The Economic Incidence of Schedule Unpredictability in Hourly Work

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Abstract

Workers in hourly service jobs frequently experience shift cancellations, schedule adjustments, and unpredictable hours, often referred to as 'just-in-time' scheduling. Despite imposing significant costs on workers, we know surprisingly little about the prevalence and costs of this practice. I use a large administrative dataset featuring information on nearly 1 million employees' scheduled and worked hours to first illustrate patterns of schedule unpredictability at thousands of small food and drink and retail businesses across the U.S. I show that baseline schedule unpredictability is widespread, and is the most severe for the lowest-wage and least-tenured workers. Using exogenous weather shocks which are known to diminish consumer demand, I examine how these customer-facing establishments pass risk of slow business days onto workers through unpredictable scheduling. I then leverage the fact that most hourly service workers earn at or near the minimum wage to examine the tradeoff between schedule predictability and wages. Following large exogenous minimum wage increases, schedule unpredictability increases by 20% per week and schedules become even more responsive to weather shocks. This highlights how some of the welfare gains workers realize from a minimum wage may be offset by increased schedule unpredictability.

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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 (BLS 2022). Many of these workers are subject to '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 days and number of hours they are scheduled to work week-to-week (The Shift Project 2024). While this may be profit-maximizing for firms wishing to reduce payroll costs, it may take its toll on workers who bear the brunt of such unpredictability.

Schedule unpredictability 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 sector, 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. However, we know very little about the determinants of schedule unpredictability and how public policy affects it. This is particularly challenging, as we rarely observe scheduling in commonly used employment data. Standard employment summaries and datasets often do not measure unpredictability or fluctuations in scheduling, as it requires a window into the scheduling practices of businesses.

In this paper, I use administrative data on both hours scheduled as well as hours worked to document the persistence of schedule unpredictability and its tradeoff with wages among hourly workers at small businesses in the food and drink and retail sectors. This data is available through the payroll and scheduling service provider Homebase. Many businesses in the US rely on 3rd party applications for human resource tools like scheduling. Homebase is one company providing such tools to over 100,000 small businesses across the country.

I first take advantage of features of the Homebase data that allow me to describe several forms of schedule unpredictability that hourly workers in the food and drink and retail sectors commonly experience. The data details how much workers were scheduled to work as of one day prior to their shift and the resulting hours actually worked for that shift. This enables me to identify last-minute changes to schedules, or 'schedule inaccuracy,' represented by the difference between these values. I additionally observe week-to-week measures of unpredictability, defined as variation in the number of hours an employee works per week and the number of days they work per week.

I establish that unpredictability among these workers is widespread. Workers typically experience more than one hour of difference between the hours they were scheduled to work and the hours they actually work per week. These patterns differ by wage group: the highest-paid workers typically work more than scheduled and the lowest-paid workers typically work less. The similarity of schedules week-to-week varies dramatically for workers as well. Predictability in the number of hours worked per week is low, with lower-paid and lowest-tenure workers having a higher coefficient of variation in their hours. In addition, although workers typically only work 3-4 days per week, which days they work changes throughout the month. Most employees work at least 6 different week days throughout the month, making it difficult to predict what a typical work week looks like.

These dimensions of unpredictability are correlated with one another, indicating that last-minute schedule changes are related to overall week-to-week unpredictability. Moreover, measures like working fewer hours than scheduled or having highly variable hours strongly predict worker turnover. This unpredictability in hours in turn translates into fluctuations in income, with take-home earnings varying heavily for workers month-to-month.[1] I also take advantage of the fact that I can follow workers across businesses in my data to show that the observed scheduling unpredictability is a business-specific characteristic and does not appear to be largely driven by worker preferences.

I next document how the incidence of unpredictability in business operations impacts the unpredictability of schedules by examining days with extreme weather. Many factors could contribute to unpredictability. For example, in these highly customer-dependent industries, fluctuations in consumer demand arising from tourism or fads could affect an establishment's demand for labor. However, many such factors are difficult to observe or are far from exogenous. I therefore use plausibly random variation induced by weather shocks. Bad weather days are known to alter household consumption patterns (Roth Tran 2019; Lai et al. 2022; Papp 2024; Lee and Zheng 2025). As such, one could expect to see an increase in schedule inaccuracy on such days, as businesses adjust to unanticipated changes in consumer demand.

I find that weather shocks negatively impact the predictability of worker schedules. The difference between scheduled and worked hours increases by 1-15% on abnormally hot or

[1] These patterns strongly align with the findings of Ganong et al. (2025), who establish high volatility in earnings among hourly workers, with low-income workers seeing the highest volatility.

cold days and by 4-35% on rainy days. This suggests that work schedules adjust with short notice in response to changes in business expectations, and that workers bear this cost. This additionally shows an avenue of weather-related risk, that extreme weather days contribute schedule unpredictability, that has not yet been explored in the literature.

I then examine how exogenous minimum wage increases affect the provision of schedule unpredictability. With the majority of these workers earning at or near the minimum wage, these increases offer a useful avenue to explore the relationship between schedule volatility and wages. To evaluate these dynamics, I rely on the well-tested methods of Cengiz et al. (2019). I use exogenous variation in the timing of large state-level minimum wage increases across the US from 2017-2022, using these increases as shocks to labor costs. I rely on policy changes in 8 states to evaluate the effects on a wide range of measures of scheduling unpredictability.

I find that a large, exogenous 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 increases roughly 100%, or an additional 4 hours per week of uncertain time. This indicates that with higher pay comes more last-minute changes to schedules and less similarity between hours worked week-to-week, suggesting that as labor becomes more costly, businesses increase schedule unpredictability, hurting workers. 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 unpredictability following a minimum wage increase. This aligns with the notion that less competition for workers would drive down provision of non-wage amenities like schedule predictability. The increase in the minimum wage is also paired with an increase in the likelihood of employee exit by roughly 5%, with no corresponding increase in entrances. This suggests that businesses may adjust to a higher wage through hiring as well as through scheduling. Remaining employees, meanwhile, receive a higher wage, but this is somewhat offset by increased unpredictability.

I next examine how these minimum wage increases interact with previously described adverse weather days to affect schedule unpredictability. One might expect higher minimum wages to exacerbate schedule inaccuracy arising from weather shocks; as the cost of labor rises, businesses may be less willing to pay workers on slow business days when their labor is not needed. Observing the combined effects of these shocks enables me to assess whether workers are more likely to bare the burden of extreme weather through the channel of schedule unpredictability following a minimum wage increase. I find that the weather-induced unpredictability is exacerbated by an additional 10th to quarter of an hour following a minimum wage increase. When it becomes costlier for a business to keep workers on a shift when their productivity is not maximized, like on a slow-business day, schedules are more frequently adjusted at the last-minute.

It may be that workers learn to anticipate schedule adjustments. To assess how predictable schedule changes are, I rely on machine learning tools. I train an algorithm on the characteristics of a worker's previous schedules, wages, company characteristics, and recent weather to predict day-ahead schedule. Even when provided with information that workers could plausibly use to forecast their schedules, the model only predicts next-day schedules within 20% of the typical hours. This highlights the difficult task employees face in attempting to reasonably anticipate their next shift. Importantly, the performance of this machine learning model becomes worse following the minimum wage increase, becoming 5% more inaccurate for workers exposed to a large minimum wage increase than those in the control group.

In my final set of results, I calculate back-of-the-envelope costs of unpredictability to workers, which offset some gains from the minimum wage increase. 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 time uses. I estimate that the additional last-minute changes to schedules 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 unpredictability, workers face an increased cost of $13-30 per week, a higher value than the total wage gain from the minimum wage increase.

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. (2024) 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 (M. K. Chen et al. 2019; K.-M. Chen et al. 2020; He et al. 2021).[2]

Many studies have documented why this schedule unpredictability is 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. Relatedly, Ganong et al. (2025) finds that earnings instability translates into consumption instability, imposing a cost on hourly workers that salaried workers do not face. On the other hand, several studies have found that increasing stability actually increases

[2]This connects to the practice of just-in-time inventory, through which firms aim to efficiently match needs along the supply chain to reduce waste (Singhal and Raturi 1990; Yang et al. 2021).

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, importantly, both scheduled hours and hours worked to showcase patters in unpredictability 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 by examining interactions with minimum wage increases. I furthermore provide insights into why businesses may continue to engage in this practice, despite apparent losses to productivity, by illustrating what happens when shocks to consumer demand occur through the channel of weather.

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 unpredictability. Yu et al. (2023) provides some initial empirical evidence on this topic, using data from one retail company to show increased volatility and increased unemployment following an increase in one state's minimum wage. I provide the first empirical evidence to show this phenomenon across businesses, industries, and several states over time, relying on data that includes a worker's schedule as of one day prior to a shift as well as their actual hours worked. This allows me to examine patterns by different worker and labor market characteristics and observe last-minute schedule changes.[3][4]

Lastly, I contribute to the body of literature on the impact of climate on labor markets. Many papers have documented how extreme weather hampers overall hours worked, especially in the poorest areas and in outdoor industries (Graff Zivin et al. 2018; Behrer et al. 2021; Rode et al. 2024). Recent literature additionally demonstrates that higher disposable income is associated with improved capacity to adapt to weather shocks (Sarmiento et al. 2024). Fewer studies 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 construction firms adjust labor demand in anticipation of seasonal rainfall volatility.

[3] This work additionally adds to the vast literature on minimum wages (Card and Krueger 1994; Dube and Lindner 2024). Rao and Risch (2024) describes how high productivity businesses may absorb workers from low productivity businesses following a minimum wage increase. It is plausible that the small businesses I observe are less able to sustain employment at higher wage rates, resulting in increased exit from these businesses.

[4] Many papers discuss trade-offs between minimum wages and non-wage amenities(Clemens, Kahn, et al. 2018; Clemens 2021; Dube, Naidu, et al. 2022; Meiselbach and Abraham 2023; Davies et al. 2025). Several have additionally shown that worker effort increases following a rise in the minimum wage (Ku 2022; Coviello et al. 2022), something that, like unpredictability, can be seen as a 'productive disamenity'.

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 (Starr-McCluer 2000; Roth Tran 2019; Lai et al. 2022; Papp 2024; Lee and Zheng 2025). It connects these consumer effects to the resultant consequences for hourly workers whose shift work is highly dependent on customer needs.

This study also informs several policy debates, the most relevant being the implementation of Fair Workweek Laws, aimed at increasing schedule stability. This provides further evidence on the magnitude of the problem of schedule unpredictability across states and businesses, and that such laws could have broad impacts among shift workers. However, many such laws exclude small businesses. This analysis displays how schedule unpredictability is evident in these establishments as well, and how laws excluding their employees may neglect to address a large portion of the affected workforce.

Furthermore, the minimum wage is among the most common tools used for labor market regulation in the US. However, these results highlight how increases in wages may be coupled with decreases in non-wage amenities if not paired with additional policies aimed at worker protection. In particular, it demonstrates how scheduling unpredictability is a major factor on which businesses adjust following increased costs, despite it being highly undesirable for workers. Lastly, as policy-makers 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 predictability of schedules, a large non-wage amenity that workers value, is also brought down. Moreover, when wages are increased without additional worker protection policies, workers become even more susceptible to this weather-induced schedule unpredictability.

This paper is structured as follows. Section 2 provides background information on hourly work in the US and policies regarding scheduling and minimum wages. I then provide a theoretical framework for my study in Section 3 and outline my data in Section 4. Section 5 discusses my empirical strategy. Section 6 details results on the characteristics of schedule unpredictability and the interactions with weather shocks. Section 7 details results on the impacts of a minimum wage and Section 8 translates select results into welfare costs to workers. Section 9 concludes.

2 Background

In the United States, over half of workers are paid hourly (BLS 2022), meaning 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 unpredictable 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 unpredictability associated with increased turnover and decreased productivity (Kesavan et al. 2022; Bergman et al. 2023).

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. Only one state (Oregon) and 10 municipalities have enacted Fair Workweek laws designed to regulate how employers set schedules with the aim of increasing stability (Lambert et al. 2025). As such, 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 to 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 the 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. 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 theoretical model describing how minimum wage increases could raise schedule unpredictability in the presence of idiosyncratic consumer demand. I consider unpredictability as an endogenous response to the risk of a low-productivity day, and therefore weakening the need for labor on that day.

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, $\bar{a} + \epsilon$, 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. This also captures that the disamenity is highest at the tails of the distribution.

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 $b > 0$. I assume they are price-takers, and that they receive price p for their output, and pay wage w.[5].

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 $h_e^* = \frac{\bar{a}}{2b}$.

[5] The businesses in my sample are small (under 50 employees) It is reasonable to assume that they are price-takers, as they would not hold a significant amount of market power.

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:

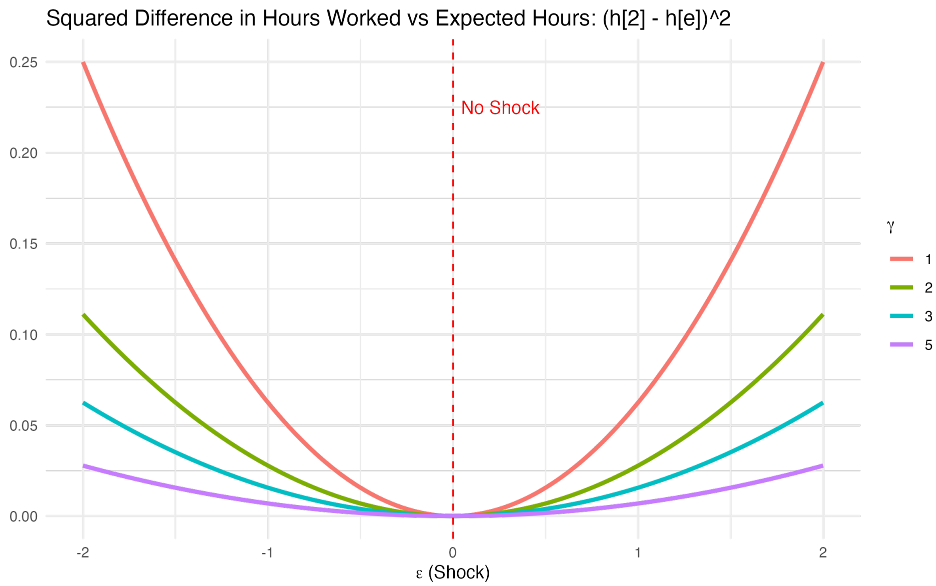
$$h_2^* = \frac{p(\bar{a}+\epsilon) + \gamma\frac{\bar{a}}{b}}{2(\gamma + pb)} \tag{7}$$

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 ϵ, 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 schedule unpredictability, we can examine the comparative statics, particularly how schedule deviations change with the ϵ 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 consumer demand shocks. Solving for this, we get:

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

Figure 1: Schedule Unpredictability vs Productivity Shock



Notes: This figure shows the squared difference between worked and scheduled hours for varying levels of shocks to consumer demand, both positive and negative. The responsiveness to these shocks is dependent on employee distaste for unpredictable schedule changes, represented by different levels of γ. A higher γ indicates a stronger distaste for last-minute changes, which will lead to worked hours more closely resembling scheduled hours at all levels of ϵ.

Now, we can see that when $\epsilon = 0$, $(h_2^* - h_e) = 0$, as there is no 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:

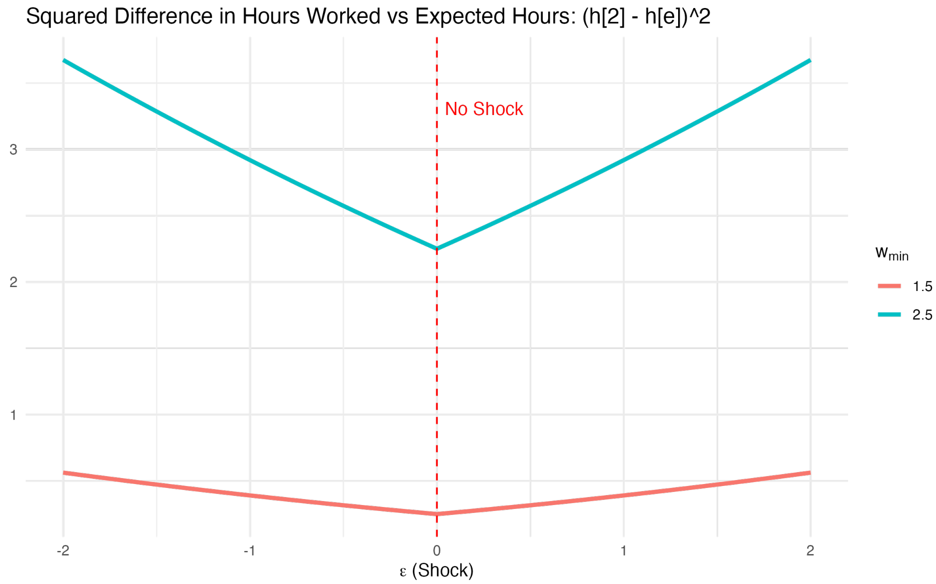
$$(h_2^* - h_e)^2 = \frac{p^2\epsilon^2}{4(\gamma + pb)^2} \tag{9}$$

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

Figure 2: Schedule Unpredictability under Different Minimum Wages



Notes: This figure shows the squared difference between worked and scheduled hours for varying levels of shocks to consumer demand, for two different levels of minimum wages. A higher minimum wage is associated with higher levels of baseline unpredictability: there is a higher difference between scheduled and worked hours at all levels of ϵ. The rate of unpredictability also increases with a higher minimum wage, with more responsiveness of schedules in reaction to shocks represented by a steeper slope.

firm's maximization problem becomes:

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

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 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 unpredictability and the rates at which this unpredictability increases in the presence of a 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 increase, then, we could expect unpredictability 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 market, resulting in increased unpredictability.

3.1 Empirically testing the model

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 establish that extreme weather days, days with high levels of precipitation or colder or hotter temperatures than normal for a given season, serve as a way of capturing the ϵ term described above. These days act as shocks to regular business operations in these consumer-facing industries, increasing the incidence of mis-scheduling for workers.

I then combine this with minimum wage increases at the state level to test for changes in the *levels* of unpredictability 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. I then test whether following a minimum wage increase, workers in the treated group see the increase in unpredictability resulting from an extreme weather day at a higher rate. This would align with the increasing responsiveness to shocks that the model predicts, as the costliness of keeping on less-than optimally productive staff increases. This would be reflected as an increase in the *rate* of unpredictability increases in response to shocks.

4 Data

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 clients' 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.[6]

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 shift 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. (2025) consider to be a representative sample when compared to the Quarterly Census of Employment and Wages. 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 unpredictable 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

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

2016 through the end of 2022, and I additionally restrict the 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 increase 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 increase, allowing me to observe effects on workers.

4.2 Minimum wage data

I pair this rich set of data on worker wages, hours, and unpredictability 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. (2019). 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 increase as a shock. This leaves 8 shocks in as many states to serve as my treatment group.[7]

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 maximum 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).

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

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 unpredictability 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

I first descriptively document patterns in schedule unpredictability among hourly workers in the food and drink and retail sectors. I then validate these measures and examine how shocks to business operations could interfere with scheduling. I do so by showing how extreme weather days adjust the scheduling patterns of these small, consumer-facing businesses, as expected. I estimate the effects of weather on hours worked and schedule unpredictability using Equation 13. 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}.

$$Y_i = \alpha + \sum_{i=1}^{10} \beta_i \cdot \text{tempdays}_i + \sum_{i=1}^{7} \theta_i \cdot \text{precipdays}_i + \mathrm{\gamma_i} + \mathrm{\delta_{cmf}} + \epsilon_i \tag{13}$$

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.

Next, following Cengiz et al. (2019), 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 unpredictability, 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 unpredictability for hourly workers and the rate of unpredictability change in response to shocks. I estimate several versions of Equation 14.

$$\mathrm{Y}_{it} = \sum_{k \neq -2} \beta_k \cdot \mathbb{I}(\text{weeks\_since\_increase} = k) + \alpha_i + \gamma_{m \times s} + \delta_{f \times y} + \theta_d + \varepsilon_{it} \tag{14}$$

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 increase was implemented. I include employee, month by industry, state by year, week of year, and increase 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 increase to my set of controlled states, which includes those states never treated with a substantial increase throughout the period and those not-yet-treated states whose increase 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. To capture a proxy for schedule unpredictability, 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 unpredictability' per week. These measures get at the overall time unpredictability 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 increase in order to observe whether the newest workers are exposed to greater changes in schedule unpredictability following the imposition of a wage increase, compared to those that have been at businesses longer, and typically have lower levels of unpredictability 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 unpredictability 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 unpredictability increase.

Returning to the notion of weather as exogenous increases to mis-scheduling, I combine these two methodologies in order to estimate the extent to which weather-induced schedule unpredictability is exacerbated by the introduction of a minimum wage increase. I do this in order to further provide evidence supporting the notion that risk is pushed off to workers as a way that businesses 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 businesses, 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 businesses of providing a smooth and predictable schedule to workers, as it impacts their need for labor. When negative weather days dampen consumer demand, businesses run the risk of over-hiring labor if they do not adjust schedules in response. This exercise therefore illustrates the real-time decision making businesses 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 13, but includes the indicator variable 'post' for whether or not an employee is working after the introduction of the minimum wage increase.

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

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

6 Results: Characteristics of Scheduling

Table 1 displays summary statistics within the two industries in my dataset: food and drink and retail. 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

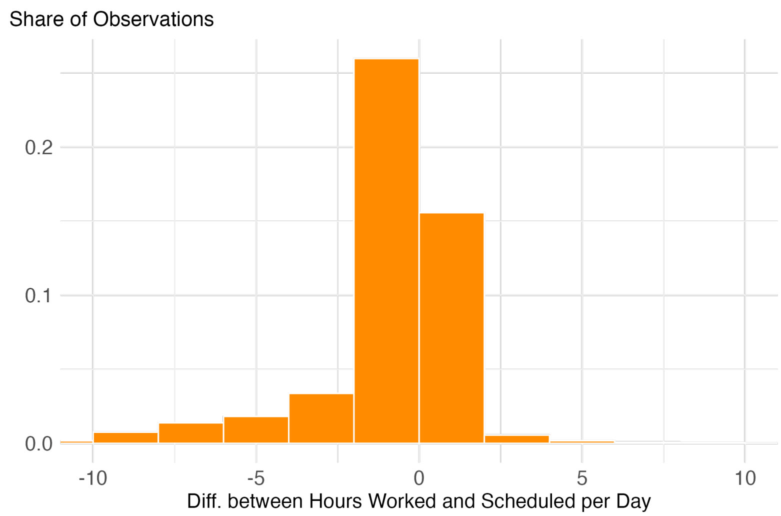
Notes: This table summarizes employee-level data for Food & Drink and Retail establishments using Homebase between 2016–2022. Hours, wages, and schedules are averages across employees. The difference between hours worked and scheduled is the absolute difference in hours between what an employee was scheduled 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 unpredictability while on the job across several different dimensions. On average, the difference per day between how much a worker was scheduled to work and how much they actually work is around 1.3 hours. This accounts for scheduling errors in either direction; either workers are asked to work more hours than initially planned for in 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 expected 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 weekdays. This again presents challenges to workers who may wish to establish regular routines.

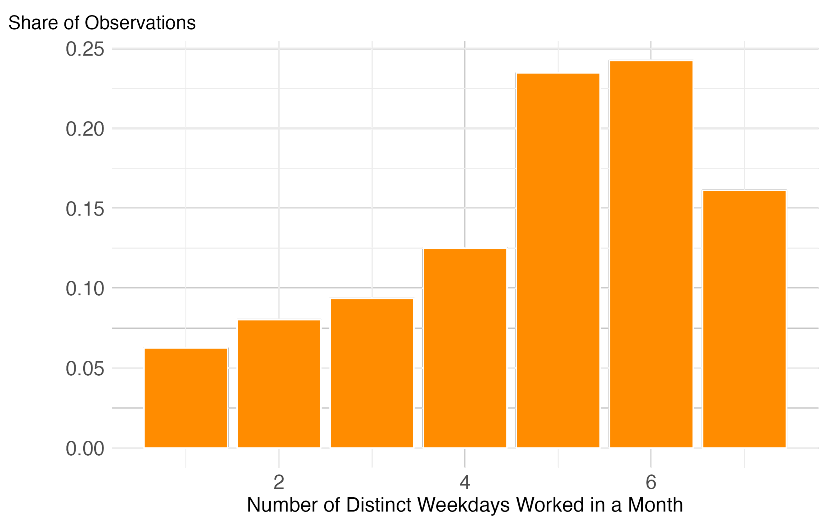
This irregular nature of this shift work has implications for the predictability of worker income as well. While salaried workers can usually predict their monthly take home income quite accurately, the same can often not be said for hourly workers, whose income solely relies

Figure 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.

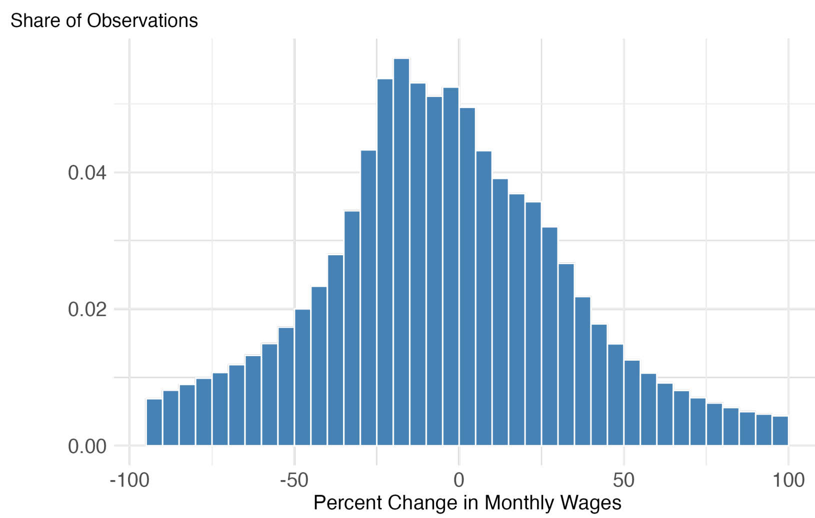
Figure 4: Different weekdays worked per month



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.

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.

Figure 6 demonstrates how these different measures of schedule unpredictability relate to each other. High variance in how many hours or days are worked in a month are positively correlated with high average differences between hours scheduled for a shift and hours actually worked. Frequent shifting in which days of the week an employee works is similarly positively correlated with these measures of schedule unpredictability.

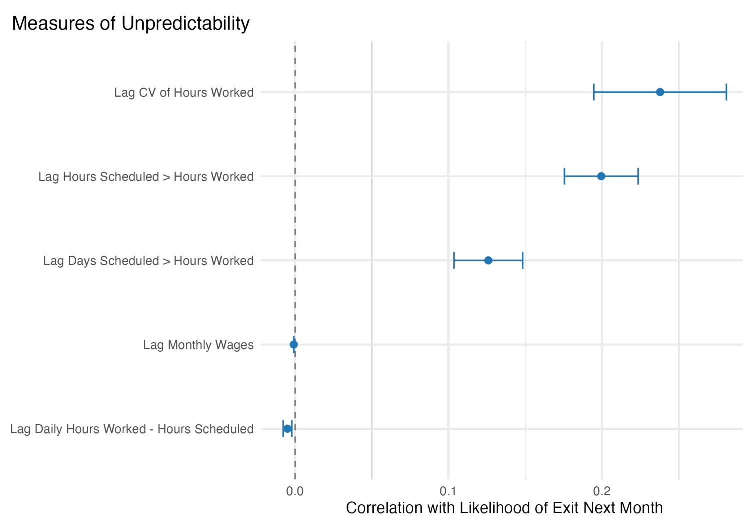
These dimensions of schedule unpredictability are in turn correlated with higher levels of turnover. Figure 7 demonstrates the relationship between measures of unpredictability in the previous month on the likelihood of employee exit this month. High levels of variation in hours worked are strongly associated with increased likelihood of an employee exiting, as does working fewer hours than scheduled to work or fewer days than scheduled to work over the course of the month. The negative coefficient on the difference between hours worked and scheduled indicates how a daily average of working fewer hours than scheduled indicates higher exits. In comparison, lagged hourly wage rates do not appear to play a significant role relative to scheduling measures. This illustrates the negative consequences of such unpredictability, as worker turnover can be costly to both employees and businesses.

Both hours worked and baseline unpredictability vary significantly across employees, and are highly correlated with their wage rates and how long they've been at their job. Typically,

Figure 6: Correlations between measures of schedule unpredictability

Notes: This matrix depicts the correlations between different measures of schedule unpredictability. High variation in hours worked per month is strongly correlated with high amounts of last-minute schedule changes, as represented by the difference between hours scheduled to work and hours actually worked. These measures are weakly correlated with working many different weekdays within a month.

Figure 7: Relationship between schedule unpredictability and employee turnover



Notes: This figure illustrates the correlational relationships between measures of schedule unpredictability and worker turnover. High levels of variation in hours worked and consistently working fewer hours or days than scheduled in the previous month are strongly correlated with higher employee exit rates in this month.

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 unpredictability 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 8 depicts how higher earners typically work more hours per week, while figure 9 shows the coefficient of variation consistently higher for the group of lower earners. In addition, figure 10 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. This indicates that schedule predictability moves with wages and tenure, rather than the workers with the most unpredictable schedules experiencing higher compensation to make up for this disamenity.

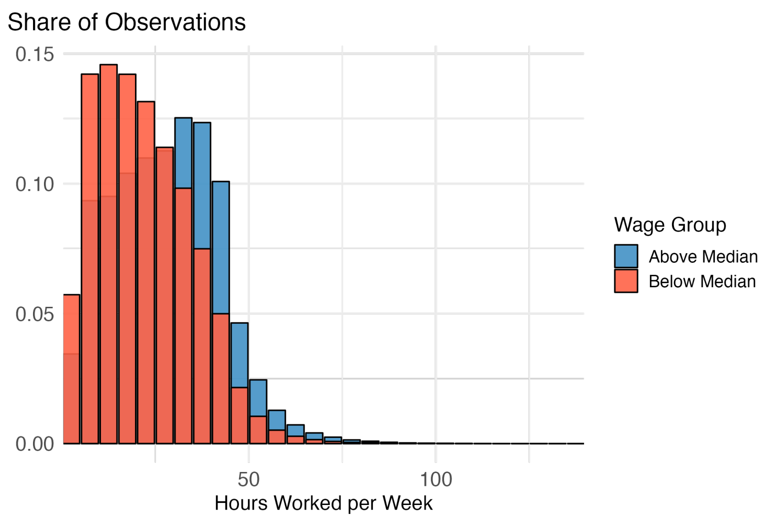
Table 2: Selected Summary Statistics by Tenure (months)

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.

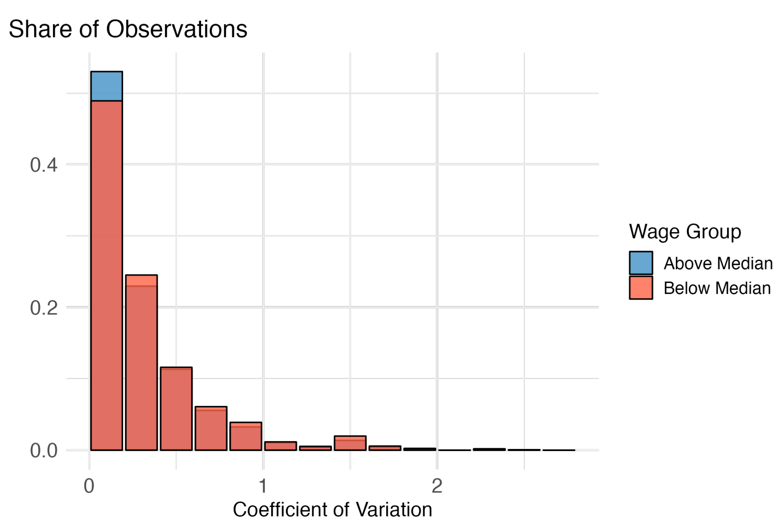
Table 3 displays job characteristics across workers in the treatment and control groups for the stacked event study, prior to a minimum wage increase. Hours worked both per week and per day are similar across groups, as are the rates of employee exits. Hourly wage rates and total wages typically earned 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

Figure 8: Hours worked per week by wage group



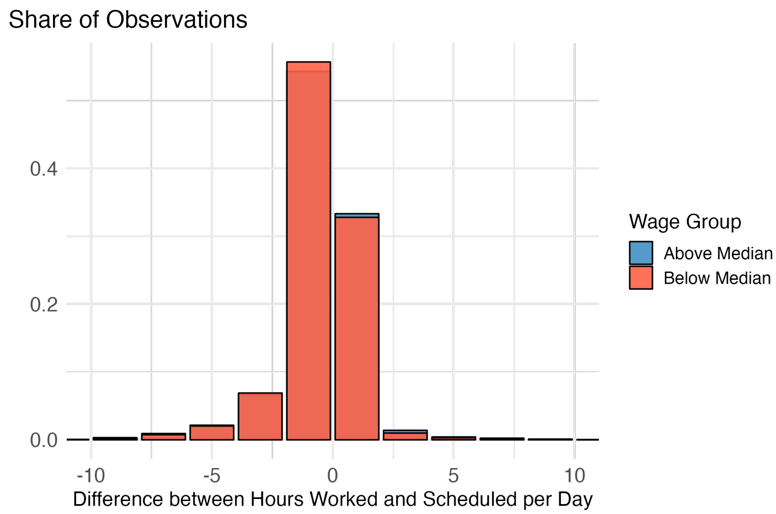
Notes: Employees who earn above the median wage at their place of employment typically also work more hours per week, with many working above the threshold for part-time employment (35 hours per week).

Figure 9: 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 10: 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.

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.

6.1 Weather and mis-scheduling

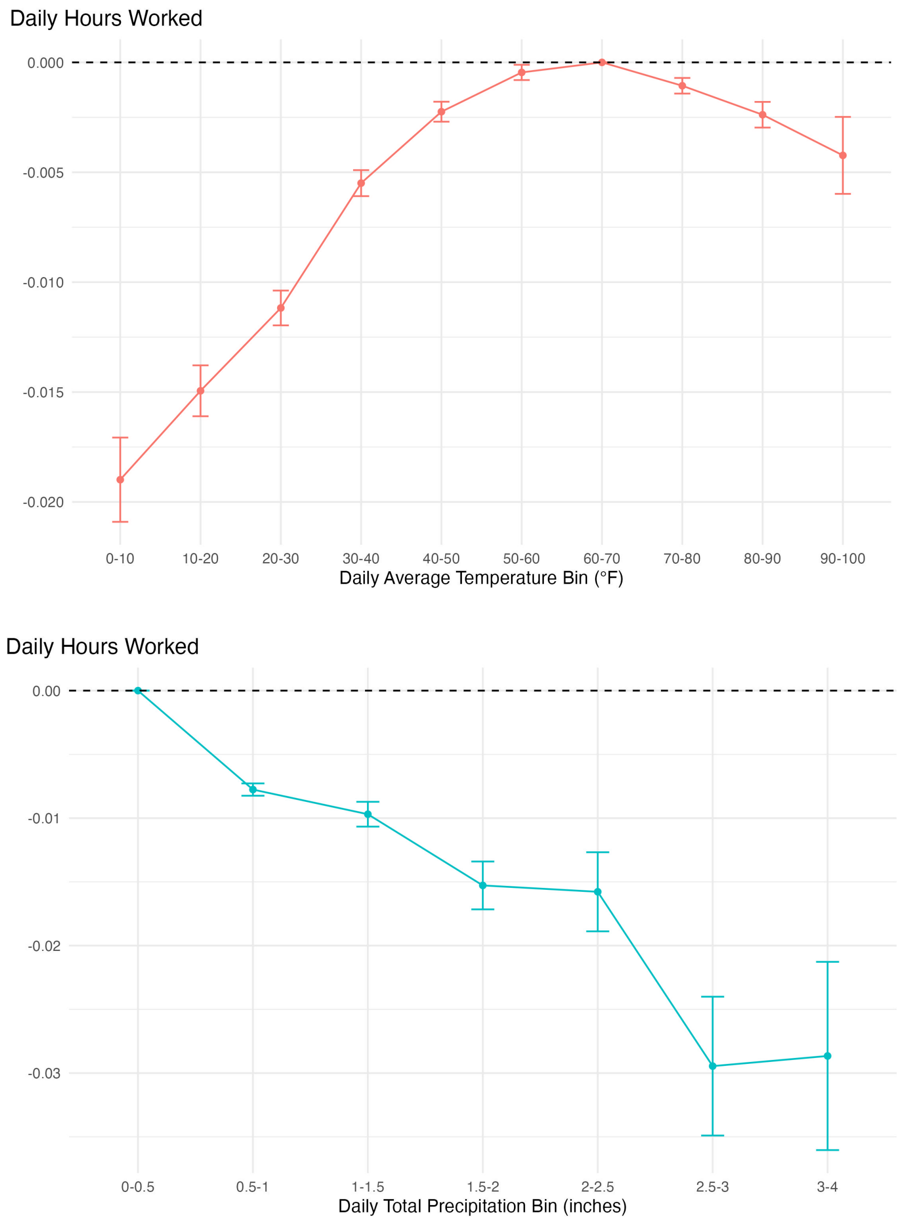
It is not immediately obvious how increasing schedule unpredictability is profit-maximizing for businesses. To provide an illustrative example of the mechanics that may be occurring, I provide further empirical evidence for the theory presented in Section 3. Many factors could contribute to an ϵ, the term representing a shock to regular business operations, consumer demand, or labor needs, being positive or negative. Supply chain disruptions, tourism trends, or viral marketing campaigns could all contribute to different staffing needs, to name a few.

Here, I rely on bad weather days introducing risk to businesses by increasing the uncertainty around expectations in consumer demand. Unlike the factors listed above, weather serves as a reasonably exogenous shock to regularly anticipated business operations, and is easily observable at the business locations. Many studies have documented how weather patterns alter consumer behavior (Lai et al. 2022; Papp 2024; Lee and Zheng 2025). This presents results on the flip side of that coin: on the workers in these industries that are dependent on customers. As the industries in this study, food and drink and retail, rely heavily on consumers, businesses may wish to hire only as much labor as they need on a particular day, given how many customers they expect to serve. Since deviations in weather change that expectation of customer behavior, it could be expected to also change the labor demand for workers in these industries.

Figure 11 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 inches, falling steeply each day that has a half-inch more rainfall.

Figure 12, 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. 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. As this is the difference between the schedule as of one day in advance and that hours worked on the given day, these changes occur at the last-minute,

Figure 11: 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.

not offering workers a significant amount of time to plan for alternative jobs or activities.

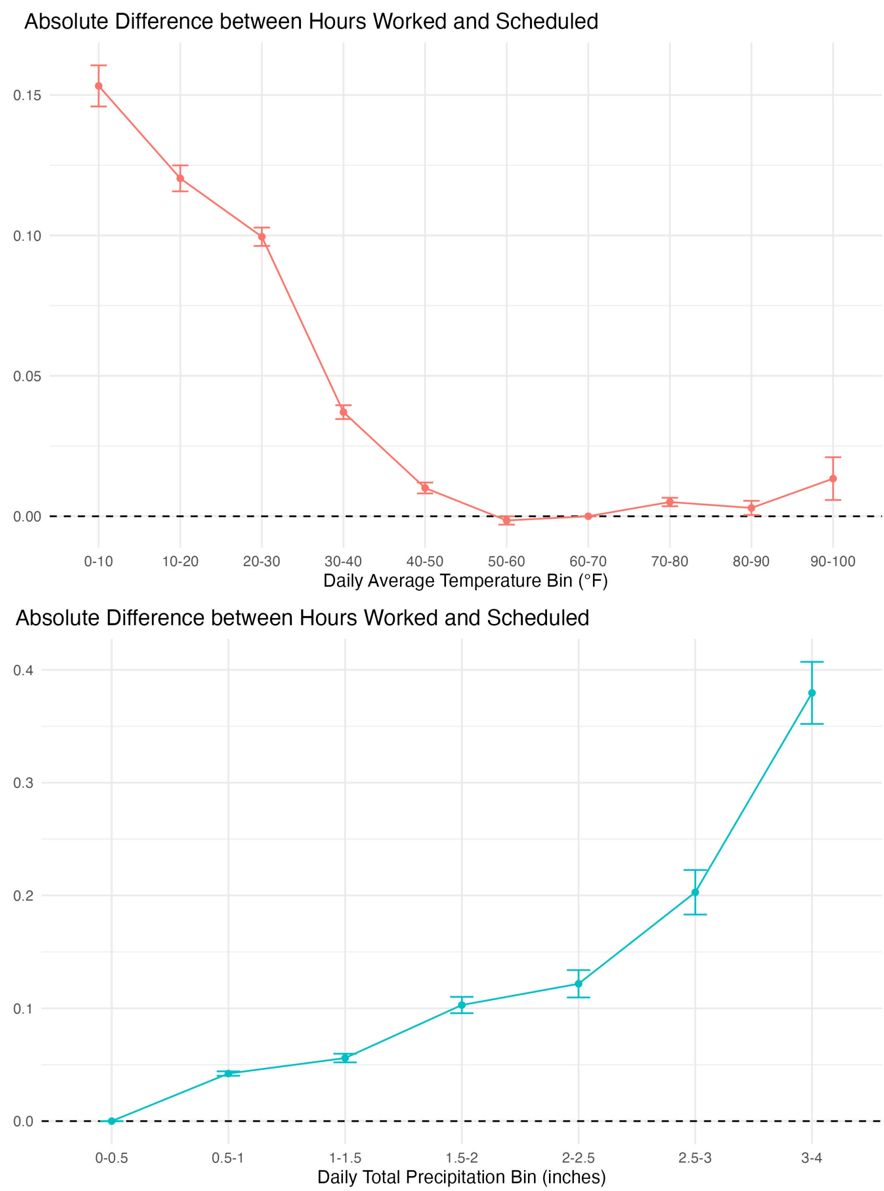
It is possible that extreme weather days impact both labor demand and labor supply simultaneously. On rainy days, it could be more difficult for employees to commute to work, and they may be more likely to cancel shifts on extreme hot or cold days. As discussed previously, the literature suggests that workers typically wish to work more hours than given and do not have the type of control over their schedules that would allow them to adjust shifts freely and frequently. However, some fraction of this observed increase in schedule inaccuracy could still stem from employee behavior rather than employers adjustments in response to business conditions.

To test this possibility, I compute the standard deviation of weekly hours for each employee-employer pair, then take the average of all employee standard deviations at the location level. This provides a measure of week-to-week stability in hours at each establishment. I then estimate these weather regressions on the 10% of locations with the lowest standard deviations. These are businesses that have very stable weekly schedules, indicating their labor demand may be less dependent on fluctuations in consumer behavior than other establishments. As such, it would be expected that these establishments would be less responsive to weather shocks. Some responsiveness to weather may arise from the labor supply side, but one would expect lower overall levels of schedule inaccuracy. Figure 13 demonstrates schedule inaccuracy on extreme weather days for workers at all establishments compared to those working at just these most stable establishments. For nearly all levels of temperature and precipitation, the difference between hours scheduled to work and hours worked is smaller for employees at the most stable businesses. This suggests that if schedule inaccuracies for stable businesses are due to labor supply changes, the remaining difference in responses to weather days for all locations are to some extent due to to labor demand adjustments.

Then, I take the bottom 10% of locations in terms of that average week-to-week SD of hours, and called those 'stable locations'. I then rerun the weather estimates on those locations, and see that for all levels of weather, they tend to have lower responsiveness in terms of hours, wages, and schedule accuracy (see images here).

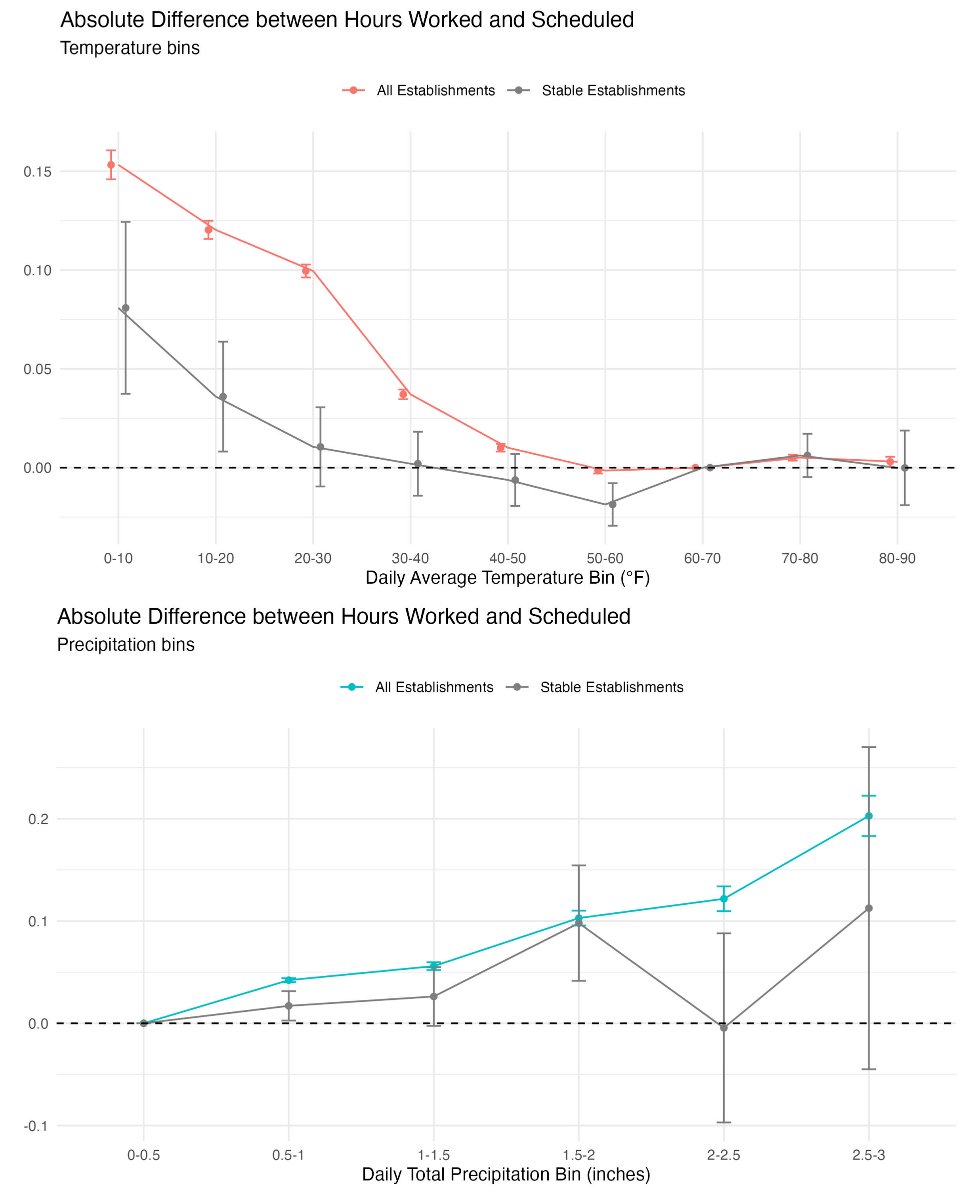
While weather deviations are only one possible contribution to the plethora of factors contributing to the puzzle of how businesses schedule many workers across many different shifts, this exercise highlights several important takeaways. It demonstrates how risk from outside factors may be pushed off onto workers through the channel of schedule unpredictability, as was the prediction from the deviations in ϵ seen in Section 3. It also demonstrates the previously unstudied phenomenon of weather impacting not just hours worked, but the predictability of hours worked. Negative weather days dampen the hours worked of employees in these industries, and often these drops in hours are not anticipated, but rather arise from

Figure 12: 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.

Figure 13: Weather and schedule accuracy among stable businesses compared to all businesses



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 lower for nearly all levels of temperature and precipitation for workers at the most stable businesses.

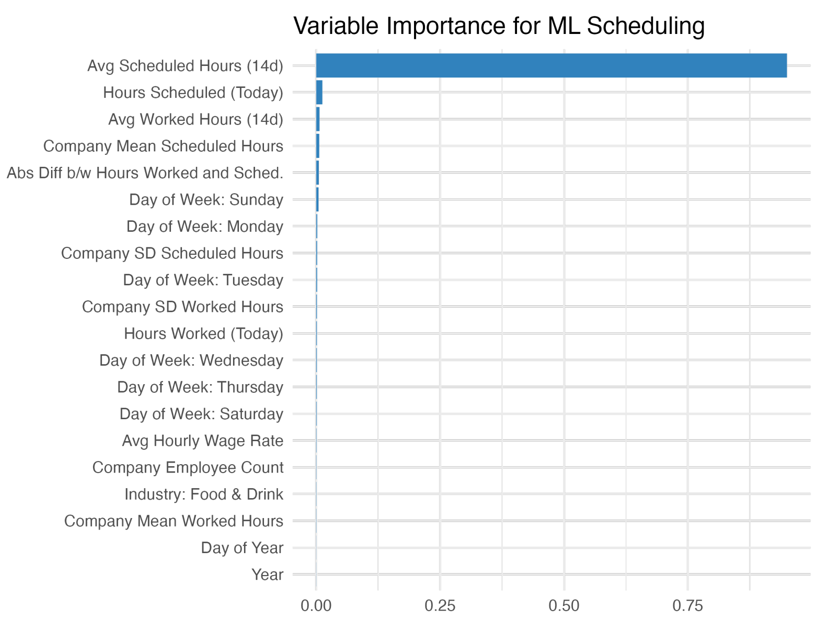
last-minute adjustments.

6.2 Machine Learning for Scheduling

While the previous sections on schedule unpredictability demonstrate underlying unpredictability of hours and the similarity of a worker's hours in a given month, they do not capture fully how predictable hours are for workers. It could be that workers are able to learn from past schedule deviations, and build in accurate expectations around unpredictability if the unpredictability is fairly regular.

To unpack this, I build a simple machine learning model to illustrate the factors contributing to a worker's schedule and test how predictable this unpredictability could be to a worker. 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 expected schedule.

Figure 14: 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. Company scheduling characteristics contribute to predictive capacity. 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.

The resulting model produces a root mean square error of 1.84. This indicates that it is accurate to roughly 1.84 hours per day on average, equivalent to roughly 27-28% of typical daily hours worked. Figure 14 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. Company-wide scheduling characteristics, such as typical hours scheduled across all employees and the standard deviation of these schedules also appear as predictors. Importantly, the weather factors of temperature and precipitation do not weigh highly on the model, further supporting the notion that weather deviations serve as true shocks to scheduling.

This RMSE being fairly high further indicates that unpredictability is widespread for workers in these industries, and not occurring at regular patterns that an algorithm could pick up on and adjust to. Even with large amounts of information going into such a model, the resulting algorithm is unable to accurately anticipate the true schedule of a worker, highlighting the disamenity that this unpredictability places on to workers.

6.3 Employee transitions and unpredictability

The machine learning model depicts how challenging it can be for employees to reasonably predict their schedules. It also indicates that the characteristics of their employer are critical to determining this schedule, with the regularity of hours scheduled within the company a predictive feature of the model. In this section, I further examine the extent to which a company bears responsibility for the unpredictability a worker faces. Some fraction of observed schedule inaccuracy could be due to employee behavior rather than employer adjustments, even with literature indicating that workers typically do not have large amounts of control over determining their schedules.

To separate out how much employee characteristics matter for schedule unpredictability compared to employer characteristics, I turn to a subset of workers who are employed by two or more Homebase establishments during my sample period. Examining these 'movers' enables the use of a traditional AKM-style model (Abowd et al. 1999) through which I parse out employee and employer fixed effects. This form of analysis has been used to show how much variance in wages or productivity across businesses are driven by workers or firms (Sorkin 2018; Metcalfe et al. 2023; Card, Rothstein, et al. 2025). In this context, I use it to determine how much employee behavior versus business behavior in scheduling contributes to overall unpredictability.

Over 2.5% of my sample arises from workers who work at two or more different businesses using the Homebase platform. When they move from one business to another, these employees retain their unique employee ID through which they access the Homebase platform. This enables the tracking of these moving employees. I remove observations from employees work two of these jobs simultaneously, and focus only on full transitions from one company to the next. After retaining workers making up the largest connected set of businesses and removing bridge movers (Bonhomme et al. 2023), 14,147 workers across almost 5,000 businesses remain in the sample. Most of these workers work at two different businesses, with a small percentage employed by three or more.

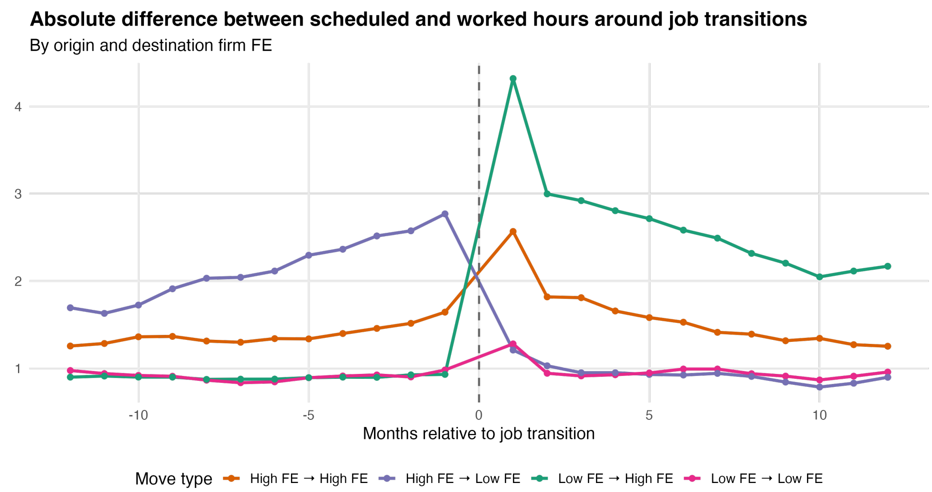
To measure inaccuracy, I use the difference between hours scheduled to work as of one day prior to a shift and hours actually worked on the day of the given shift. I regress this difference on the set of employer-employee linked movers using company and worker fixed effects. The results indicate that 0.34 of all variability in this schedule unpredictability is due to worker characteristics, while 0.42 is due to business characteristics and 0.7 is due to residuals. These worker and business fixed effects have a negative covariance, with the most predictable employees typically matched to the most unpredictable businesses and vice-versa.

To further illustrate how businesses play a larger role in determining unpredictability than workers, I test how unpredictability changes for employees when they transition from one business to the next. I divide businesses into quartiles based on their fixed effects from the AKM regression to determine which businesses on average have the highest and lowest levels of unpredictability. Then, I calculate how an individual worker's average unpredictability changes as they move from one business to another.

Figure 15 depicts what happens to worker-level unpredictability when they move from the highest unpredictability businesses to the least, or from the lowest unpredictability businesses to the highest. When a worker transitions from a business with high unpredictability fixed effects to one with low unpredictability fixed effects, they realize a significant drop in their individual average unpredictability. When a worker transitions from a high unpredictability business to another high unpredictability business, their overall level of unpredictability remains relatively stable. On the other hand, workers transitioning from low unpredictability businesses to high unpredictability businesses realize a sharp increase in their unpredictability while workers moving from low businesses to low businesses remain at low levels of unpredictability. Interestingly, all workers experience a brief increase in unpredictability around the time of job transition before settling into a steady pattern.

This indicates the extent to which workers take on the unpredictability of their company upon moving jobs. One could expect that a perpetually low unpredictability worker would exhibit little schedule unpredictability no matter their employer. However, this demonstrates that the companies themselves matter significantly in setting the patterns of worker unpre-

Figure 15: Evolution of unpredictability through job transitions



Notes: This figure displays how workers adopt the scheduling characteristics of the companies they join when transitioning from one job to another. If a worker moves from a high-type unpredictability business to a low unpredictability business, their unpredictability subsequently drops significantly, and vice-versa.

dictability. A stable employee, after transitioning to a company with overall large levels of unpredictability, begins to exhibit those same levels of unpredictability. This indicates that while workers may have some degree of agency over their schedules, their employer determines large amounts of their fluctuations. Appendix figure A3 displays this result on a balanced panel of workers while appendix figure A4 displays the results of the AKM model on wages. In an additional verification procedure, I perform an event study similar to the empirical estimation strategy of Finkelstein et al. (2016), in which I regress a worker's change in unpredictability on the change in their company level unpredictability relative to the months since transition. Figure A5 in the appendix similarly shows that workers take on a significant amount of the unpredictability of their employers.

7 Results: Scheduling and the Minimum Wage

I next present results on the effects of minimum wage increases on the schedule unpredictability of hourly workers in 7.1 and the interaction between minimum wage increases and weather effects in 7.2.

7.1 Minimum wage and unpredictability

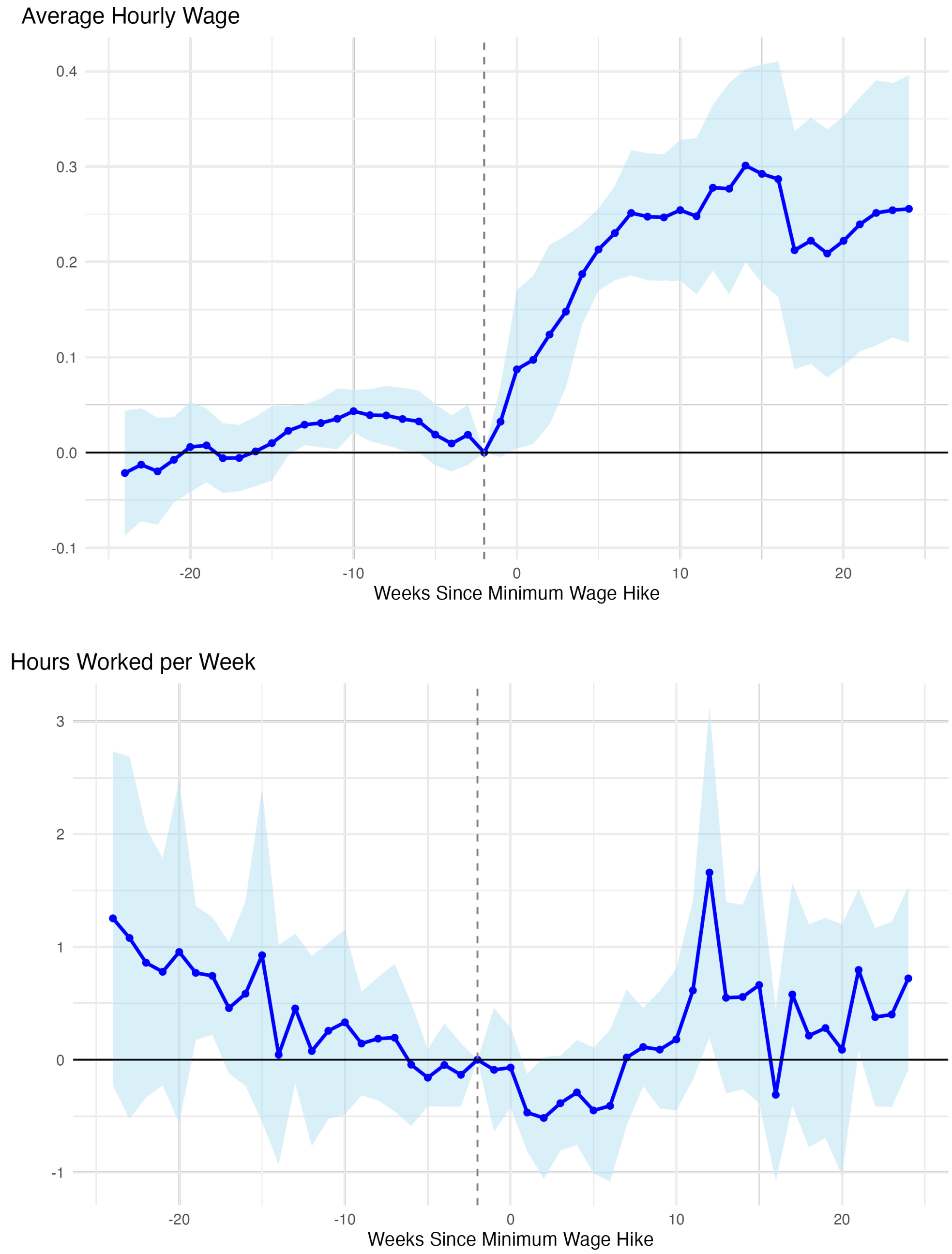
I first show the impacts of a state minimum wage increase on the average hourly wage and daily take-home income of service sector workers in my sample. Figure 16 shows that the minimum wage is highly binding in this context, as so many of the workers in these industries are employed at or slightly above minimum wage. The first plot shows a roughly \$0.3 increase in the average hourly wage among workers after the imposition of an increase.[8] The second plot demonstrates that this is not compensated with fewer hours worked per week; there is no statistically significant decrease in hours per week per employee. Such results showcase that the minimum wage is relevant and binding, bringing up workers' hourly earnings, but without leading to a drop in their amount worked. The lack of negative effect on hours 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 17 displays that there is a small increase in the rate of employees exiting a business following an increase, by roughly 5%. There is no corresponding increase in worker entrances; rather, less hiring appears to take place following a minimum wage increase. This differs somewhat from the findings in Cengiz et al. (2019) that employment in low-wage jobs remains steady following an increase. However, this does not capture the equilibrium employment effects, as it only represents exits at small businesses that are present in the sample. As discussed in Rao and Risch (2024), there is substantial heterogeneity in minimum wage responses among businesses with different levels of productivity. Workers who separate from these businesses could find employment at other businesses more equipped to maintain employment at higher wage rates compared to the small businesses observed here.

The following figures depict different ways to proxy for overall changes in schedule unpredictability. As the model in Section 3 predicts, a level shift would be expected to occur, with unpredictability increasing following the onset of a higher minimum wage. Figure 18 displays results indicating that employers do indeed adjust along the margin of schedule unpredictability. 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 increase, 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 an increase, 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 unpredictability, as if a worker were scheduled for a certain number of hours, that means they would need to leave these hours open and available to work, forgoing other means of earning income during these times. A widening gap en-

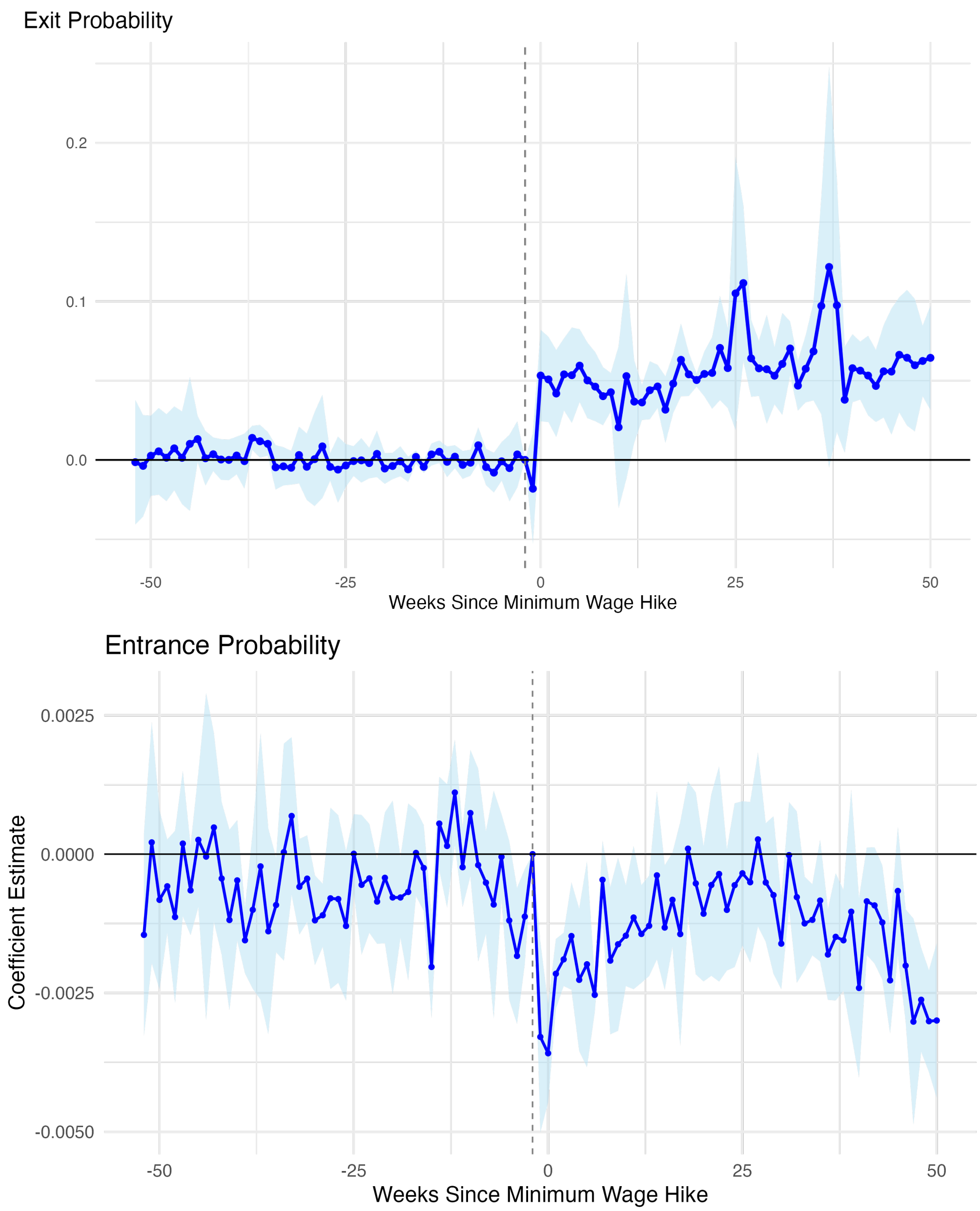
[8] This is less than the typical \$1 or greater increase as many workers earned above the old minimum wage, but less than the new minimum wage.

Figure 16: Effect on average hourly wages and weekly hours worked



Notes: Following the onset of a minimum wage increase, 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 statistically significant decrease in hours worked per week due to businesses compensating by hiring workers for fewer hours.

Figure 17: Effect on probability of exit and entrance



Notes: Following the onset of a minimum wage increase, exit rates increase and stabilized at a rate of 5% higher than prior to the increase. Entrances fall slightly, indicating a net churn lower than prior to the minimum wage increase.

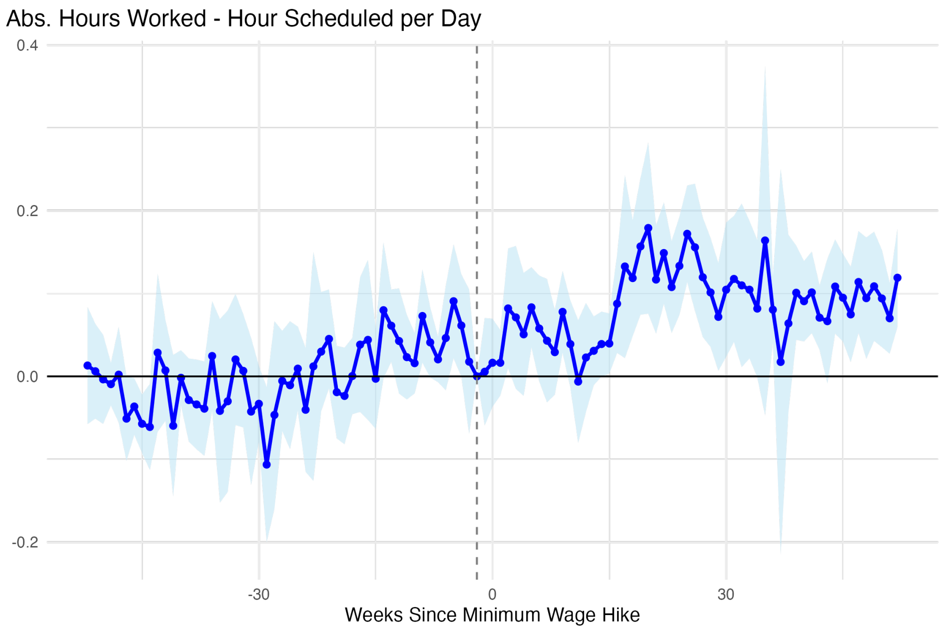
tails that their gap between expected earnings and realized earnings also increases, with little possibility of replacing lost hours given the last-minute nature of the schedule adjustment.

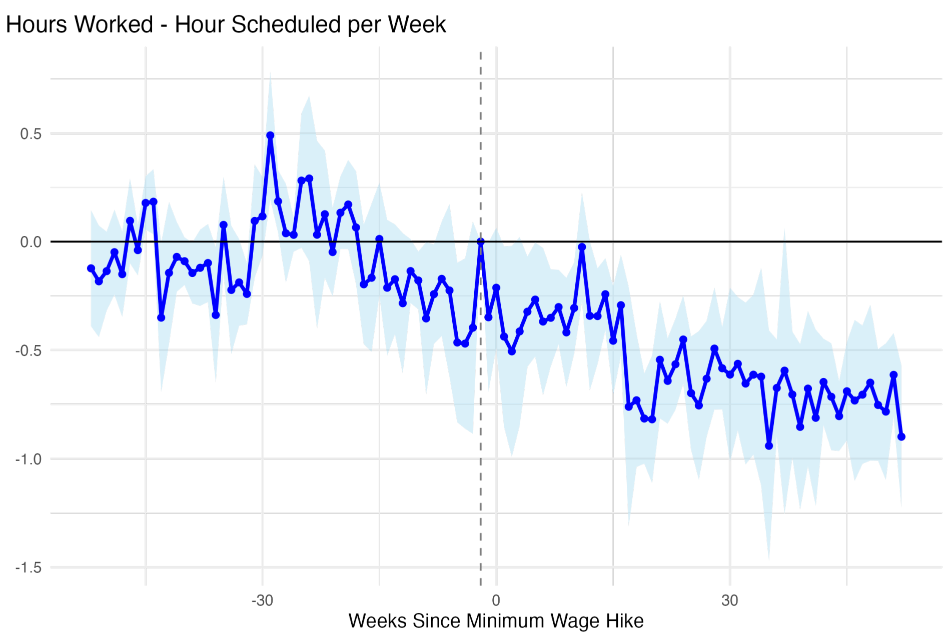
A different way of thinking about schedule unpredictability is to consider how predictable an employee's schedule is week-to-week. I represent this unpredictability in two ways, showing the effects in Figure 19. The first plot depicts the change in the the 4-week rolling average of week-to-week autocorrelation. 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 increase, 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 increase indicates again that the variation in weekly hours worked increases for workers following a minimum wage increase, by nearly 4 hours. This is roughly a 100% increase in the standard deviation of weekly hours over a month.

Taken together, Figure 18 and Figure 19 paint a picture of how businesses adjust on the margin of schedule unpredictability to offset higher labor costs. Since Figure 7 demonstrates that exits rise while entrances stay constant or fall, it can be inferred that these are the resulting conditions for workers who stay at these businesses following the rise in the minimum wage. As such, this demonstrates to some extent a compensating wage differential, through which remaining workers receive a higher wage but are exposed to increasing unpredictability. This unpredictability 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 unpredictability, which as Figure 6 illustrates, is correlated with last-minute schedule adjustments. This week-to-week variation makes 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 unpredictability 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.[9]

[9]These results are robust to: dropping 2020 from the sample due to the Covid-19 pandemic and holding the panel of workers constant (Figure A6, Figure A7).

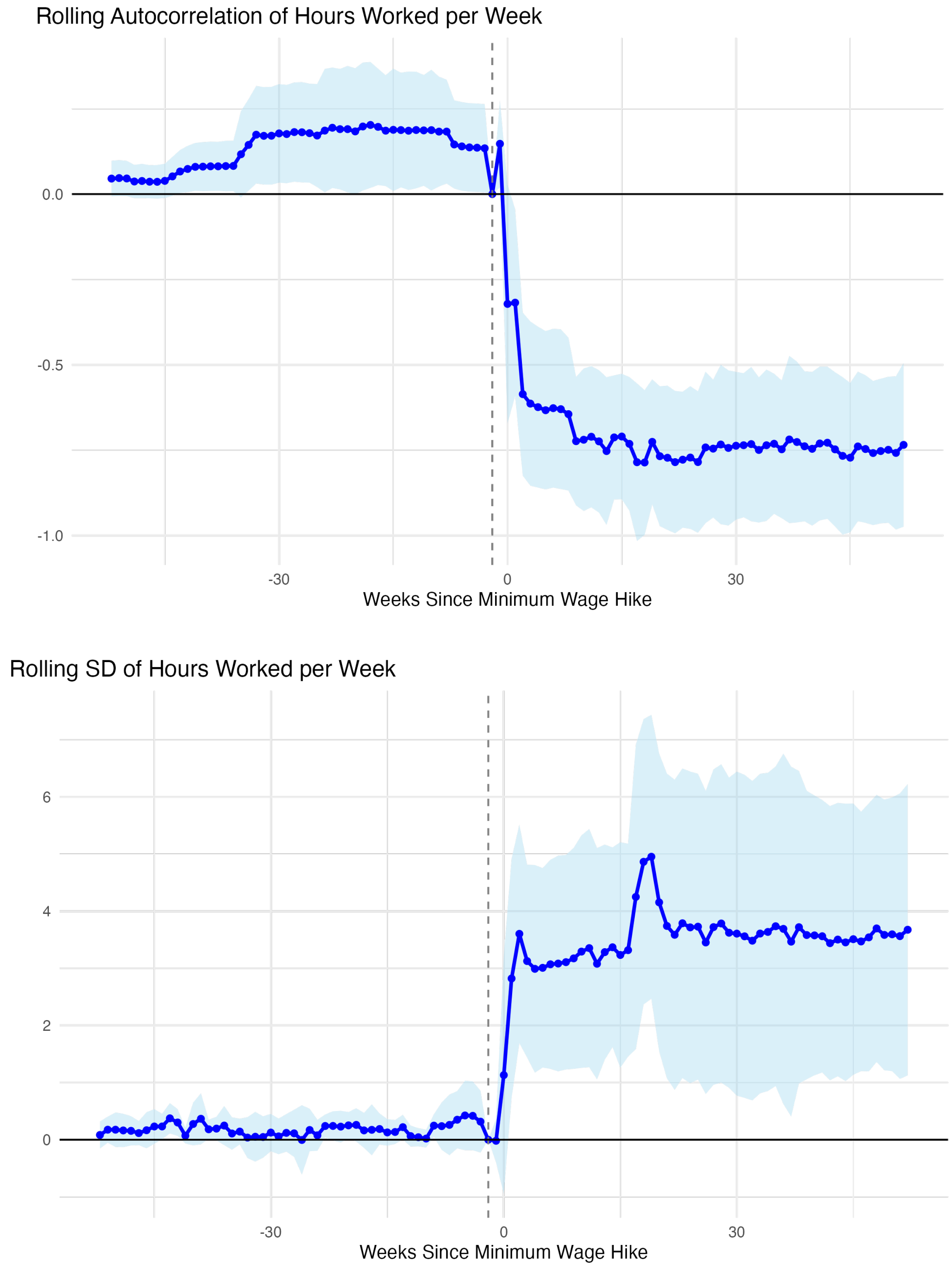
Figure 18: Effect on last-minute scheduling unpredictability





Notes: Following the onset of a minimum wage increase, 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.

Figure 19: Effect on autocorrelation and standard deviation of weekly hours



Notes: Following the onset of a minimum wage increase, 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.

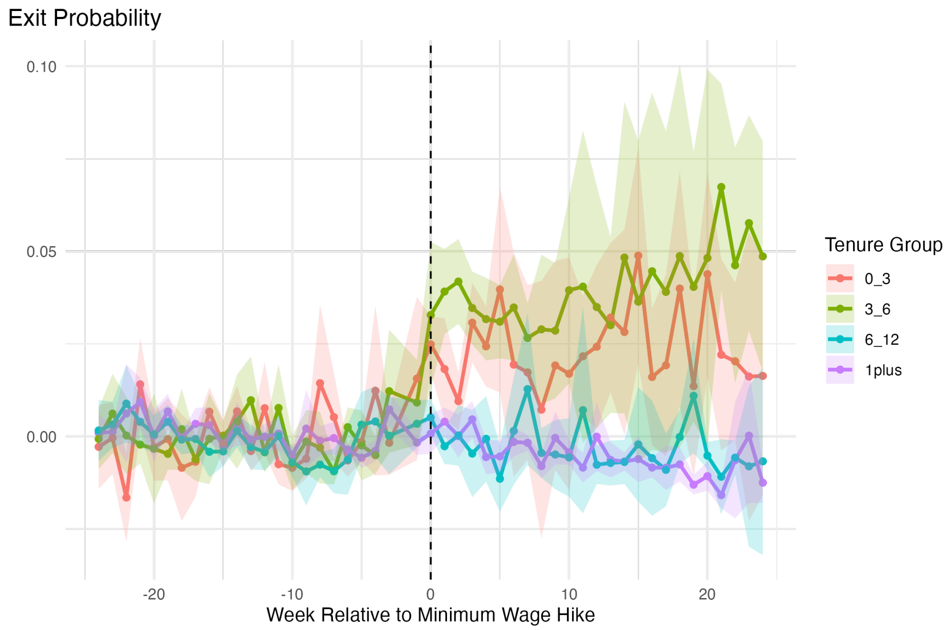
7.1.1 Heterogeneity

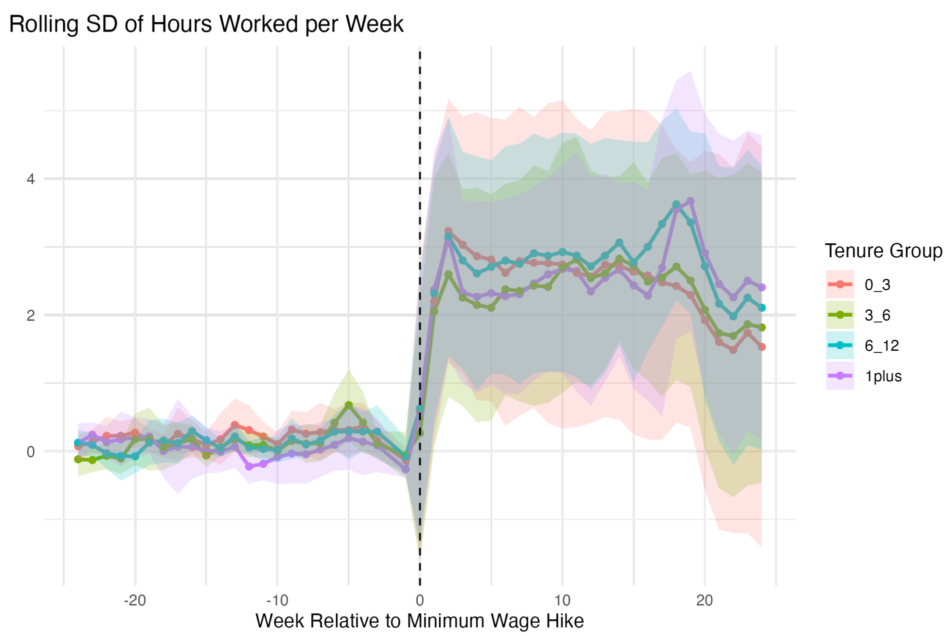
To further investigate these dynamics, I examine heterogeneity by tenure of worker at the time of the increase and unemployment rate of the county at the time of the increase. These can be considered as elements that could contribute to differing levels of γ in the model presented in Section 3. Newer hires could be willing to take on higher levels on unpredictability while they gain favor with their employers, for instance. On the other hand, if workers would find it easy to find alternative means of employment, like when local unemployment levels are low, they may have a higher distaste for unpredictability.

As discussed in Section 4, tenure is highly correlated with worker pay, hours worked, and baseline unpredictability. Workers at a business for longer typically receive more favorable hours and access to more hours if they so wish (as indicated by higher-paid employees 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 unpredictability would be pushed off to lower-tenured employees still 'earning their stripes' with a company. Figure 20 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, unpredictability increases appear to impact all workers equally, with the standard deviation of weekly hours increasing approximately the same amounts for all employees. Unpredictability fails to be driven by newest, lowest-paid employees with already high levels of unpredictability.

I additionally examine the effects on unpredictability by unemployment at the time of the imposed wage increase. 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 unpredictability in their work place. Figure 21 suggests that labor market slack does influence unpredictability 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 increase. The standard deviation of weekly hours, however, increases the most for those employees in the highest unemployment counties in the month of the increase. Although statistically insignificant, this suggests that more competition among workers is correlated with higher increases in unpredictability. If it is more difficult for an employee to find work elsewhere, they may endure more unpredictability to avoid searching for a new job.

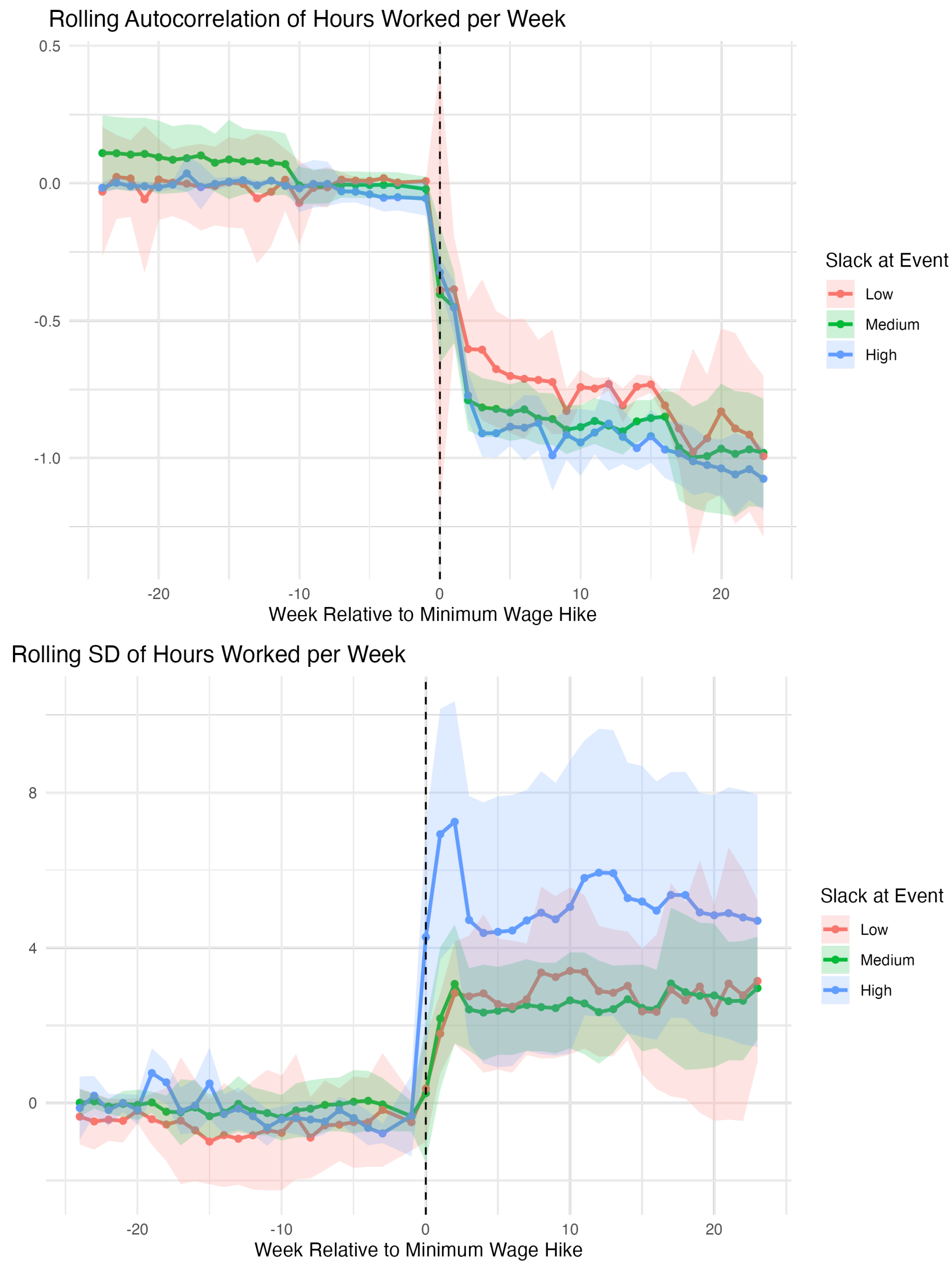
Figure 20: Exit and week-to-week similarity by tenure





Notes: Following the onset of a minimum wage increase, employee exits were driven by the employees that were the lowest-tenured at the time of the increase, while exit rates remained fairly constant for those that had been at an establishment for 6 months or more. Week-to-week unpredictability, 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 21: Week-to-week predictability by slack



Notes: Following the onset of a minimum wage increase, 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, unpredictability did not increase as much following the increase in the labor cost floor.

7.2 Weather-induced schedule shocks and minimum wage

While the results presented illustrate that unpredictability does increase following a minimum wage increase, it is not immediately evident why this is cost-saving behavior for businesses. I use the established patterns of bad-weather days inducing schedule unpredictability to outline how businesses may more frequently rely on adjusting labor in order to recuperate costs imposed by a minimum wage, resulting in higher unpredictability. This increase in the *rate of responsiveness* to shocks is showcased by the steeper slopes in reaction to higher levels of ϵ predicted by the model in Section 3.

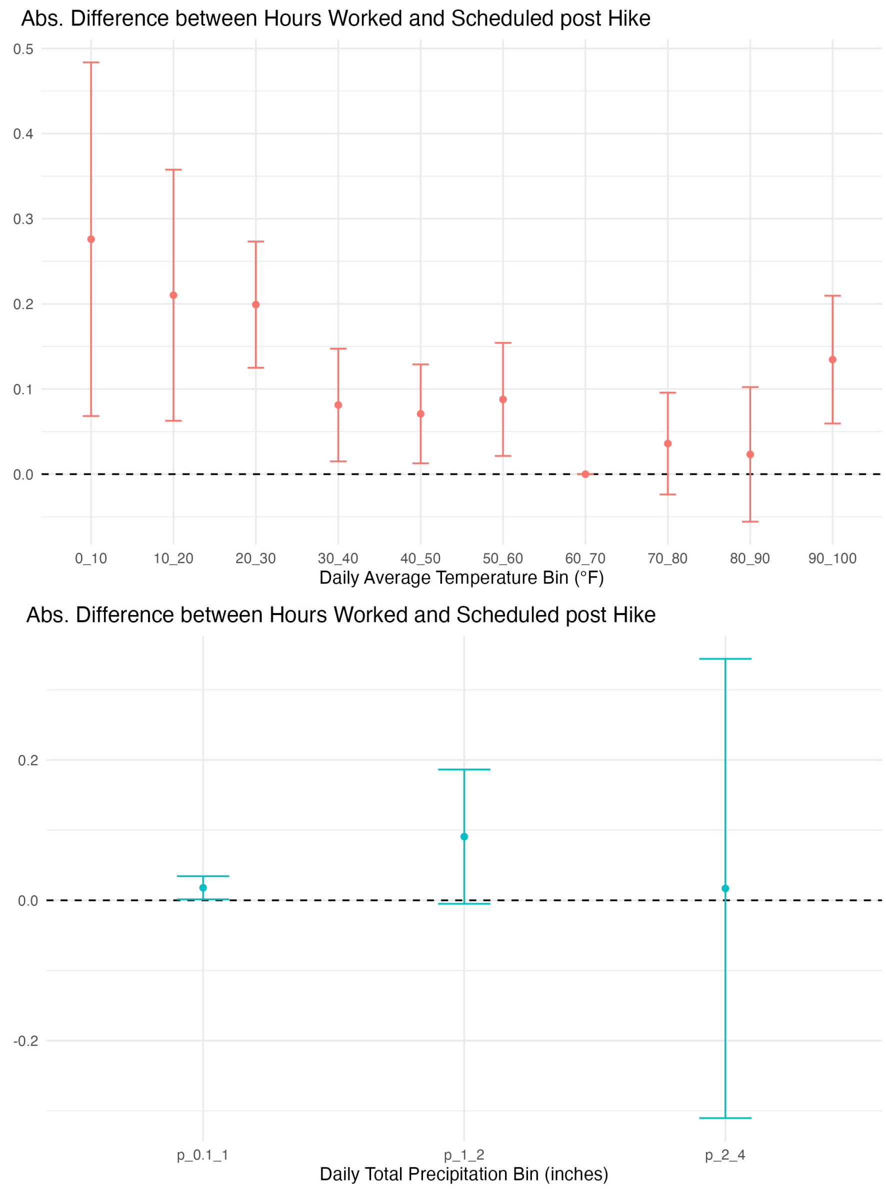
The risk-sharing behavior shown to occur on bad-weather days should be exacerbated following a minimum wage increase. An increase in the minimum wage means that the cost of labor increases. Before a minimum wage, it may have been cost effective for businesses to maintain employee schedule regularity 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 unpredictability 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 business 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 22 displays the occurrence of precisely this phenomenon, showing how the previously shown effects of weather on schedule unpredictability are exacerbated in counties for which a large minimum wage increase 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 an increase, workers post increase experience and additional 8-17 more minutes of inaccuracy. On high precipitation days, it adds an additional roughly 5 minutes.[10]

Further illustrating this point, Figure 23 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

[10]Effects for the highest levels of precipitation could be dampened because inaccuracy was already so high to begin with. These are rare events with steep consequences for businesses, and the maximum amount of adjustment could have already been taken on days prior to a minimum wage increase, leaving little room for further adjustment.

Figure 22: Minimum wage and weather effects: absolute hours difference



Notes: Following the minimum wage increase, 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.

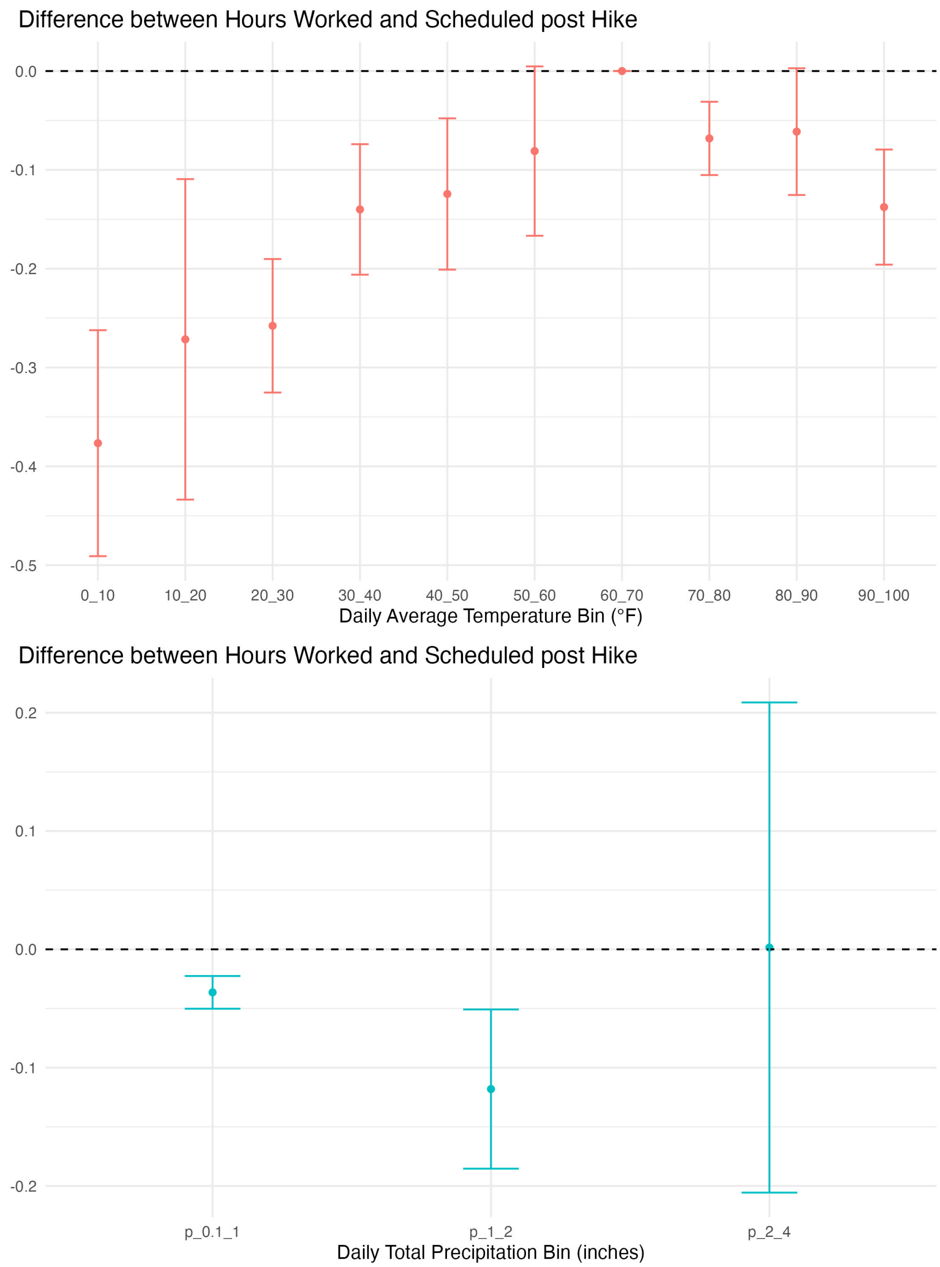
weather days. For extreme temperature days, this value ranges from 8-22 minutes less than scheduled, and around 2-8 minutes less than scheduled for each additional high precipitation day, relative to control groups. This is consistent with the idea that businesses hedge the risk of slow consumer demand 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.

7.3 Machine learning model and the minimum wage

I return to the machine learning model created to predict a worker's day-ahead scheduled hours. I use this model to predict scheduled hours post-increase, for treated and control workers separately. Consistent with previous empirical findings, the schedule becomes harder to predict for the ML model following the increase for treated workers. The root mean square error (RMSE) per day becomes 1.99 hours for untreated and 2.09 hours for the treated group. The treated group RMSE is roughly 5% higher. Assuming an employee works four days per week, this entails schedules being roughly 24 minutes less predictable through the machine learning model per week in the treated group. Already shown to be a difficult task, the challenge of predicting worker schedules becomes harder following the imposition of the minimum wage.

In addition, in the treatment group, the model consistently under predicts hours scheduled, predicting on average 7.23 hours scheduled, when in realization the average is 7.25. In the control group, on the other hand, the mean predicted is 6.96 scheduled hours and the mean actual is 6.94. This is again consistent with businesses regularly over-scheduling workers for more than the resultant labor needs in the treated period post increase.

Figure 23: Minimum wage and weather effects: net hours difference



Notes: Following the minimum wage increase, 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 an increase, employees worked less than they were scheduled to work on bad weather days.

8 Welfare calculations

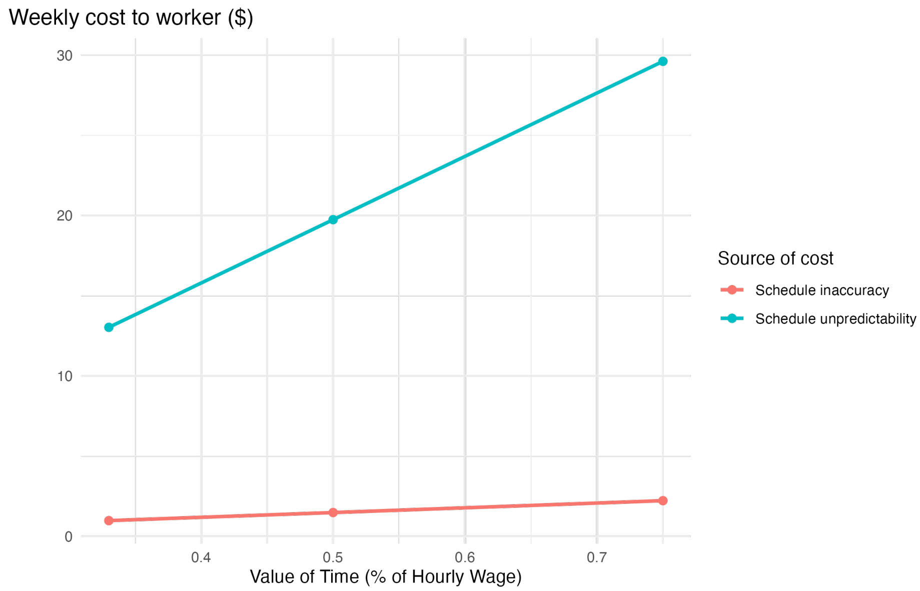
There are several possible ways to consider how this increased unpredictability eats into some of the welfare gains workers acquire through increased minimum wages. Here, I present back-of-the-envelope calculations reflecting these costs pushed onto workers, through both increased last-minute changes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

Such unpredictability 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 increase, 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 unpredictability increases. Following a minimum wage increase, 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 increase, resulting in a net loss per week of \$3.02-19.61. Ranges of weekly costs are shown in Figure 24

Figure 24: 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 increase 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 increase 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.

9 Discussion and Conclusion

In this paper, I examine an understudied aspect of hourly work: schedule unpredictability. I do so by using a large employee-employer linked administrative dataset with the unique feature of having both scheduled hours and worked hours observable. This enables me to establish baseline patterns in unpredictability across thousands of workers within small food and drink and retail businesses across the United States. I explore how various dimensions of schedule unpredictability, including last-minute schedule adjustments, week-to-week variations in number of hours and days worked, and changes in which days of the week employees work, correlate positively with each other. I additionally establish how these measures are correlated with higher rates of worker turnover, and that month-to-month income fluctuations vary substantially for hourly workers in these sectors. These patterns of unpredictability are experienced at the highest levels by the lowest-wage and least-tenured employees.

It can be challenging to observe not only these patterns themselves but any potential drivers of increased unpredictability, as many factors could contribute to changes in business operations that necessitate labor adjustments. I explore one potential contributor, weather shocks, as an explanatory variable that has the advantages of being plausibly exogenous. I demonstrate that these events, which are known to substantially alter consumer behavior, result in adjustments to workers' schedules in industries that are highly customer-dependent. The difference between scheduled hours as of one day prior to the shift and actual worked hours on the shift significantly increases as temperatures approach extreme heat or cold and precipitation increases, suggesting that the risk of slow business days may be somewhat pushed onto workers through the mechanism of schedule adjustments.

I next examine schedule unpredictability in the context of one of the most common economic policy levers, the minimum wage. As 80% of minimum wage workers are employed by the industries that are most prevalent in my sample, this is a highly salient policy. My results indicate that there is significant tradeoff between wages and schedule stability, with businesses adjusting along this margin following a minimum wage increase. Schedule inaccuracy and overall variation in week-to-week hours worked increase, without any significant overall changes to total hours worked. At the same time, rate of employee exits from establishments increases, without a corresponding increase in entrances.

I then combine these two exogenous shocks: minimum wage increases and days with abnormally extreme weather. Schedule inaccuracy increases even further on extreme weather days following an increase in the minimum wage. This suggests that as labor costs rise, it may be more costly for businesses to keep an employee hired on their regular shift on a day when their labor is not necessary due to lower than expected consumer demand. This results in businesses passing off the risk of a slow-business day onto workers more frequently after an increase in the minimum wage.

Finally, I use estimates for worker value-of-time to determine the net welfare of employees following a minimum wage increase, accounting for this increased schedule unpredictability. 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, 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 limiting just-in-time scheduling, their gains may be reduced through increased employer dependence on unpredictable scheduling to compensate. This is exacerbated by the finding that exits increase slightly among these small businesses without a matching increase in worker entrances, indicating fewer available jobs at these establishments, while the jobs left are more unpredictable. This unpredictable scheduling threatens worker productivity and health, especially for parents navigating childcare scheduling or low-income workers struggling to budget for necessary expenses and seeing large swings in their monthly income.

This study also 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 unpredictability. 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 unpredictability is placed on workers, along with the negative consequences that accompany it.

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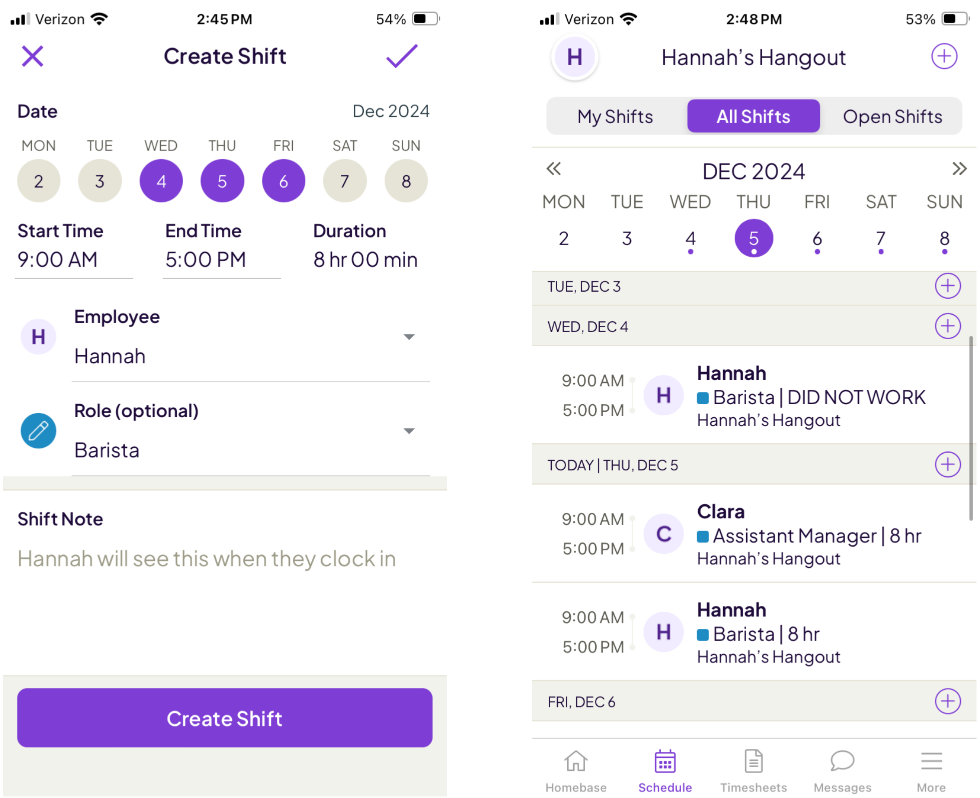
Appendix

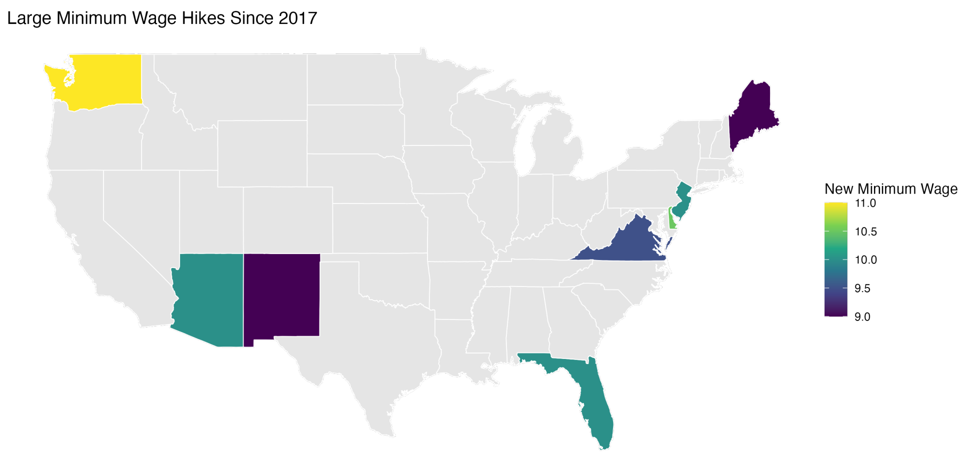
A Additional Tables and Figures

Appendix Figure A1: Example of Homebase platform



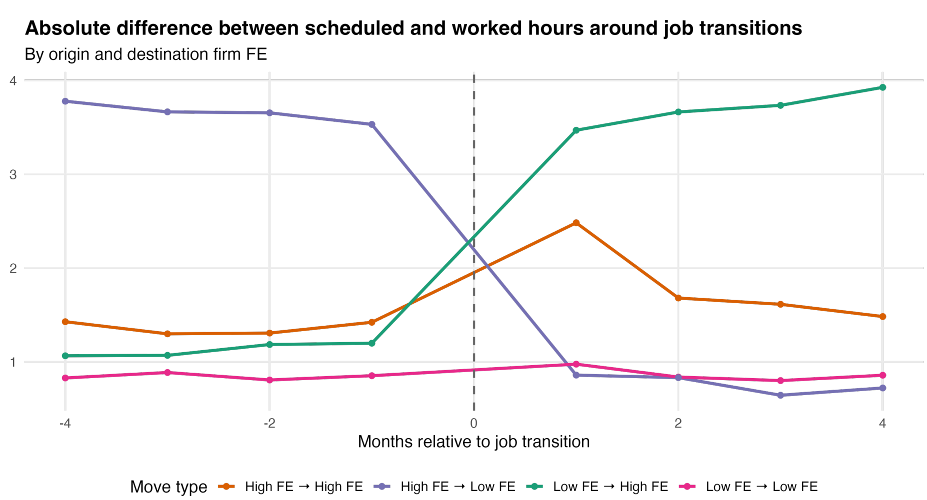
Notes: These images show the user platform of the Homebase application for a fictional cafe, from the perspective of a store manager. The image on the left displays how a manager creates new shifts on Wednesday, Thursday, and Friday from 9am to 5pm, and assigns these shifts to the employee Hannah. She 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



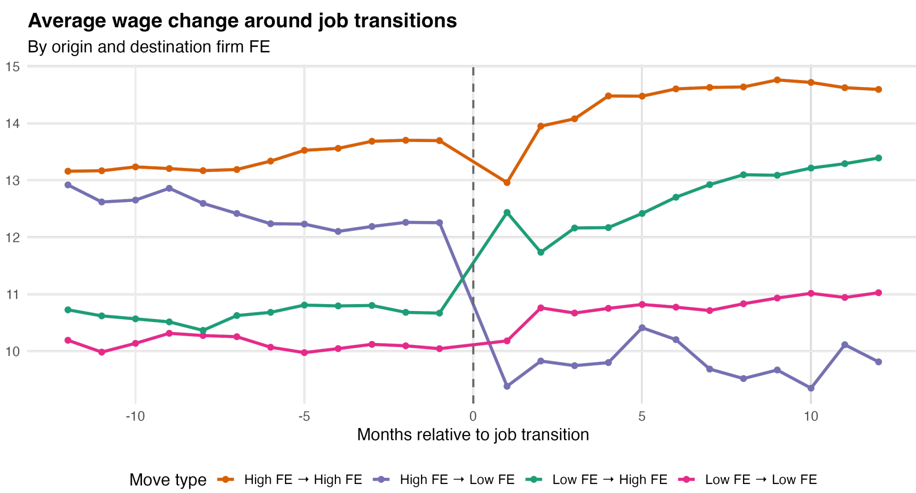
Notes: This map displays the states in the continental U.S. that experienced a minimum wage increase of greater than \$1 in the sample period without any such increase in the 2 years prior. The resulting new minimum wages in the 8 states included range from \$9 to \$11.

Appendix Figure A3: Evolution of unpredictability through job transitions, balanced panel



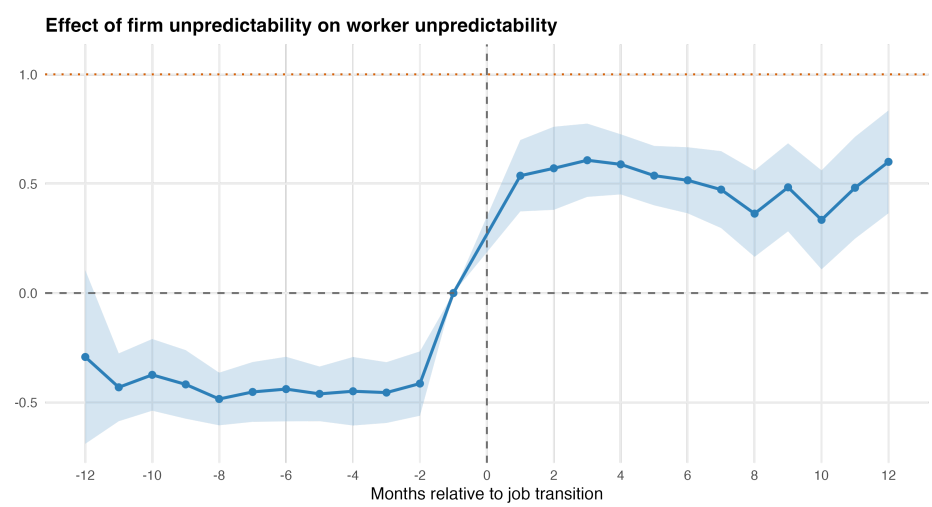
Notes: This figure displays how workers adopt the scheduling characteristics of the companies they join when transitioning from one job to another, on a balanced panel of workers present for at least 4 months before and after the month of the job transition. If a worker moves from a high-type unpredictability business to a low unpredictability business, their unpredictability subsequently drops significantly, and vice-versa.

Appendix Figure A4: Evolution of wages through job transitions



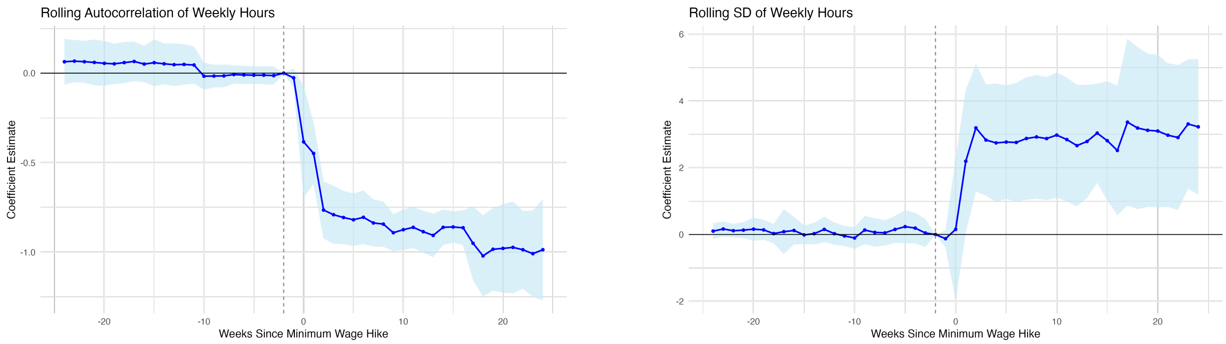
Notes: This figure displays how workers adopt the wage characteristics of the companies they join when transitioning from one job to another. Workers typically only move to higher-wage businesses, and largely adopt those higher wages post-transition.

Appendix Figure A5: Event study of worker unpredictability through job transition



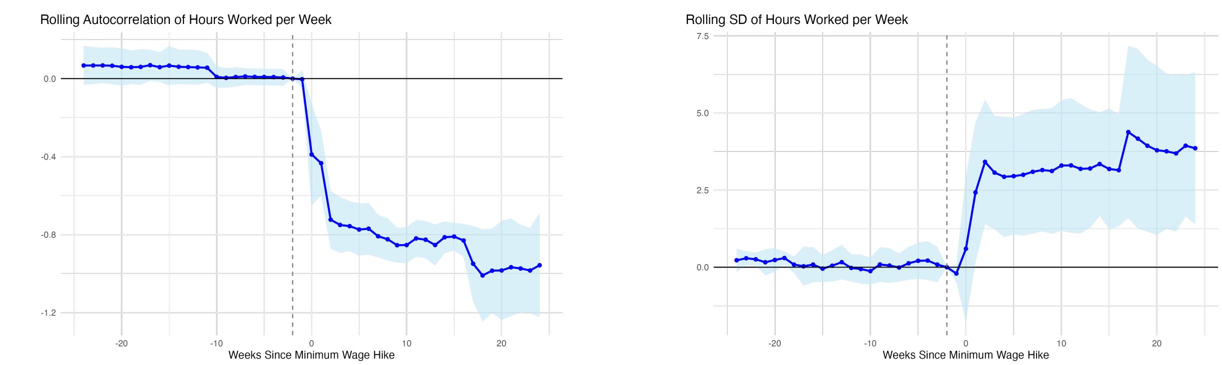
Notes: This figure shows the amount of a company's unpredictability a worker takes on following their transition into that business. Estimates for company unpredictability fixed effects are taken using the leave-one-out method, in which the moving employee is excluded from the calculation. The event study depicts that after moving, workers take on over half of the unpredictability of a company. Negative pre-trends indicate possible sorting of workers who are most likely to move to high unpredictability businesses.

Appendix Figure A6: 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 A7: 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 increase. Results are similar to main results, indicating that employee entrance or exit are not driving the results.