and worked hours by wage group

Notes: This figure shows the distribution of the difference between the day-ahead scheduled hours and the resulting worked hours, for those working above and below the median wage at their place of business. The lowest-paid employees are typically more likely to be scheduled for more hours than they actually work, while the highest-paid employees tend to work more hours than they were scheduled to as of the day before a shift.

states to serve as my treatment group.[2]

Table 3 displays job characteristics across workers in the treatment and control groups, prior to a minimum wage hike. Hours worked both per week and per day are similar across groups, as are the rates of employee exits. Hourly wage rates and total wages typically earned per worker per day are slightly higher in the control group. The control group consistently has lower measures of last-minute schedule changes. The difference between hours scheduled to work as of one day prior to a shift and hours worked on the day of the shift are consistently more negative per day and per week for those in the treatment group, indicating that overall, these workers tend to be over-scheduled relative to the actual needs on the day-of their shift. They tend to also have more days in which they were scheduled to work and then do not work at all, as represented in the days worked minute the days scheduled to work. The coefficient of variation of hours worked during the week is likewise higher for the treatment group. However, when looking at the rolling standard deviation of hours worked per week and the rolling autocorrelation of hours worked per week, or how similar hours worked per week in a given month are for each worker, values are largely similar.

Table 3: Summary Statistics by Treatment Group

Variable	Control	Treated
Hours Worked (Weekly)	24.32	24.13
Hours Worked (Daily)	6.65	6.71
Total Wages (Daily)	73.30	67.33
Hourly Wage	10.80	9.87
Exit Rate (Weekly)	0.01	0.01
Hours Diff (Weekly)	-2.23	-2.99
Hours Diff (Daily)	-0.64	-0.83
Days Worked - Scheduled	-0.23	-0.25
CV of Hours Worked	0.30	0.37
Rolling SD of Hours	3.74	3.53
Rolling Autocorrelation of Hours	-0.25	-0.25

Notes: This table summarizes employee-level data for workers in establishments in control states versus treated states. Wages and frequency of last-minute shift cancellations tend to be higher for the treated group. Hours worked, exit rates, and week-to-week similarity of hours worked are similar across groups.

4.3 Weather data

I examine the responsiveness of schedules to shocks to consumer demand by studying effects from weather anomalies on workers' schedules. To do so, I use county-level, daily maxi-

[2]See appendix Figure A2 for map of qualifying states.

mum and minimum temperature and precipitation data, originally created by PRISM Climate Group (2014) and processed using a balanced panel of weather stations by Schlenker (2024). I pair this data by day and county with the establishment scheduling data found in Homebase in order to examine how daily weather impacts hours worked, take-home income, and schedule volatility of workers employed in the food and drink and retail sectors.

4.4 Unemployment data

In order to approximate overall health of the labor market, I use the Bureau of Labor Statistics' monthly measure of unemployment at the county level, available through the Local Area Unemployment Statistics (U.S. Bureau of Labor Statistics 2025a). This provides a measure of how challenging it could be for a worker to find alternate work arrangements, with a high unemployment rate representing a more competitive market for employees searching for work. I define levels of unemployment in county-level quartiles, with the lowest quartile representing low unemployment (below 3.3%), the middle 50% representing medium unemployment, and the highest 25% representing high unemployment levels (above 5.7%).

5 Empirical strategy

Following Cengiz et al. (2019a), who looked at employment effects of minimum wage increases, I use a stacked event study design. I exploit large increases to state-level minimum wages to estimate the causal impacts of these wage increases on schedule volatility, among other worker outcomes, at the weekly level. In this manner I am able to test the theoretical implications of the models presented in Section 3: that a minimum wage increase will increase the baseline level of volatility for hourly workers and the rate of volatility change in response to shocks. I estimate several versions of Equation 13.

$$\mathrm{Y}_{it} = \sum_{k \neq -2} \beta_k \cdot \mathbb{I}(\text{weeks\_since\_hike} = k) + \alpha_i + \gamma_{m \times s} + \delta_{f \times y} + \theta_d + \varepsilon_{it} \tag{13}$$

Here, Y_{it} represents the outcome of interest for employee i at time t. The main explanatory variable is represented by β_k, an indicator variable for the weeks since the wage hike was implemented. I include employee, month by industry, state by year, week of year, and hike fixed effects. This controls for seasonal effects throughout the year. I cluster standard errors at the state level. I compare treated states before and after the minimum wage hike to my set of controlled states, which includes those states never treated with a substantial hike throughout the period and those not-yet-treated states whose hike occurs after this window.

My outcomes of interest include average hourly wage rate, average wages earned per day and per week, hours worked per day and per week, and likelihood of exit from the establishment in a given week. Related to volatility, I examine effects on the average difference between the hours an employee was scheduled to work on a given day and the hours they actually worked on that day, and the total of this 'scheduling inaccuracy' per week. These measures get at the overall time volatility a worker experiences from unforeseen schedule adjustments and last minute changes. I additionally measure the impacts on the rolling autocorrelation of weekly hours over the previous month, and the rolling standard deviation of weekly hours. Taken together, these measures represent a worker's overall regularity of schedule and their ability to predict the total hours they will work per week, and subsequently, their expected weekly income.

I then further estimate all of these measures across tenure of worker at the time of the wage hike in order to observe whether the newest workers are exposed to greater changes in schedule volatility following the imposition of a wage hike, compared to those that have been at businesses longer, and typically have lower levels of volatility to start with, as seen in Table 2.

I additionally estimate these effects by county-level unemployment in the month that the shock occurs. This enables me to observe if schedule volatility changes are exacerbated in counties where unemployment is high. In these instances, steep competition for employment would lead workers to have a lower reservation wage and therefore accept a higher level of volatility increase.

Next, I estimate the effects of weather on hours worked and schedule volatility using Equation 14. Here, Y_{it} represents the outcome of interest for employee i. The coefficient β_i represents the effect for employee i on this outcome of a day being in one of 10 temperature bins (split into 10° groups), and θ_i represents the effect of a day being in one of 7 precipitation bins (divided by 0.5 inches of rain). I include worker fixed effects γ_i and county by month by industry fixed effects δ_{cmf}.

$$Y_i = \alpha + \sum_{i=1}^{10} \beta_i \cdot \text{tempdays}_i + \sum_{i=1}^{7} \theta_i \cdot \text{precipdays}_i + \gamma_{\text{i}} + \delta_{\text{cmf}} + \epsilon_i \tag{14}$$

I compare outcomes to the scenarios in which temperatures lie between 60 and 70° F and there is no precipitation. These estimates provide an understanding of how weather outside of the ideal temperature or precipitation ranges change the hours an employee works on that day and their schedule inaccuracy for that day.

Finally, I combine these two methodologies in order to estimate the extent to which weather-induced schedule volatility is exacerbated by the introduction of a minimum wage hike. I do this in order to further provide evidence supporting the notion that risk is pushed off to workers as a way that firms engage in rent-seeking after they are required to pay a higher wage. While the minimum wage increases serve as shocks to the labor costs of firms, it can be difficult to pinpoint exogenous shocks to a non-wage amenity. Bad weather days serve as such a shock, imposing a higher cost to firms of providing a smooth and predictable schedule to workers, as it impacts their need for labor. When negative weather days dampen consumer demand, firms run the risk of over-hiring labor if they do not adjust schedules in response. This exercise therefore illustrates the real-time decision making firms undertake to balance the tradeoff between imposing a non-wage disamenity onto workers or paying the cost of their higher labor. I estimate Equation 15, which is identical to Equation 14, but includes the indicator variable 'post' for whether or not an employee is working after the introduction of the minimum wage hike.

$$Y_i = \alpha + \sum_{i=1}^{10} \beta_i \cdot \text{tempdays}_i \cdot \text{post}_i + \sum_{i=1}^{7} \theta_i \cdot \text{precipdays}_i \cdot \text{post}_i + \gamma_{\text{i}} + \delta_{\text{cmf}} + \epsilon_i \tag{15}$$

The coefficients of interest therefore capture the differences in how weather affects schedule volatility before and after the cost of over-hiring workers goes up.

6 Results

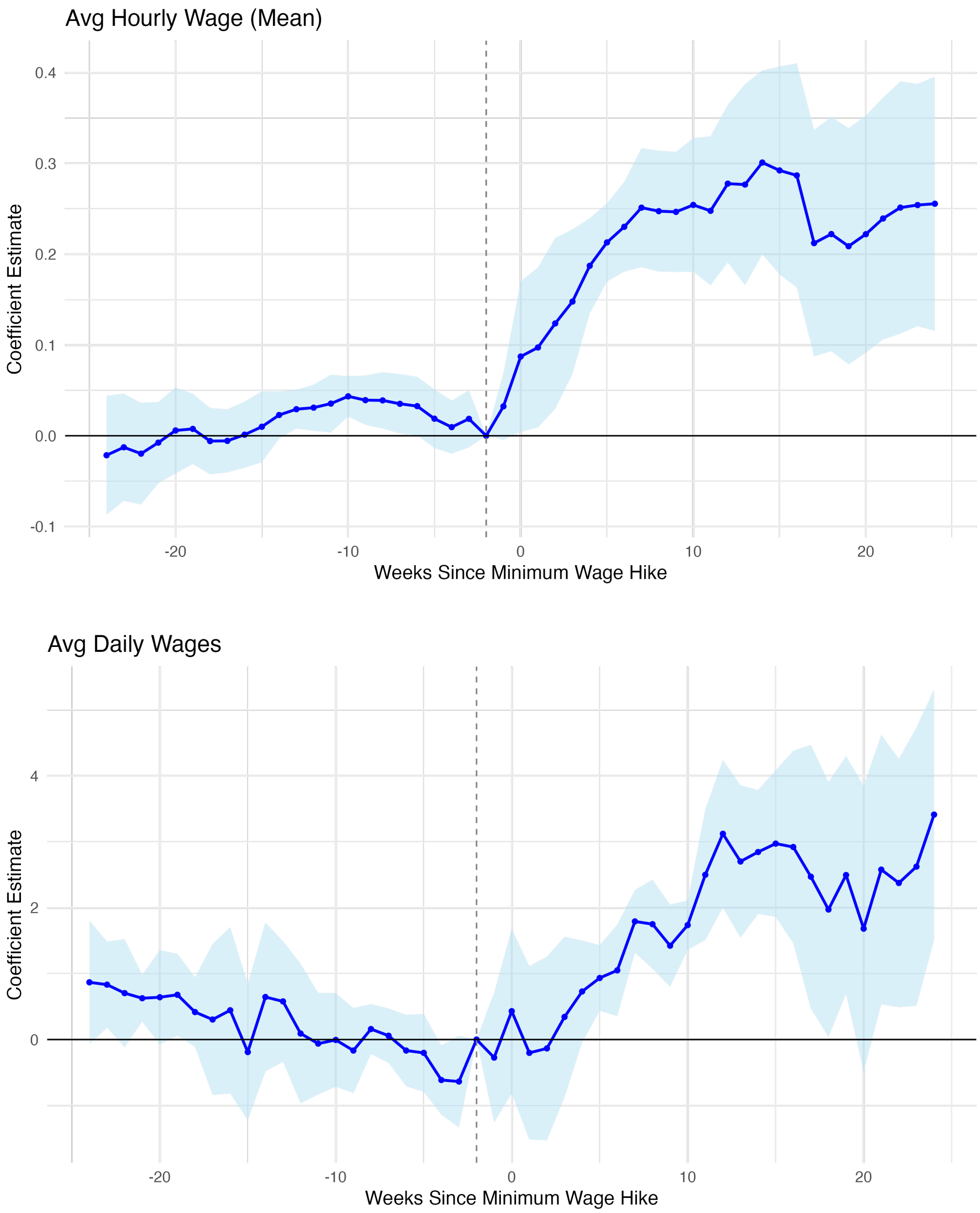
I present results on the effects of minimum wage increases on the schedule volatility of hourly workers in 6.1, the effects of weather variation on schedule volatility in 6.2, and the interaction of the two in 6.3.

6.1 Minimum wage and volatility

I first show the impacts of a state minimum wage hike on the average hourly wage and daily take-home income of service sector workers in my sample. Figure 9 shows that the minimum wage is highly binding in this context, as so many of the workers in these industries are employed at or slightly above minimum wage. The first plot shows a roughly \$0.3 increase in the average hourly wage among workers after the imposition of a hike.[3] The second plot demonstrates that this is not compensated with fewer hours worked per day; average daily wages rise for workers in the aftermath of a hike by \$2-3.

[3]This is less than the typical \$1 or greater increase as many workers earned above the old minimum wage, but less than the new minimum wage.

Figure 9: Effect on average hourly and daily wages



Notes: Following the onset of a minimum wage hike, employees in treated establishments experienced an average hourly wage increase of roughly $0.25-0.3. This increase in hourly wage was not paired with a decreased in hours worked per day due to firms compensating. Their average daily wages likewise increased by roughly $2-$3.

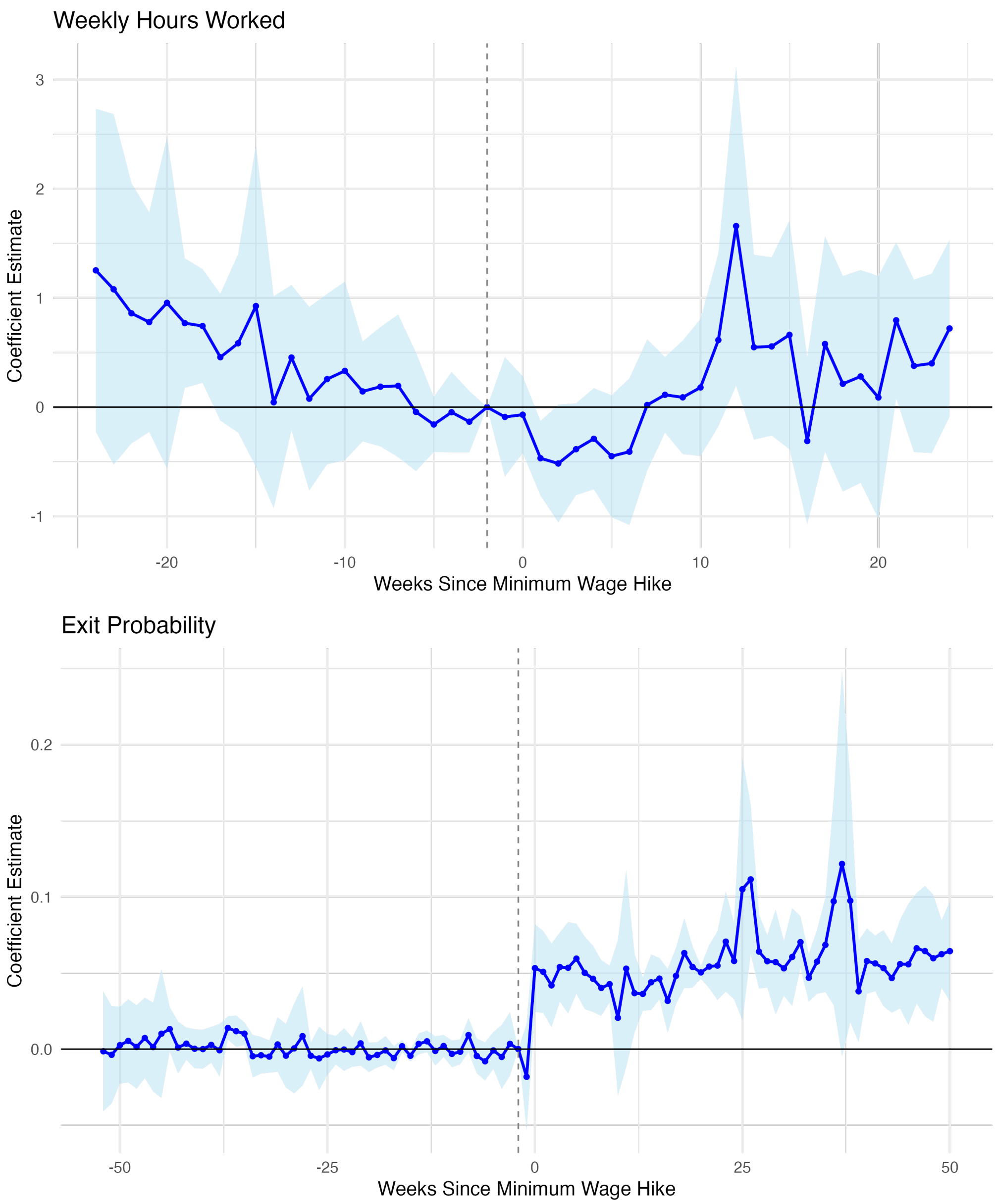
This point is further showcased in Figure 10 displays that there is a lack of evidence for any change in the hours worked per week for employees after a hike is introduced. The second plot shows that there is a small increase in the rate of employees exiting a firm following a hike, by roughly 0.5%. This differs somewhat from the findings in Cengiz et al. (2019b) that employment in low-wage jobs remains steady following a hike. However, this does not capture the equilibrium employment effects, as it only represents exits at small businesses in the sample. Workers who separate from these businesses could find employment at other firms in the area who were more equipped for the hike.

Such results showcase that the minimum wage is relevant and binding in this context, bringing up workers' hourly an daily earnings, but without leading to a drop in their amount worked. There is, however, a modest increase in separations from firms, although it is unclear whether this is due to firms cutting employment in response to the increased cost of labor, or due to employee choice in response to other margins of compensation that change along with the minimum wage. The lack of negative effect on hours, however, aligns with the theoretical grounding that employers can adjust along margins other than employment in order to recoup costs introduced by a minimum wage.

Figure 11 displays results indicating that employers do indeed adjust along the margin of schedule volatility. The first plot reflects changes in the absolute daily difference between hours worked and and hours scheduled. This total scheduling inaccuracy increases in the weeks following the hike, leveling off at an increase of around 0.1 of an hour, or six minutes. The second plot similarly presents the net difference between hours worked and hours scheduled per week. This value grows more negative, leveling off around a decrease of 0.75 of an hour, or 45 minutes. This indicates that after a hike, workers consistently are scheduled more hours than they end up working, widening this negative gap. This trend represents a scheduling overestimate, with workers more commonly being overscheduled relative to the hours they actually end up working. This is an important measure of volatility, as if a worker were scheduled for a certain number of hours, that means they would need to leave these hours open as available to work, forgoing other means of earning income during these times. A widening gap entails that their gap between expected earnings and realized earnings also increases, with little possibility of replacing lost hours given the last-minute nature of the schedule adjustment.

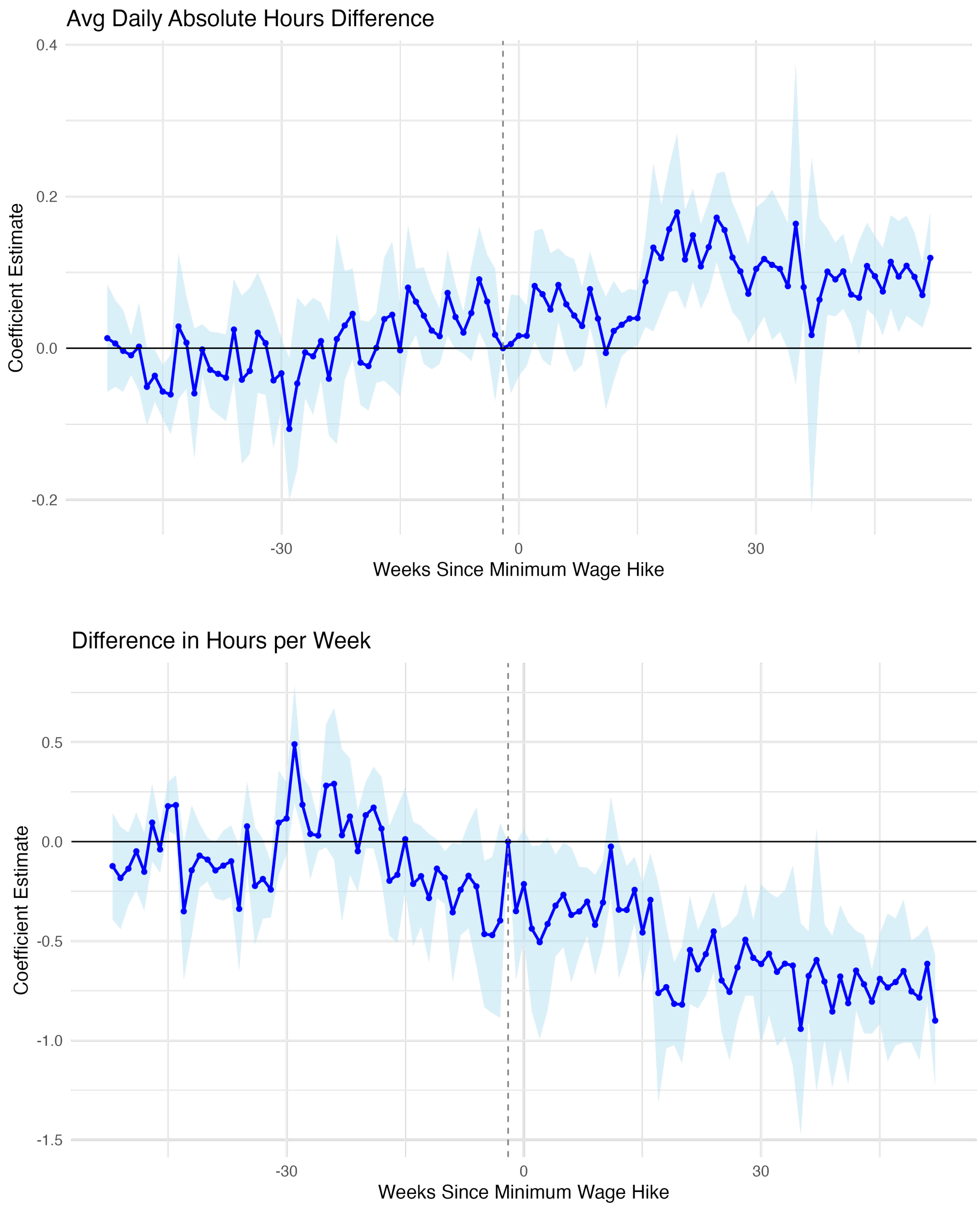
A different way of thinking about schedule volatility is to consider how predictable an employee's schedule is week-to-week. I represent this volatility in two ways, showing the effects in Figure 12. The first plot depicts the change in the the 4-week rolling average of week-to-week autocorrelation. This captures in the past month, how similar a worker's hours per week this week are from last week's hours per week. Following the minimum wage hike,

Figure 10: Effect on weekly hours worked and probability of exit



Notes: Following the onset of a minimum wage hike, employees did not see a reduction in their average hours worked for week, indicating that businesses did not compensate higher wages with hiring workers for fewer hours. However, exit rates increased and stabilized at a rate of 0.5% higher than prior to the hike.

Figure 11: Effect on scheduling inaccuracy



Notes: Following the onset of a minimum wage hike, the absolute difference between the hours an employee was scheduled to work as of one day before a shift and the actual hours worked on the day of the shift increase by about 1/10th of an hour. The net difference per week of this scheduling inaccuracy becomes relatively more negative, with total hours scheduled to work being greater than hours actually worked by an additional 45 minutes. This represents the change towards overscheduling workers more frequently, and then cutting their planned hours on the realized day.

a sharp decline in this predictability is observed, indicating worker schedules becoming less regular. This drop is equivalent to a roughly 20% lower similarity between week to week hours. Similarly, the plot below shows the 4-week rolling standard deviation of weekly hours worked. The steep increase following the minimum wage hike indicates again that the variation in weekly hours worked increases for workers following a minimum wage hike, by nearly 4 hours. This is about a 100% increase in standard deviation of weekly hours over a month.

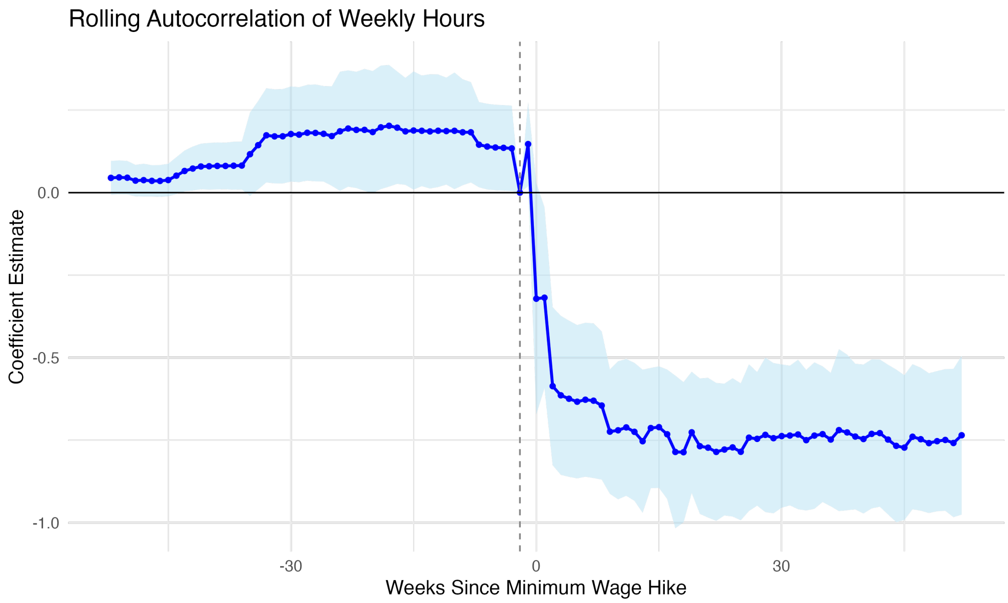
Taken together, Figure 11 and Figure 12 paint a picture of how firms adjust on the margin of schedule volatility to compensate for increased wages. This volatility impacts workers in the short term, increasing the likelihood that they will face shift changes or cancellations at the last minute. This particular type of unpredictability presents challenges for workers on the day-of a given shift; if they expected to work 7 hours, for example, and later find out they will only work 5, they may have already paid for child care for the full shift, or be unable to find a different sort of work to compensate for those 2 hours they held open, but for which they did not garner wages. However, these trends also depict impacts to more overall volatility, making it harder for workers to estimate the amount that they can expect to work in any given week. As workers are not paid for hours they do not work, this also therefore impacts their ability to predict how much take-home income they will earn in a given week. This income volatility can impact employees' capacity to budget, plan expenses, or even estimate the amount of government benefits they may be eligible for in a given month, since eligibility is linked to certain income thresholds.[4]

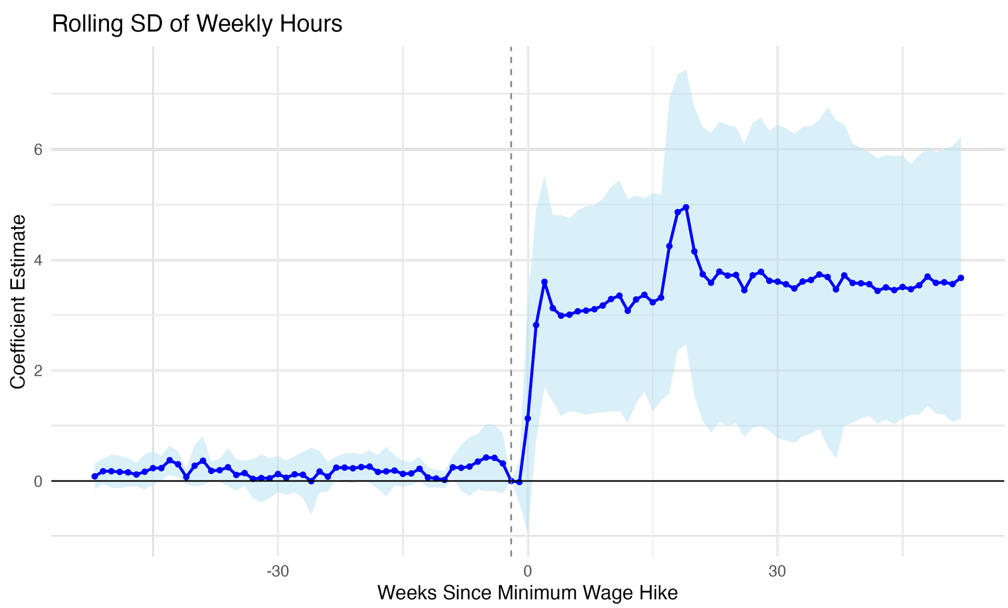
6.1.1 Heterogeneity

To further investigate these dynamics, I examine heterogeneity by tenure of worker at the time of the hike and unemployment rate of the county at the time of the hike. As discussed in Section 4, tenure is highly correlated with worker pay, hours worked, and baseline volatility. Workers at a business for longer typically receive more favorable hours and access to more hours if they so wish (as indicated by typically working more hours than scheduled). As such, it is uncertain if they would be expected to bare the brunt of these side-effects of minimum wage increases, or if volatility would be pushed off to lower-tenured employees still 'earning their stripes' with a company. Figure 13 shows that exits are driven by workers that have been employed at a given location for 6 months or less, perhaps indicating the use of a 'last in, first out' policy. On the other hand, Figure **??** displays that volatility increases appear to impact all workers equally, with the autocorrelation of weekly hours decreasing and the standard deviation of weekly hours increasing approximately the same amounts for all

[4]These results are robust to: dropping 2020 from the sample due to the Covid-19 pandemic and holding the panel of workers constant (Figure A3, Figure A4)

Figure 12: Effect on autocorrelation and standard deviation of weekly hours





Notes: Following the onset of a minimum wage hike, similarity of hours week-to-week declines. Rolling autocorrelation of the previous 4 weeks' hours worked decreases by roughly 20%. The rolling standard deviation of hours worked over the previous 4 weeks increases, adding an additional roughly 4 hours of unpredictability.

employees. Volatility fails to be driven by newest, lowest-paid employees with already high levels of volatility.

I additionally examine the effects on volatility by unemployment at the time of the imposed wage hike. Unemployment by month at the county level can capture how hard it would be for an employee to find alternate work if they exited from their current job, reflecting the overall state of the local economy. When unemployment rates are high, a worker could face more competition from others out of work when searching for a job, and thus have a higher tolerance for volatility in their work place. Meanwhile, Figure 14 suggests that labor market slack does influence volatility increases as expected. Week-to-week autocorrelation falls the least for workers in the counties with the lowest unemployment rates in the month of the hike. The standard deviation of weekly hours, however, increases the most for those employees in the highest unemployment counties in the month of the hike. Although statistically insignificant, this suggests that more competition among workers is correlated with higher increases in volatility. If it is more difficult for an employee to find work elsewhere, they may endure more volatility to avoid searching for a new job.

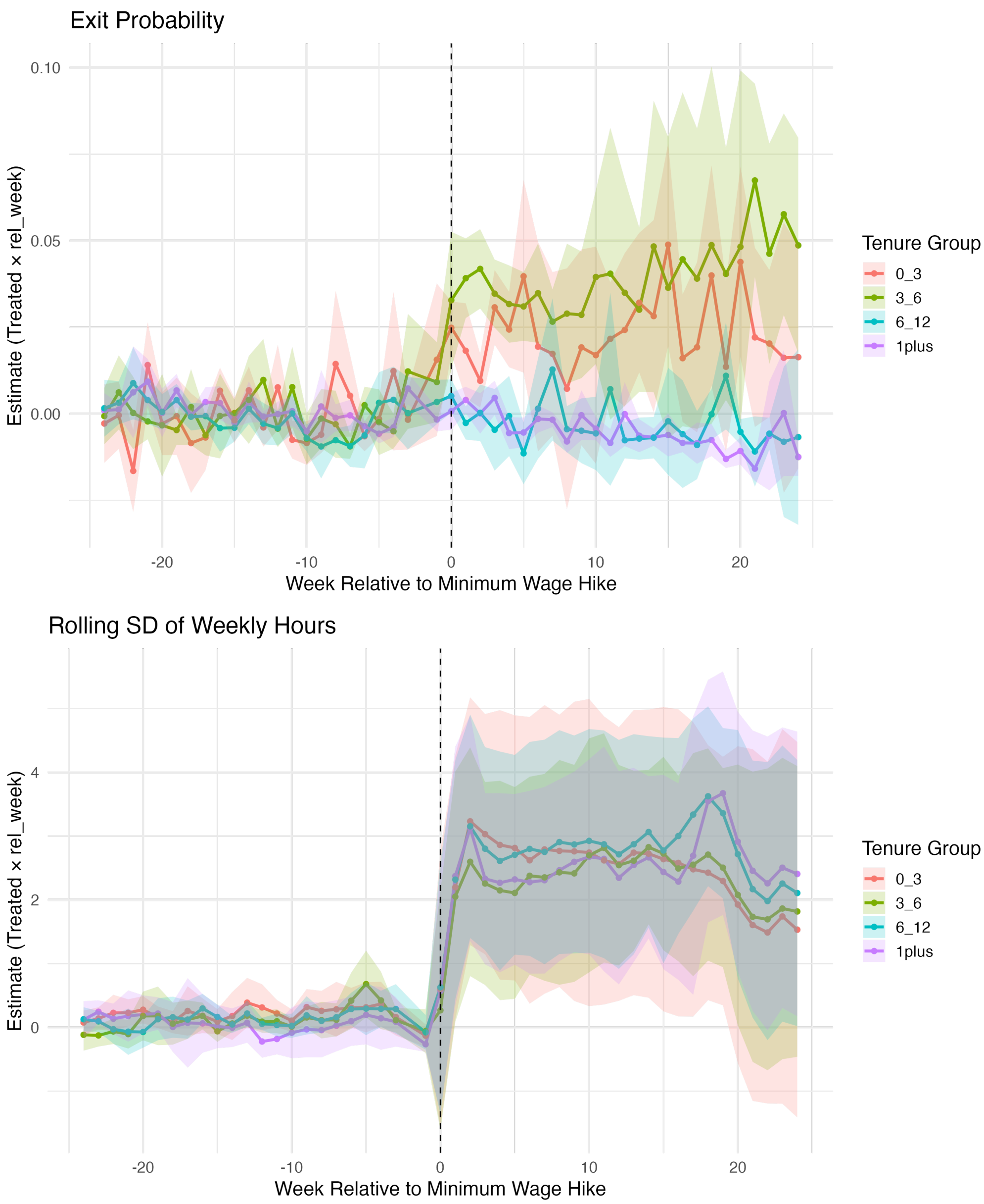
6.2 Weather and volatility

It is not immediately obvious how increasing this schedule volatility is profit-maximizing for firms following a minimum wage hike. To provide an illustrative example of the mechanics that may be occurring, I provide further empirical evidence for the theory presented in Section 3. There, I provide the example of bad weather days introducing risk to firms by increasing the uncertainty around expectations in consumer demand. As these are industries that rely heavily on consumers, firms may wish to hire only as much labor as they need on a particular day, given how many customers they expect to need to serve.

In this section, I outline how weather outside of the ideal ranges offers a shock to the scheduling needs of employers. As discussed previously, there is a large body of literature outlining the ways in which weather impacts consumer behavior in retail and food sectors; this presents results on the flip side of that coin, on the workers in these industries that are dependent on customers.

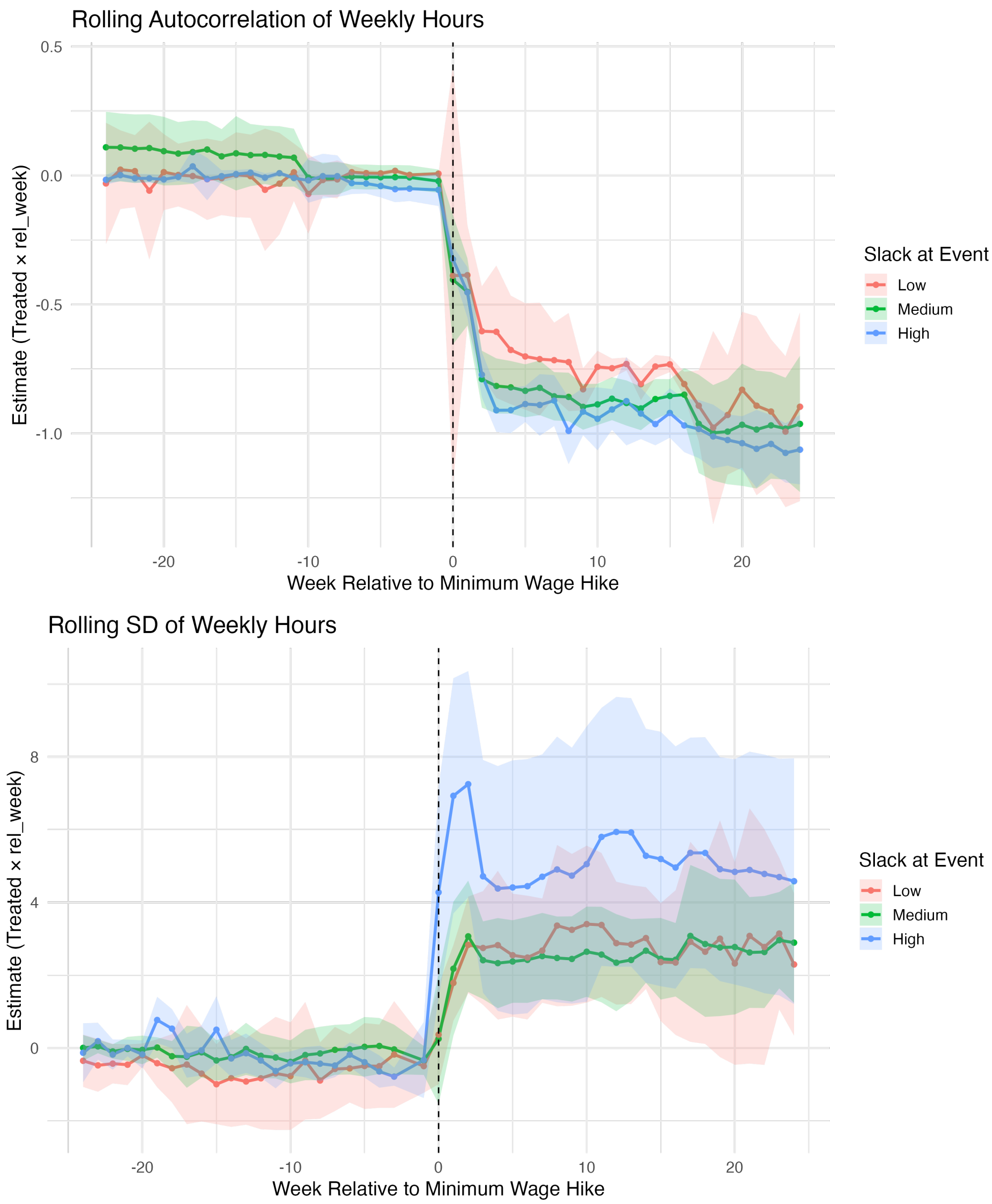
Figure 15 depicts the hours worked by employees in these service sectors across the spectrum of temperatures. Employees work the highest number of hours during days that lie in the range of 50-70°, while hours drop off when temperatures are the hottest or the coldest. These results include county by month by industry fixed effects, day-of-week fixed effects, as well as worker fixed-effects. This means that seasonality is not driving these results, as comparisons are within-month. Similarly, hours worked drop with any amount of precipitation above 0

Figure 13: Exit and week-to-week similarity by tenure



Notes: Following the onset of a minimum wage hike, employee exits were driven by the employees that were the lowest-tenured at the time of the hike, while exit rates remained fairly constant for those that had been at an establishment for 6 months or more. Week-to-week volatility, however, increased equally for employees across all tenure groups, indicating that preferential treatment in terms of schedule stability was not provided to the most-tenured employees.

Figure 14: Week-to-week predictability by slack



Notes: Following the onset of a minimum wage hike, autocorrelation of week-to-week hours over employees' previous 4 weeks decreased the least for employees in counties with the lowest levels of slack, as measured by county-month level unemployment. Standard deviation of weekly hours over employees' previous 4 weeks increased the most for counties with the highest level of slack. This indicates that in the counties with the strongest labor markets, and least competition among workers, volatility did not increase as much following the increase in the labor cost floor.

inches, falling steeply each day that has a half-inch more rainfall.

Figure 16, meanwhile, shows that it is not just hours worked that is altered by suboptimal weather. These figures depict how the absolute difference between hours scheduled to work and hours actually worked increases outside of the optimal temperature and precipitation bins. Hot and cold temperatures, or any level of precipitation, lead to increases in schedule inaccuracy for the worker. An additional day between 90-100° increases scheduling inaccuracy by 1.3% above baseline, while an additional day below 30° increases schedule inaccuracy between 10-15%. A small amount of precipitation increases schedule inaccuracy by 4-5%, while heavy rainfall days result in 10-38% jumps in inaccuracy.[5] This aligns with the notion that on lower-than-optimal consumer demand days, risk of slow business is pushed off to workers, leading to shift cancellations or decreases, often at the last-minute.

6.3 Weather-induced schedule shocks and minimum wage

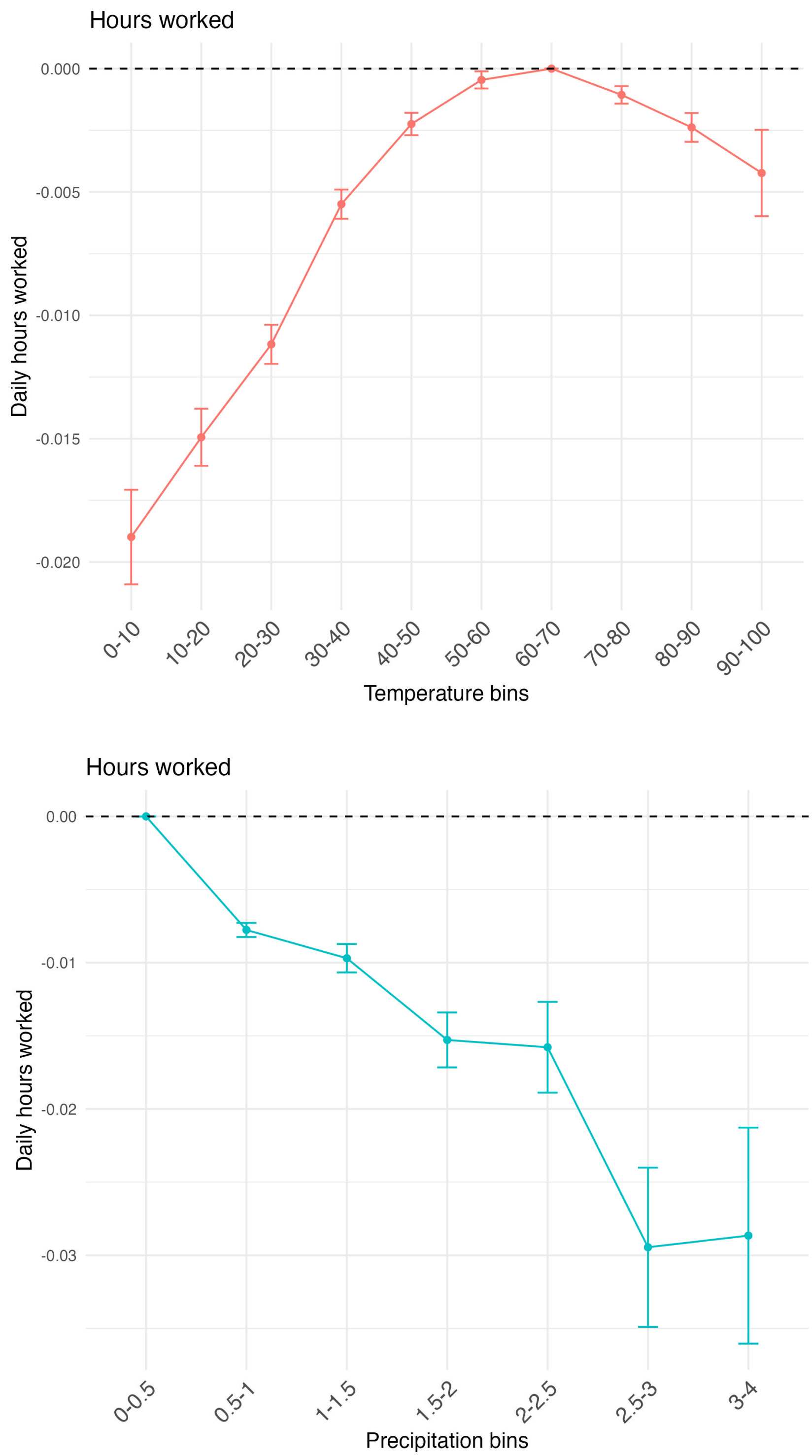
While the results presented illustrate that volatility does increase following a minimum wage hike, it is not immediately evident why this is cost-saving behavior for firms. I use the examples of bad-weather days inducing schedule volatility to outline how firms may last-minute adjust labor in order to recuperate costs imposed by a minimum wage, resulting in higher volatility.

The risk-sharing behavior shown to occur on bad-weather days should be exacerbated following a minimum wage hike. An increase in the minimum wage means that the cost of labor increases. Before a minimum wage, it may have been cost effective for firms to maintain employee schedule regularity on slow business days in order to keep employees satisfied with lower wages. After the imposition of a minimum wage, however, the cost of keeping on a worker when the consumer demand on a day does not warrant it increases. Additionally, a worker may be willing to take on more volatility in exchange for receiving a higher wage when they do work. Therefore, on a slow business day resulting from lower-than-usual consumer demand, a firm paying higher minimum wages may be more likely to slash hours for workers no longer expected to be needed in order to compensate for higher wages.

As the model in Section 3 theorizes, the risk-sharing behavior shown to occur on bad-weather days should be exacerbated following a minimum wage hike. An increase in the minimum wage means that the cost of labor increases. Before a minimum wage, it may have been cost effective for firms to maintain employee schedule regularity on slow business days in order to keep employees satisfied with lower wages. After the imposition of a minimum wage, however, the cost of keeping on a worker when the consumer demand on a day does not warrant it increases. Additionally, a worker may be willing to take on more volatility

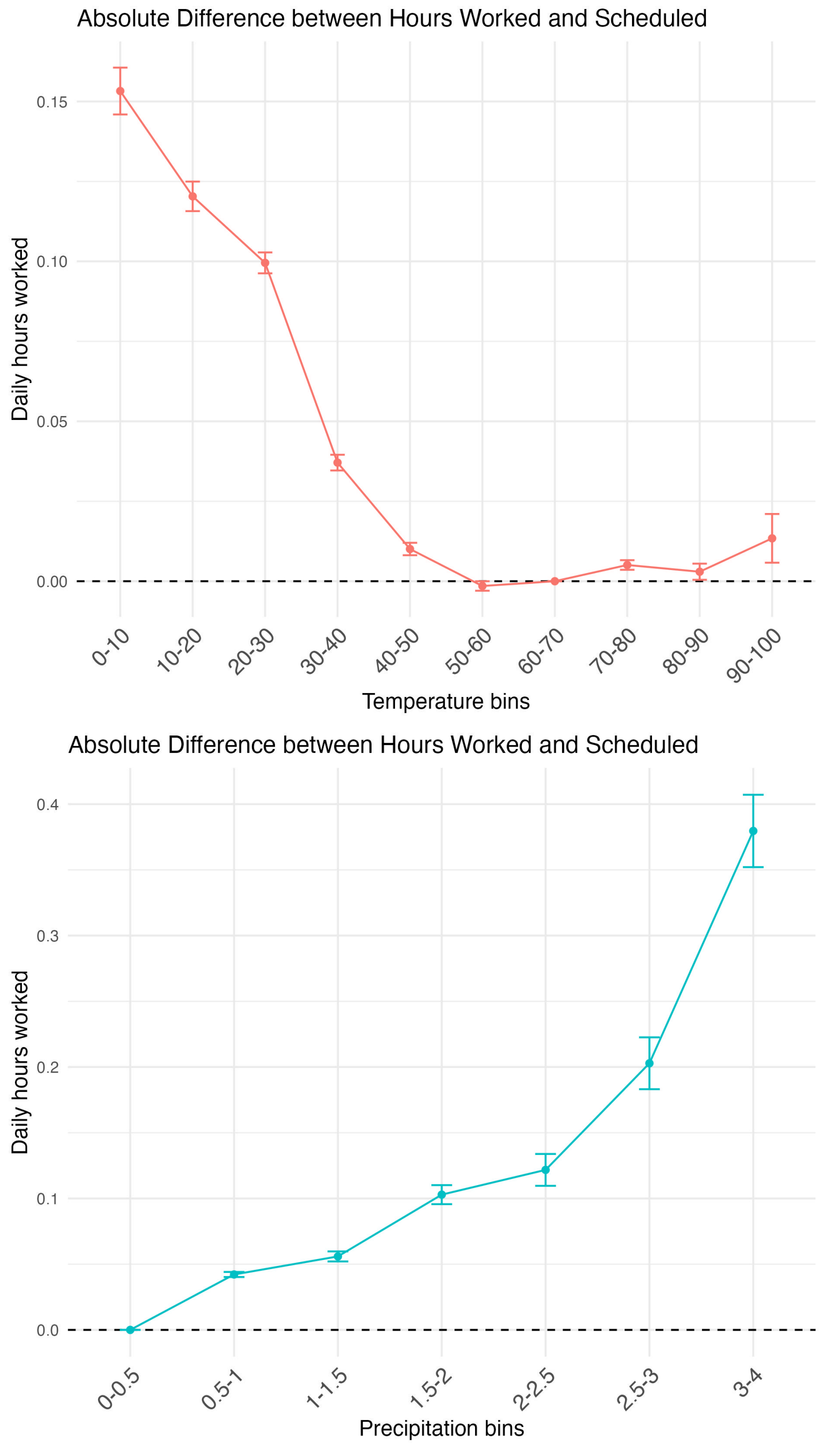
[5]For how these vary by climatic region, see Figure A5 and Figure A6

Figure 15: Weather and hours worked



Notes: Hours worked per day is highest in optimal temperature bins of 50-70° and decreases in increasingly hot or cold temperatures. Hours worked per day is highest on days without precipitation, and decreases with any level of precipitation.

Figure 16: Weather and schedule accuracy



Notes: The absolute difference between hours scheduled as of one day prior to a shift and hours worked on the day of the shift is lowest in optimal temperature bins of 50-70° and increases in increasingly hot or cold temperatures. The absolute difference in hours is lowest on days without precipitation, and increases with any level of precipitation.

in exchange for receiving a higher wage when they do work. Therefore, on a slow business day resulting from lower-than-usual consumer demand, a firm paying higher minimum wages may be more likely to slash hours for workers no longer expected to be needed in order to compensate for higher wages, resulting in an increased rate of change of unpredictability in response to shocks.

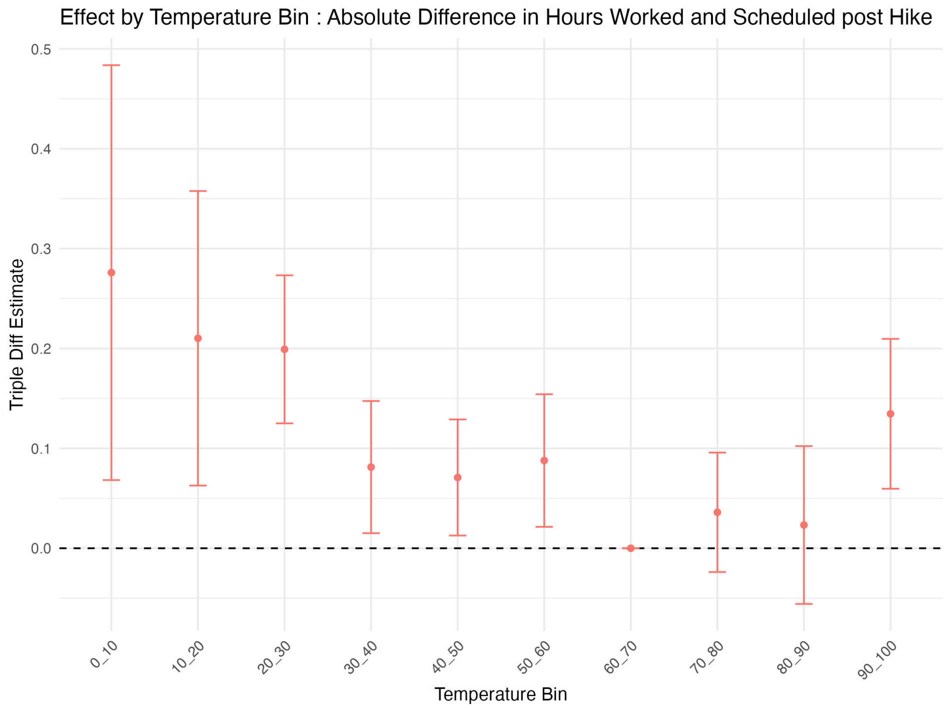
Figure 17 displays the occurrence of precisely this phenomenon, showing how the previously shown effects of weather on schedule inaccuracy are exacerbated in counties for which a large minimum wage hike has been imposed in the last 6 months. Relative to workers in the control group, treated workers experience higher absolute differences between scheduled hours and worked hours at the tails of the temperature distribution, and most of the precipitation distribution. On extreme temperature days that were already likely to results in higher schedule inaccuracy before a hike, workers post hike experience and additional 8-17 more minutes of inaccuracy. On high precipitation days, it adds an additional roughly 5 minutes.

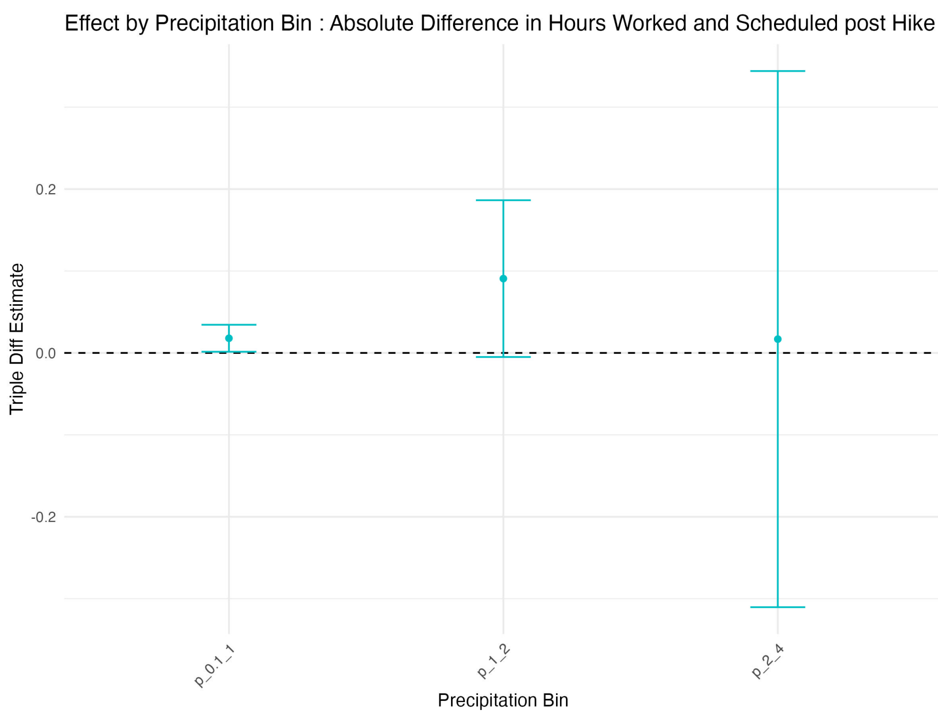
Further illustrating this point, Figure 18 displays the net difference between hours worked and hours scheduled rather than absolute values. The finding that this difference is consistently negative shows the direction of this scheduling inaccuracy-that workers are scheduled for more than they end up working (rather than working more than scheduled) on suboptimal weather days. For extreme temperature days, this value ranges from 8-22 minutes less than scheduled, and around 2-8 minutes less than scheduled for each additional high precipitation day, relative to control groups. This is consistent with the idea that firms hedge the risk of slow consumer demand days by scheduling hours they expect they may need from laborers, and then cutting these hours in the instance of a slow day. This behavior appears to be exacerbated following the imposition of a minimum wage, consistent with the theoretical findings of Section 3.

6.4 Machine Learning Model

While the previous results on changes in schedule accuracy, autocorrelation, and standard deviation of week-to-week hours get at the similarity of a worker's hours in a given month, they do not capture fully how predictable hours are for workers. In this section, I replicate my results by using a simple machine learning model to illustrate the factors contributing to a worker's schedule, and how schedule predictability drops as the cost of labor rises. I take the perspective of a worker attempting to predict their day-ahead scheduled hours. I train a machine learning model on workers in treated and control states, prior to any minimum wage increases, to perform exactly this prediction problem. Using the previous two weeks' scheduled hours, worked hours, weather, wages, tenure, and day-of-week characteristics, this model simulates how a worker would use this information to make an educated guess on their

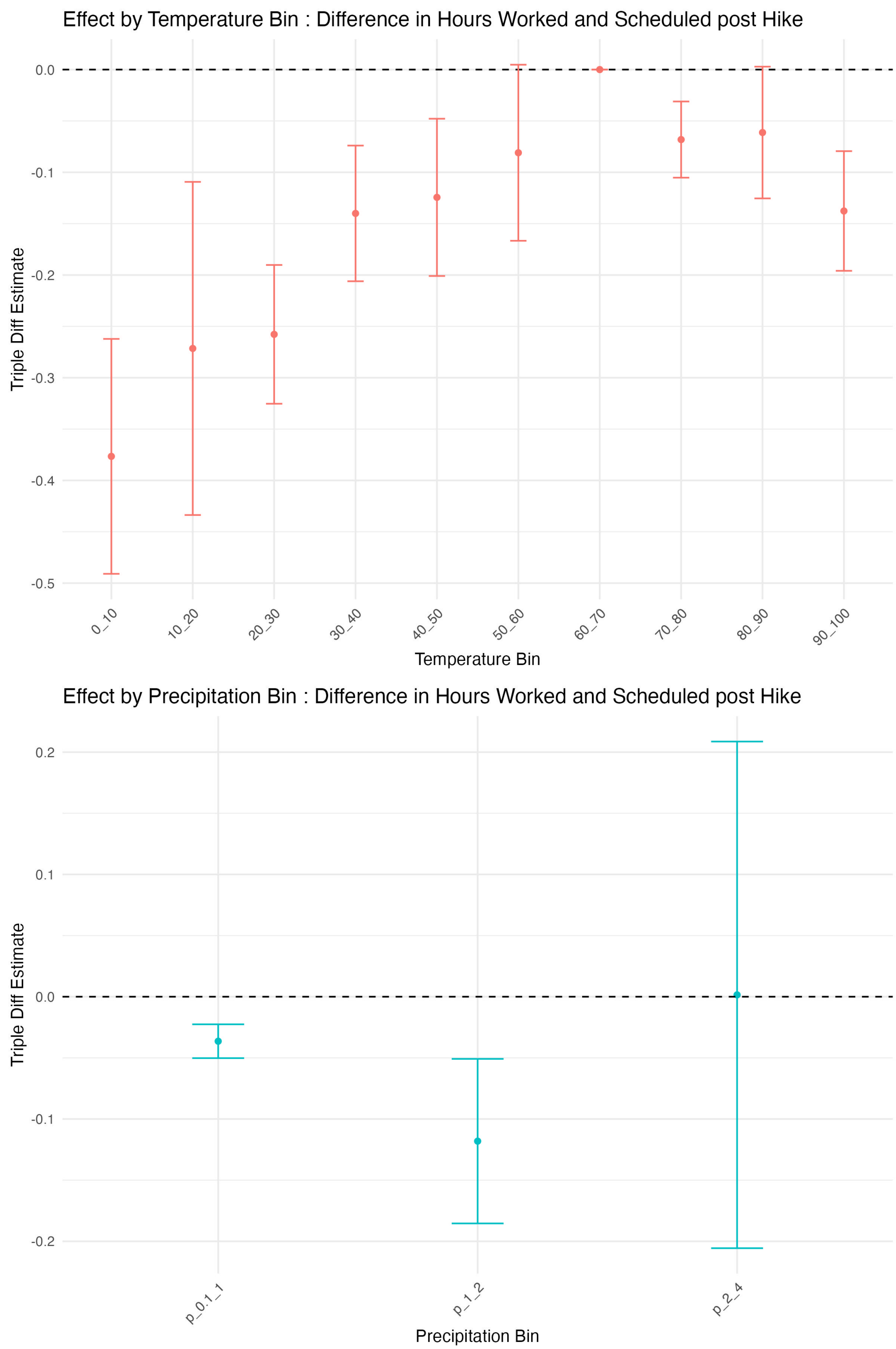
Figure 17: Minimum wage and weather effects: absolute hours difference





Notes: Following the minimum wage hike, the absolute difference between hours scheduled as of one day prior to a shift and hours worked on the day of the shift increase relatively more in treated counties on days with extreme temperatures or any level of precipitation.

Figure 18: Minimum wage and weather effects: net hours difference

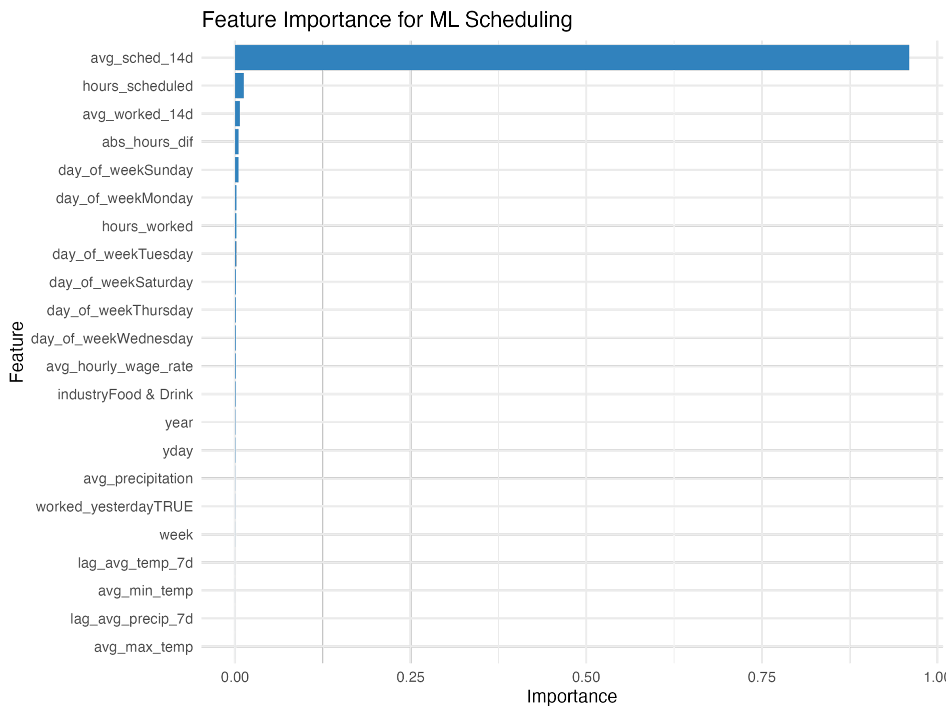


Notes: Following the minimum wage hike, the difference between hours scheduled as of one day prior to a shift and hours worked on the day of the shift increase relatively more in treated counties on days with extreme temperatures or any level of precipitation. This indicates that more frequently in treated counties following a hike, employees worked less than they were scheduled to work on bad weather days.

expected schedule.

The resulting model is accurate to roughly 1.84 hours per day on average, equivalent to roughly 27-28% of typical daily hours worked. Figure 19 shows the weightings placed on the various predictors included. The highest weighting by far is placed on schedule of the prior two weeks, while other important predictors include hours actually worked, how much was scheduled and worked the day prior, and which day of the week it is.

Figure 19: Feature Importance: ML model



Notes: This figure shows the weighting on variables relied on in the machine learning model when predicting the next day's scheduled hours. The average number of hours scheduled per day over the previous 2 weeks are the most predictive, followed by the hours scheduled for today and average hours worked over the past 2 weeks. Also important in the model are the absolute difference between scheduled and worked hours, and which day of the week the scheduled day falls on.

I then use this model to predict scheduled hours post-hike, for treated and control workers separately. Consistent with previous empirical findings, the schedule becomes harder to predict for the ML model following the hike for treated workers. The root mean square error per day is 2.03 hours for untreated and 2.12 hours for the treated group. Assuming an employee works four days per week, this entails schedules being roughly 11 minutes less predictable through the machine learning model per week.

In addition, in the treatment group, the model consistently under predicts hours scheduled, predicting on average 7.20 hours scheduled, when in realization the average is 7.24. In the control group, on the other hand, the mean predicted is 6.92 scheduled hours and the mean actual is 6.9. This is again consistent with firms regularly over-scheduling workers for more than the resultant labor needs in the treated period post hike.

7 Welfare calculations

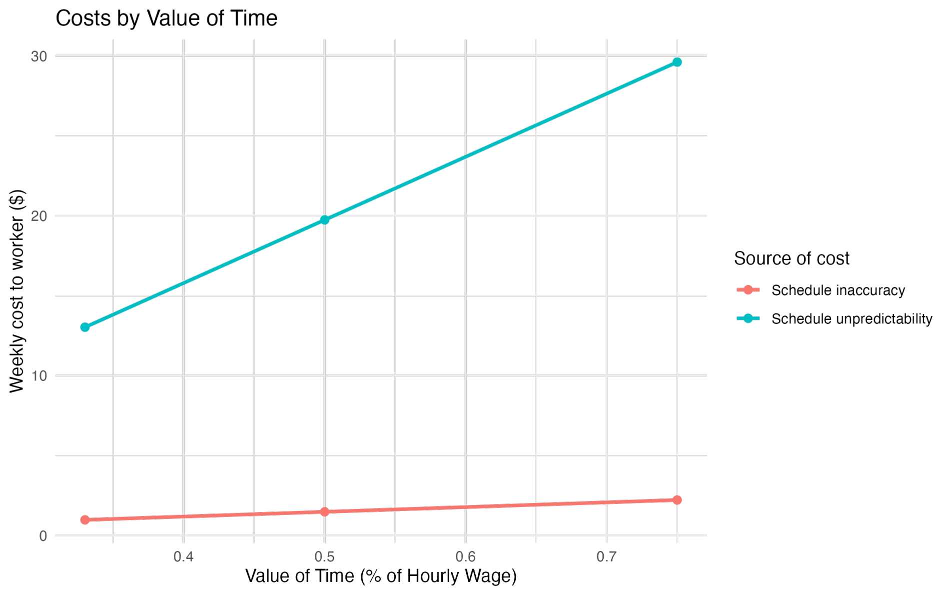
There are several possible ways to consider how this increased volatility eats into some of the welfare gains workers acquire through increased minimum wages. Here, I present back-of-the-envelope calculations reflecting these costs pushed onto workers, through both increased last-minute changes to schedule and an overall increase in the unpredictability of regular worked hours.

Such volatility imposes additional time costs on the worker; if they have to work more or less than expected on a given day, this removes their ability to better plan for things like childcare or other work arrangements. If overall weekly hours become less predictable, it makes it more challenging to know what one's work schedule will look like, and the amount of time they could allocate to other jobs or activities. As such, we can assume that this uncertainty imposes costs equivalent to the worker's value of time. The federal government typically assigns a value of time equivalent to 33%-50% of mean wages, while recent literature has calculated values closer to 75% (Goldszmidt et al. 2020). I show calculations for this range of value of time assumptions.

If we think only about the increased schedule inaccuracy on the day of a shift, we can estimate costs using the change in the absolute difference between worked and scheduled hours per day. On average, in the year following the hike, this increased by 0.086 of an hour, or 5.16 minutes, per day. Workers typically work 3.4 days per week, implying a weekly increase in scheduling inaccuracy of 17.54 minutes, or about 0.3 of an hour. Workers in this treatment group earn on average $9.87 per hour. Using the range of values of time this is 0.3 of an hour is therefore equivalent to $0.98-2.22 per week. The minimum wage increased weekly compensation by around $10 per week. Therefore, this increased cost is equivalent to 9.8-22.2% of weekly monetary gains.

We could instead, however, attempt to quantify the cost of overall week-to-week volatility increases. Following a minimum wage hike, the standard deviation in weekly hours rose by nearly 4 hours. This implies that workers had to hold their schedule open to the possibility of hours worked by an additional 16-17% of their typical hours worked per week. Again, assuming value of time ranging from 33-75% of average wage rate per hour, employees would need to be compensated an additional $13.02-29.61 per week. Instead, they gain an additional $10 per week on average after the hike, resulting in a net loss per week of $3.02-19.61. Ranges of weekly costs are shown in Figure 20

Figure 20: Welfare costs to workers



Notes: Costs are calculated in terms of the value of time lost to uncertain schedules. Schedule inaccuracy is represented by the increase post hike in the average weekly difference between the hours a worker is scheduled to work as of one day prior to their shift and the hours they actually work on the day of their shift. Schedule unpredictability is represented by the increase post hike in the rolling standard deviation of weekly hours worked over the previous 4 weeks, or how similar weekly schedules are to each other over the past month.

8 Discussion and Conclusion

In this paper, I examine an understudied aspect of hourly work, schedule volatility, in the context of one of the most common economic policy levers, the minimum wage. My results highlight the fact that there is significant tradeoff between wages and schedule stability, with firms adjusting along this margin following a minimum wage hike in order to recuperate higher labor costs.

Firms may do so because employees would be willing to accept more of this non-wage disamenity if provided with higher wages, and such practices may be cost-maximizing to firms. As detailed, it allows firms to more precisely match hours of work to consumer demand on a given day. My examples using bad weather days illustrate this exact point; firms are more able to pass of the risk of a slow-business day onto workers as long as these workers receive a higher wage.

Most conservatively, I estimate that the increase in the last-minute schedule changes takes away roughly 10-22% of the monetary gains a minimum wage provides through the cost of uncertain time. If taking into account broader decreases in predictability of week-to-week schedules, however, I estimate a net decrease of $3-20 per week to workers.

These results highlight the fact that a minimum wage increase alone may be insufficient in increasing workplace quality for hourly workers in the service industry. Without protections against just-in-time scheduling, their gains may be reduced through increased dependence on volatile scheduling to compensate. This volatile scheduling threatens worker productivity and health, especially for parents navigating childcare scheduling or low-income workers struggling to budget for necessary expenses.

Finally, this study draws attention to an increasingly challenging issue facing the labor market: extreme weather. While several studies emphasize the hours lost due to bad weather, this body of literature misses two key points. First, it is often not recognized that it may not be the choice of the workers to not work on an extreme temperature or precipitation day; it could come from the employers deciding that they do not want to pay workers on days when it may not be profitable for them to do so. Since workers are not paid for the hours they do not work in these settings, this passes off large amounts of risk onto them. Second, I focus on an overlooked aspect of weather effects, the increase to schedule volatility. It is not just that hours decrease in the face of bad weather, but that the uncertainty surrounding hours worked increases. The more employers treat labor as a spot market, hiring only what they need down to the last minute, the more volatility is placed on workers, along with the negative consequences that come with it.

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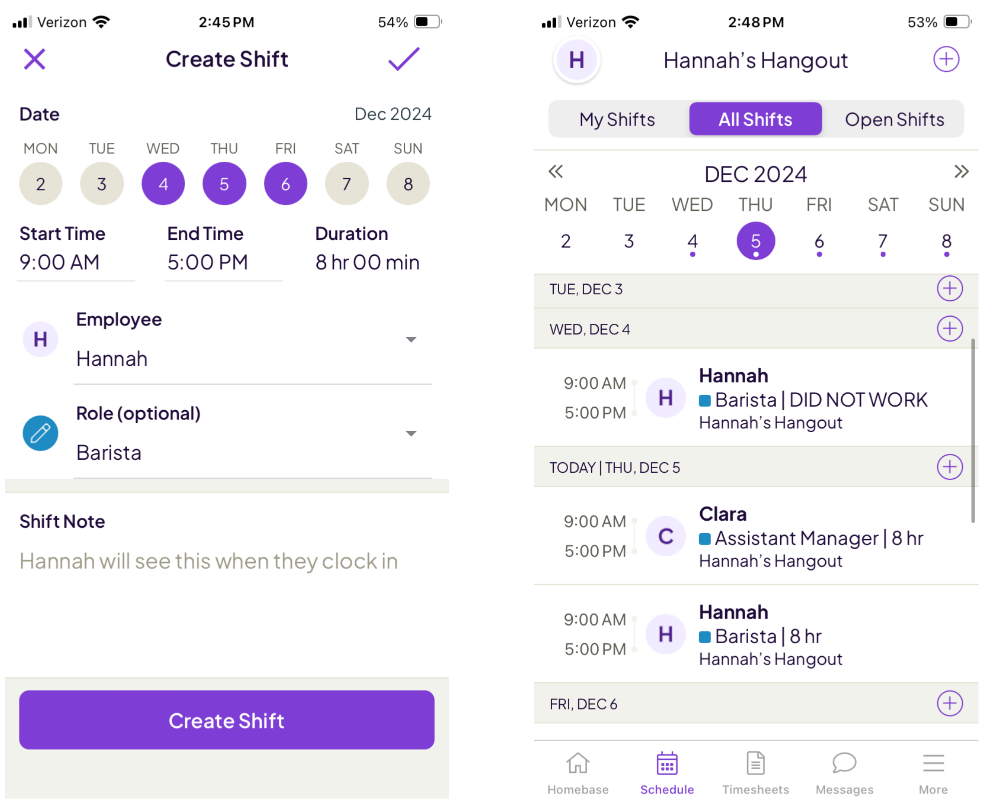
Appendix

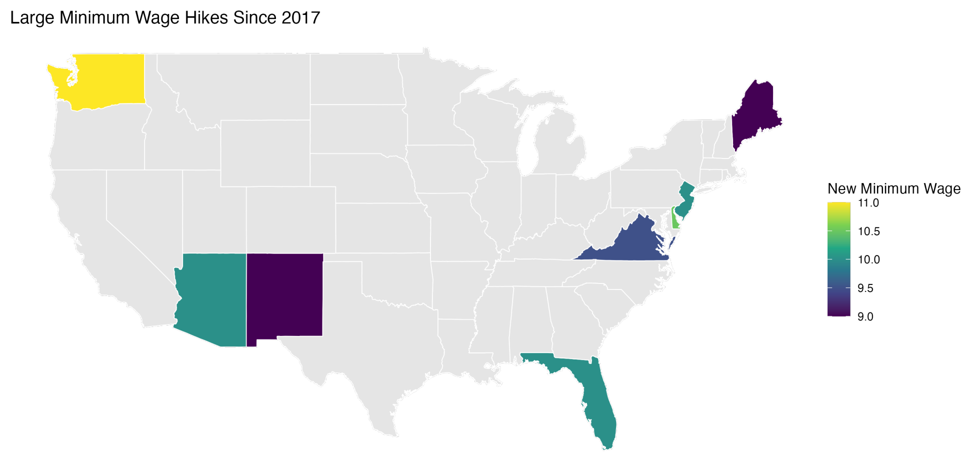
A Additional Tables and Figures

Appendix Figure A1: Example of Homebase platform



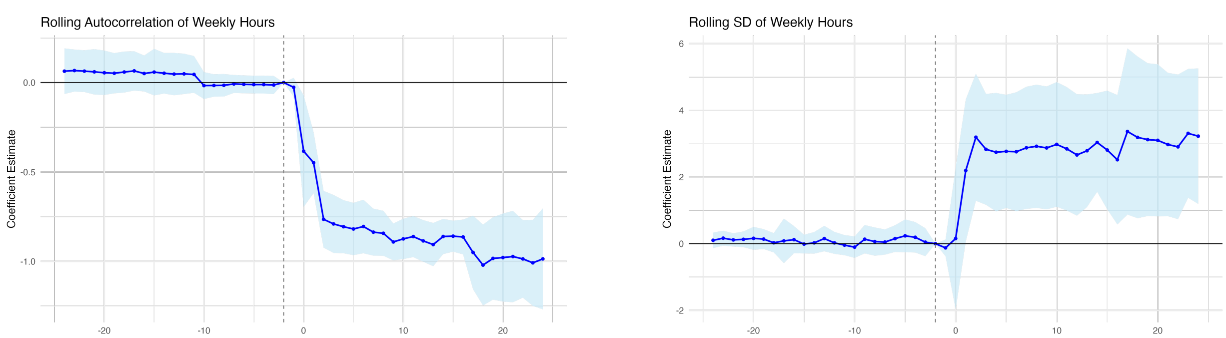
Notes: These images show the user platform of the Homebase application for a fictional cafe, from the perspective of a store manager. The image on the left displays how a manager creates new shifts on Wednesday, Thursday, and Friday from 9am to 5pm, and assigns these shifts to the employee Hannah. She is assigned to the role of Barista during these shifts. The image on the right displays the scheduled shift summary view. This shows that Hannah did not work on Wednesday, but is scheduled to work alongside assistant manager Clara on Thursday.

Appendix Figure A2: States with qualifying minimum wage increases



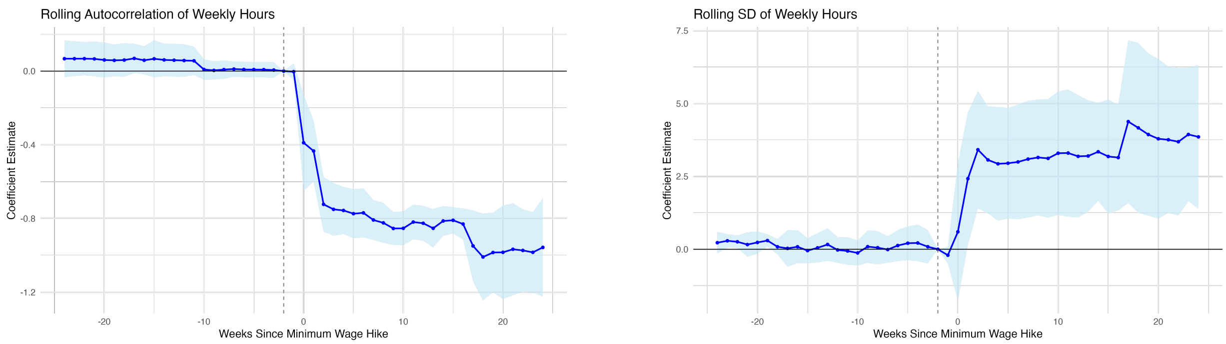
Notes: This map displays the states in the continental U.S. that experienced a minimum wage hike of greater than $1 in the sample period without any such hike in the 2 years prior. The resulting new minimum wages in the 8 states included range from $9 to $11.

Appendix Figure A3: Results dropping 2020 from sample



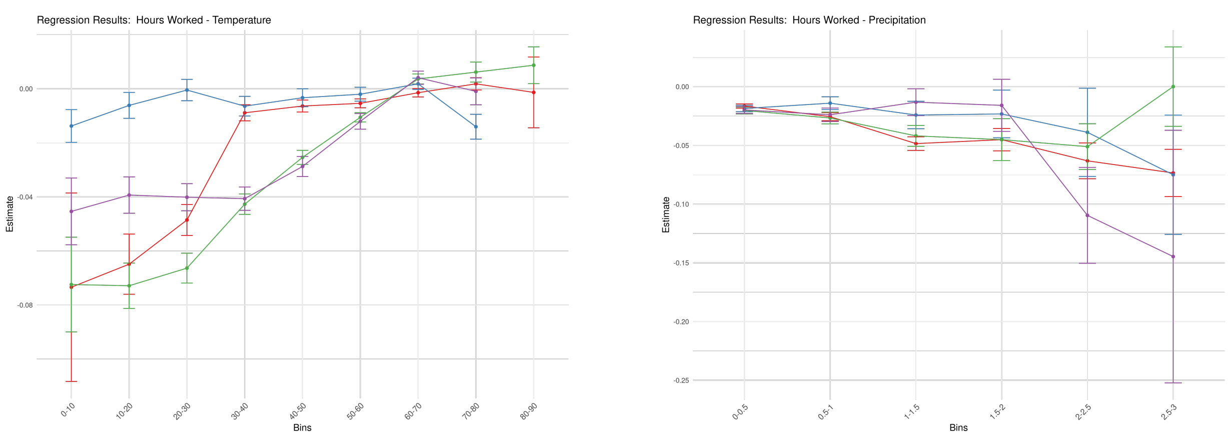
Notes: These figures display the results for rolling autocorrelation and standard deviation of week-to-week hours over the prior 4 weeks of working for employees, excluding the year 2020 from the sample. Results are similar to main results, indicating that the Covid-19 pandemic is not driving the results.

Appendix Figure A4: Results with a balanced panel of workers



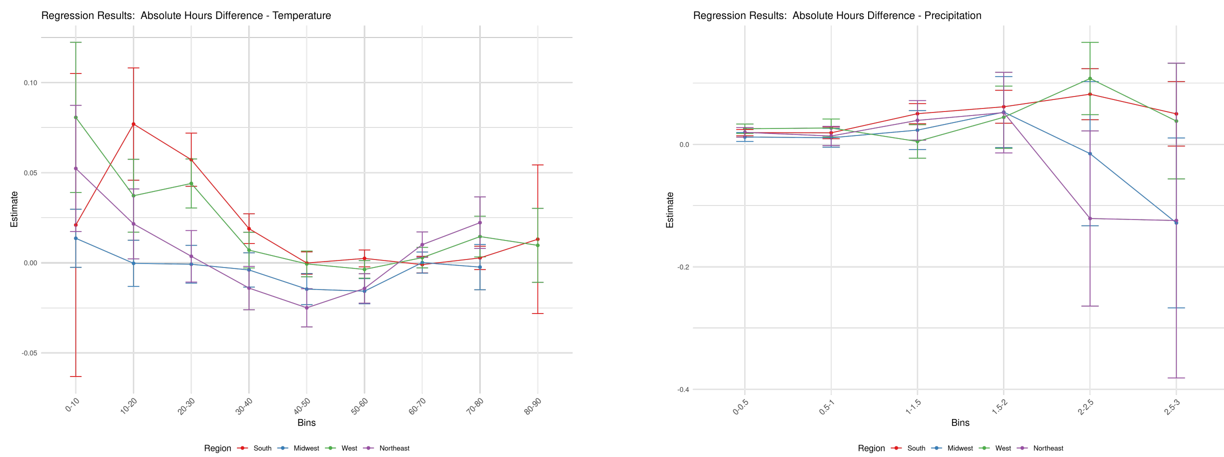
Notes: These figures display the results for rolling autocorrelation and standard deviation of week-to-week hours over the prior 4 weeks of working for employees, keeping a balanced panel of workers over the 6 months pre and post minimum wage hike. Results are similar to main results, indicating that employee entrance or exit are not driving the results.

Appendix Figure A5: Weather effects on hours worked by climatic region



Notes: These figures display how hours worked respond to various temperature and precipitation bins, separated by climatic region. Hours worked drop most quickly for the southern and western states in the coldest temperature bins, while the Midwest hours worked remains fairly constant in even the coldest temperatures. On the other hand, hours worked remain steady in the West and South, the hottest temperatures do not lead to drops in hours worked as they do in the Midwest and Northeast. Precipitation impacts all areas negatively, with the South and West reacting the most quickly to any level of precipitation.

Appendix Figure A6: Weather effects on absolute difference between scheduled and worked hours by climatic region



Notes: These figures display how the difference between hours worked and hours scheduled to work responds to various temperature and precipitation bins, separated by climatic region. Difference in hours increases most quickly for the southern and western states in the coldest temperature bins, while the Midwest remains fairly constant in even the coldest temperatures and the Northeast sees an increase only in the coldest temperature bins. Difference in hours increases in the Northeast in the hottest temperatures, and trends upwards to a lesser extent in the South and Midwest.