7-7-2025

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Upjohn Institute working paper ; 25-420

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W.E. UPJOHN INSTITUTE FOR EMPLOYMENT RESEARCH

WORKING PAPER

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July 2025

**ABSTRACT**

This paper models fair workweek regulations that require employers to provide employees with (1) schedule predictability via advance notice of their work schedule and premium payments for short-notice changes, and (2) access to hours meaning they must offer open hours to existing employees before hiring new workers. We develop a theoretical model of employers' responses to these provisions and their implications for employment. Guided by the model, we estimate the effects of recently-adopted fair workweek regulation in New York City's fast-food sector using a synthetic difference-in-differences design. We find a null employment effect.

**JEL Codes:** J08, J21, K31, M51, H73, J63

**Key Words:** fair workweek; schedule predictability; access to hours; local labor markets; employment; synthetic difference-in-differences

# 1 Introduction

In recent years, U.S. workers and their unions have successfully pushed for new kinds of labor regulation at the local level. Facing tough employer opposition in efforts to unionize the private sector using traditional strategies, the Service Employees International Union (SEIU) and other unions advocate local labor regulation in geographic areas of strength as a way for low-wage service workers to advance their interests. New York City (NYC) fast-food workers birthed the Fight for $15 a decade ago and, in recent years, put a lot of resources into organizing and advocating to restrict employer power through municipal labor regulations. These efforts produced the NYC Fair Workweek Law that went into effect in November 2017 and applies to chain fast-food employers in NYC's five counties.

The fair workweek (FWW) law contains multiple provisions to increase workers' schedule predictability, stability, and control. One provision requires firms to pay *schedule-change penalties* to employees for changes made on short notice. In the absence of this regulation, employers may insure against demand fluctuations – in particular, the consequences of understaffing – by keeping a pool of part-time workers seeking more hours; that way, if more labor is needed in a pinch, they have access to many workers who could fill in on short notice. This practice of "just-in-time" scheduling has been rapidly growing in recent years (Kamalahmadi et al. 2021). The profit gains made by firms through this practice may come at the expense of worker earnings, and schedule and job stability (Choper et al. 2022).

Another provision of the NYC FWW law gives part-time and recently laid-off employees the right of first refusal on newly available hours before their employer can legally hire a new employee. We refer to this as the *access to hours* (ATH) provision. The motivation for this provision is for firms to provide more hours to workers who want them.

Advocates hope these regulations will increase the quality of NYC fast-food jobs and create added protection for workers against employer retaliation as they organize to improve job quality. However, opponents argue the regulations could reduce production efficiency, raise prices, diminish service quality, and harm potential employees who effectively lose access to these earning opportunities. As many city councils and state legislatures consider similar scheduling laws, it is valuable to illuminate potential effects. Since 2020, five other U.S. cities have enacted similar FWW laws: Berkeley (California), Los Angeles, Chicago, Evanston (Illinois), and Philadelphia (HR Dive 2024).

This paper examines the effect of FWW laws on employment theoretically and empirically. We develop a theoretical model to clarify employers' incentives and potential reactions under common FWW provisions: schedule-change penalties and ATH. To generate predictions, we compare the model's steady-state outcomes with each provision against a baseline economy without the regulations. The model predicts that the NYC FWW law's different provisions have countervailing effects, yielding an ambiguous prediction for the overall employment effect. To test our theory, we assess the impact of NYC's FWW law for fast-food workers on their employment; in particular, we analyze publicly-available data at the county-industry-quarter level with synthetic difference-in-differences designs (Arkhangelsky et al. 2021). This design compares changes in the newly-regulated sector to changes in similar sectors either in the same counties but different industries or in the same industry but different counties around the country. The weights on potential comparison sectors are chosen to match outcome trends with the newly-regulated sector in the pre-policy period. The empirical analysis finds a robust null employment effect. Further context and robustness tests suggest that none of the provisions is likely to have a large effect. The scenario where sizable countervailing effects of the provisions cancel out is unlikely.

The theoretical model considers the staffing and scheduling problem of a firm facing uncertain demand. Firms can only hire new workers at the end of the period and face a constant hiring cost to add to their current workforce. Before demand for any given shift in the period is known, the firm sets a *regular schedule* where each of its employees is scheduled to work certain shifts. Once demand is revealed for a particular shift, the firm tries to adjust the number of employees working during that shift to meet demand. If too many employees are scheduled, the employer cuts employees from the schedule and faces a small removal cost. This removal cost reflects potential reductions in productive effort by removed employees during their other shifts if they feel jerked around and demoralized. If too few employees are scheduled relative to demand, the employer attempts to fill the gap with other employees in their workforce who are not scheduled for that shift. Since there is no time to hire new employees on such short notice, employers tend to maintain a bench of employees above what they need at any one time and ask employees on the bench to fill in as needed. If the firm cannot staff up sufficiently to meet a surge in demand for a shift, it experiences a staffing shortfall cost.

In this baseline environment, firms balance conflicting incentives in setting the regular schedule. On one hand, they wish to schedule many workers per shift to avoid shortfall costs. On the other, they wish to schedule fewer workers to avoid removal costs. They also face conflicting incentives in deciding workforce size. On one hand, they want a large workforce (implying a large bench) that could fill in on short notice and help avoid a staffing shortfall. On the other, maintaining a larger workforce requires greater hiring costs because of exogenous job destruction. These firm incentives change as the different FWW provisions are introduced.

The paper's main contributions are twofold. First, we generate theoretical predictions for the NYC law's two major provisions: schedule-change penalties and ATH. Modeling FWW provisions in this way is unique in the literature, although our theory shares similarities with the worker-availability model of McCrate et al. (2019). Further, our model is relevant outside the NYC context because other FWW laws have similar collections of provisions.

The predictions are as follows. First, when a policy requiring *removal penalties* is instituted, such that the firm has to pay a financial penalty to the employee each time the employer cancels a scheduled shift, the firm reduces the number of employees scheduled for each shift (to avoid removal penalties) and increases its total workforce (so more employees are on the bench to fill in on short notice). Because there are more employees and fewer hours to go around, average employee hours fall. Second, when *add penalties* are instituted, such that the employer has to pay a financial penalty to the employee each time the employer adds an unscheduled shift, the opposite happens. The firm increases the number of workers scheduled (to avoid the add penalties) and decreases their workforce (since it is less likely to fall short of demand), which, in turn, increases hours per worker. Lastly, the effects of ATH are the same as the add penalties. Because firms are required to offer newly-available hours to existing workers before hiring more workers, average hours per worker increase and fewer hires are made, which leads to a smaller workforce. The employer compensates for having a smaller workforce – which makes avoiding shortfall harder – by scheduling more workers per shift. In sum, the removal penalties push employment up, but add penalties and ATH push it down. Effects on the number of employees scheduled per shift and average hours per employee are the opposite. For each outcome, the overall effect is ambiguous in sign and depends on the relative magnitudes of the opposing mechanisms.

The second main contribution is an empirical analysis of the NYC FWW law, which covered fast-food chains' employees. This adds to a small but growing literature on labor market effects of FWW laws (Yelowitz 2022; Kwon and Raman 2023; Pickens and Sojourner 2025). Most of the existing FWW effects literature focuses on outcomes like well-being and sleep (e.g.: Harknett et al. 2021; Ananat et al. 2022), rather than employment or other labor-market outcomes. To analyze outcomes for the NYC fast food industry, we draw on employment measures at the industry-county-quarter level from the Quarterly Census of Employment and Wages (QCEW). We rely on a proxy for the affected population: we observe employment in the fast-food industry (limited-service restaurants) but cannot isolate affected workers within it (e.g., chain versus non-chain employment). While the model makes predictions for average hours per worker and for scheduling decisions, data limitations prevent us from testing these predictions directly. In studying recent FWW laws in Philadelphia, Chicago, and Los Angeles, Kwon and Raman (2023) find no significant effects on scheduled work or average worker hours, but they do not examine employment. Because our model predicts effects on employment and average hours move in opposite directions, Kwon and

Raman (2023)'s estimated null on average hours suggests we would find a null employment effect, assuming the different contexts operate similarly. That is what we find.

Furthermore, we cannot separately identify the effects of the law's different provisions. Given our theoretical predictions, the null empirical result suggests one of two scenarios: (1) multiple provisions have sizable effects that cancel out; (2) none of the provisions have a sizable effect. Further context from two robustness checks points to the second scenario being more likely. In particular, we run two robustness tests designed to isolate the effect of schedule-change penalties in other environments. A first test runs analysis on a similarly passed FWW law in another location that does not have ATH: Oregon's FWW law, which went into effect in July 2018. A second test runs an analysis on the NYC retail industry. The 2017 NYC FWW law also applied to this industry, but without schedule-change penalties or ATH. Both tests find null employment effects, suggesting the second scenario: neither schedule-change penalties nor ATH has sizable employment effects.

In summary, while we can not evaluate directly, large effects on employment from any of the provisions seem unlikely. In a discussion section, we investigate possible reasons for this. First, considering previous research, a lack of enforcement or compliance is a possible culprit. Second, examining Current Population Survey (CPS) data on involuntary part-time workers suggests a significant ATH effect is unlikely. In the two years after passage (2018-2019), only 2.8% of restaurant workers nationally are involuntary part-time – i.e., part-time *and* report not being able to find full-time work as the reason. Though the rate could be higher for NYC fast food workers or in a slacker labor market, significant effects may not manifest unless there are many more involuntary part-time workers. As a counterpoint, involuntary part-time statistics do not capture all workers who want additional hours. Statistics from Golden and Kim (2020) suggest that 40% of part-time workers want more hours. Further, this rate is higher for low-income individuals, hourly workers, service occupations, workers whose hours are decided by their employer, and workers with variable schedules. Contrary to the CPS data, these statistics suggest a significant ATH effect in the fast-food industry is possible.

The rest of the paper proceeds as follows. Section 2 provides background on the 2017 NYC legislation, and Section 7 overviews the relevant literature. Section 3 introduces our theoretical model, and Section 4 presents its predictions; a more thorough exposition is left to Appendix A. Section 5 overviews our data and empirical methods, and Section 6 details the main results. A robustness analysis of these results is left to Appendix D. Section 8 offers a discussion, and Section 9 a conclusion.

# 2 Background

On May 24, 2017, the NYC Council passed the *Fair Workweek Law* almost unanimously (46-4) (ECM 2022). On May 30, 2017, Mayor Bill de Blasio signed it into law, and it became effective 180 days later: November 26, 2017.

The law has the following provisions for the fast-food industry: (1) before they start employment, employers must provide workers with a *regular schedule* – includes the number of hours an employee can expect to work per week, with days, times, and locations of hours; (2) employers must give two weeks' notice for changes to this schedule; (3) for changes made within two weeks, the worker must consent, and a premium must be paid; (4) workers can say no to working additional hours; (5) employers must provide existing employees *access to hours* (ATH);[1] (6) *clopening shifts* – 2 shifts over 2 days with less than 11 hours rest between – are forbidden unless the worker consents and a premium is paid; and (7) employers must keep records of employee schedules, workers' written consent, and premiums paid.

These provisions apply to all of NYC's chain fast-food establishments – "a business that is part of a chain, primarily serves food and beverages, offers limited service, and is one of 30 or more such establishments nationally" (DCWP 2023a). The law is enforced by the

[1] The provision "requires employers to offer available [hours] to current employees when they anticipate hiring new employees" (DCWP 2023a). If multiple workers at the same business location want the same hours, the employer can choose to award hours "in any nondiscriminatory manner it chooses" (DCWP 2023a). If an employee accepts a *recurring* shift, their employer must add this shift to their regular schedule.

NYC Department of Consumer and Worker Protection (DCWP). If a suspected violation occurs, workers can confidentially file a complaint with the DCWP; the DCWP investigates the complaint, and if it concludes a violation occurred, the employer may be responsible for financial damages and other forms of relief to affected workers, as well as fines paid to the city. In addition to responding to complaints, the DCWP can investigate employers on its initiative. Furthermore, to help educate stakeholders, the DCWP regularly conducts outreach to employers and workers about the FWW law.[2]

**Incorporating the law in our model:** Our theoretical analysis in Sections 3 and 4 – which considers different legal regimes to study effects from different parts of the law – incorporates the first five provisions in either the *schedule-change environment* or the *ATH environment*; the combination of the two is the *FWW environment*. A period represents a hiring cycle. Turnover occurs between periods, not within. The "regular schedule" is represented by the mass of workers per shift the firm chooses at the beginning of the period. In the schedule-change environment, staffing changes made to the regular schedule after demand is revealed are subject to short-notice add or removal penalties. In the ATH environment, firms are required to give existing workers as many newly-available hours as they want. While we do not consider the right to refuse hours in the model directly, it is incorporated indirectly.[3] In the end, we present results on the employment, scheduling, and hours consequences of a removal penalty, an add penalty, and ATH. As noted below, removal penalties are more costly than add penalties under the NYC FWW law. For this reason, the effects of removal

[2]A separate part of the law applies to NYC retail workers. In a robustness exercise in Appendix D, we explore effects on retail workers; Appendix D.1 gives relevant legal details. The provisions for fast-food workers were expanded in 2021 to raise the termination standard to "just cause" among other changes. To make sure this expansion (and COVID-19) does not affect our estimates, we end our analysis in 2019. The effects of this just cause law are analyzed in Pickens and Sojourner (2025).

[3]The firm can offer hours to workers in two ways: on short notice and for their regular schedule. If an employee cannot refuse hours from an employer on short notice, this is functionally equivalent to requiring them to be available at a given time. One can think of the firm expecting workers to be available on short notice as them being on the regular schedule in our model. As for additions to the regular schedule, before FWW, the worker cannot refuse such additions, but after FWW, they can. In the baseline and schedule-change model environments, workers are not collectively given as many additional hours as they want (see Assumption 1) so the firm does not need to force workers to take hours. In the ATH environment, existing workers are given (exactly) as many additional hours as they want. Based on Assumption 1, the firm would prefer to give them fewer hours so the firm again will not force workers to take hours.

penalties likely dominate the effects of add penalties.

Though we believe our model captures the most impactful parts of the NYC law, it does not capture all its nuances. First, short-notice add and removal penalties vary by the amount of notice given. Short-notice adds vary from $10 to $15 per change while removals vary from $20 to $75. We do not consider variation within penalty type. The law also penalizes short-notice schedule changes that do not affect hours. For simplicity, our model does not consider such changes or penalties. Furthermore, we do not include the last two provisions in the model – (6) and (7) above. We expect they have minor economic consequences for firms at most.[4] Nevertheless, we believe our empirical estimates mostly capture the combined effect of the short-notice penalties and ATH.

# 3 Theoretical Model

In what follows, we consider the problem of a firm facing variable demand. Before each period starts, the firm sets a regular schedule assigning employees to shifts. After the schedule is set, the firm learns what demand will be during a particular shift. To maximize profits, the firm adds or removes employees to or from the shift schedule on short notice to meet demand.

To simplify analysis, we abstract from considering wages or a production function. Instead, the firm is primarily concerned with avoiding a staffing *shortfall* on each shift – when it cannot find enough workers to meet demand.[5] We assume the firm learns demand shortly

[4] For firms with many employees, clopenings can likely be avoided easily with strategic scheduling. For firms with fewer employees, it may be harder. If a firm relies on using clopening shifts, the clopening provision could incentivize them to increase their workforce, making it easier to avoid clopenings on the regular schedule and having a larger pool of workers to avoid clopenings on short notice. If this is the case, the clopening provision may have a similar effect to the short-notice removal penalty.

[5] Formally, to abstract from wages and production, one can assume that the marginal product from every unit of labor is the same as the wage (other than the costs specified in the model). Also, since we abstract from wages, we do not consider the role of a minimum wage, which existed and was growing in NYC at the time the FWW law became effective. Relative to an environment with no wage floor, a minimum wage could potentially decrease labor demand, reducing total employment or hours. It could also increase competition on the labor supply side, motivating workers to put up with greater schedule unpredictability and instability. Therefore, introducing provisions designed to promote schedule predictability or stability could have more of

before the shift starts, so there is no time to hire new workers. It can only fill a gap between demand and scheduled staff by quickly attempting to add existing workers not already scheduled for that shift to the schedule. Such workers can reject this short-notice request, so shortfall is a credible threat.

The firm makes hiring and scheduling decisions to minimize various costs. In all environments, there is a financial cost of staffing shortfall, a per-unit hiring cost, and a worker removal cost of varying degrees. Intuitively, the firm wants to schedule enough workers per shift so a staffing shortfall is not likely. However, it also wants to avoid worker removal costs, which are necessary if demand is sufficiently low. Further, it wants to employ many employees on the bench who could fill a staffing shortage on short notice. However, maintaining a larger workforce entails additional hiring costs. Ultimately, the firm makes hiring and scheduling decisions based on costs, which vary across the different regulatory environments.

This section develops the various environments and characterizes the firm problem in each. The next section presents predictions from the model. Appendix A completes the theoretical analysis: A.1 gives assumptions on primitives and key functions; A.2, A.3, and A.4 prove the three main predictions.

## 3.1 Baseline environment

Consider a firm operating in discrete time that discounts the future according to $\beta \in (0, 1)$. There is a large mass of workers that the firm can employ. We denote their *workforce* as $N \in \mathbb{R}_+$. Each period, there are $S \in \mathbb{N}$ *shifts* – a unit of time where production occurs. Each worker can be scheduled for a particular shift and can work multiple shifts. The firm schedules a mass of *workers per shift* (denoted $n \in \mathbb{R}_+$) to minimize the costs described below. The choice of $n$ is consistent across shifts. The difference between the firm's number of employees and the number on a regularly-scheduled shift, $N - n$, is the size of the employer's

an effect in a minimum wage environment because they would prevent more unpredictability and instability. However, since our model does not consider worker preferences for schedule predictability and stability, it does not capture such a mechanism.

*bench*. As will become clear, a bigger bench means a lower probability of a costly staffing shortfall, but also more hiring costs.

After the *regular schedule* $n$ is set, firms face unpredictable demand. Before each shift starts, the firm receives a demand shock $z$ from a continuous distribution with PDF $f(z)$, CDF $F(z)$, and support on $[0, \bar{z}]$. This $z$ is the mass of workers the firm will need during that shift to meet demand. If $z < n$, the firm removes a mass $n - z$ of workers from the shift's schedule. For each unit of workers removed, the firm incurs an effort cost $\phi_e > 0$ ('$e$' for effort). If the cost of removal were zero, the firm would schedule all its employees during every shift and maintain no bench. If $z > n$, the firm tries to get some of their bench (i.e., their other $N - n$ workers) to fill the remaining *gap* – the $z - n$ workers needed on short notice; we assume there is no time to hire new workers before production occurs.[6] It will not be able to find these replacement workers with probability $g(z - n, N - n)$. That is, workers on the bench have the right to refuse an additional shift, and the firm will not fill the gap with some probability. In this case, the firm experiences a staffing *shortfall* and incurs a cost $\phi_s > 0$ ('$s$' for shortfall).[7]

After production occurs, a fraction $\delta_w \in (0, 1)$ of the firm's employment relationships is exogenously destroyed. Of the remaining employees, a fraction $\delta_s \in (0, 1)$ of their regularly scheduled *hours* are vacated. This could reflect changes in personal circumstances or preferences. In the model, this serves to stop an unrealistic outcome where an employee's hours could grow without bound until their job is destroyed. For convenience, we assume each shift is one hour long, but this assumption does not affect our results.[8]

[6] In practice, firms may avoid spot markets for labor because of hiring costs and the firm-specific human capital that existing workers already have (McCrate et al. 2019).

[7] Instead of having a constant shortfall cost, we could scale the cost by the size of the unfilled gap. This would significantly complicate the model as we would have to consider a distribution over the mass of workers who could fill in on short notice. We consider a constant cost to keep the analysis relatively simple. Two additional notes. First, hours accepted on short notice do not become part of a worker's regular schedule. Second, we make several assumptions on $g : [0, \bar{z}] \times \mathbb{R}_+ \to [0, 1]$ that are detailed in Appendix A along with the relevant intuition.

[8] While exogenous job destruction (via $\delta_w$) is necessary for our results, exogenous shift destruction (via $\delta_s$) is not. Also, note that employees can work differing hours, although we do not keep track of such differences in our analysis. As described in the next paragraph, existing employees will *collectively* take additional hours, but we do not keep track of how many hours each worker takes, only the total number of hours taken.

Looking to the next period, the firm can fill these openings in their schedule (or add to their schedule) in two ways: offering additional hours to their existing workforce or hiring new workers. It is convenient to think of their decision as choosing a mass of hours to fill ($Y_{fill}$) and then splitting them between existing workers and new hires. Of the $Y_{fill}$ hours, we assume the $(1-\delta_w)N$ remaining workers *could* fill up to $h(Y_{fill},(1-\delta_w)N)$; this amount represents how many hours existing workers collectively want.[9] However, the firm may not want to give all these hours to existing workers. In the baseline environment, the firm chooses an amount ($Y_e$) of hours to give to existing workers. The firm hires a mass $H \in \mathbb{R}_+$ of new workers and offers them each $y_h \in \mathbb{R}_+$ hours where $y_h$ is fixed.[10] For each unit of workers hired, the firm incurs cost $\kappa > 0$.

Through their choice of $Y_{fill}$, $H$, $y_h$, and $Y_e$, this pins down the workforce ($N'$) and workers per shift ($n'$) next period:

$$N' \;\leq\; (1-\delta_w)N \;+\; H, \tag{1}$$

$$Sn' \;\leq\; (1-\delta_w)(1-\delta_s)Sn \;+\; Y_e \;+\; Hy_h, \tag{2}$$

$$Y_e \;\leq\; h(Y_{fill},(1-\delta_w)N). \tag{3}$$

The first two equations, (1) and (2), are the laws of motion for the workforce and total hours, respectively. For (2), on the right-hand side, the first term is regularly scheduled hours from the current period that continue into the next period. The second term is (newly-available) hours given to existing workers, which is constrained by the number of hours that remaining workers could fill (equation (3)). The third term is hours given to new hires. The left-hand side is the total mass of hours on the regular schedule for next period.

The firm enters a period with a workforce of size $N$ and $n$ workers per shift on the regular

[9] Note that the amount of hours existing workers would accept is independent of how much they are already working. This decision is discussed further at the end of Section 8. Also, assumptions on the function $h : \mathbb{R}^2_+ \to [0,1]$ are described in the appendix along with the associated intuition.

[10] Since a shift is a discrete object, $y_h$ can be thought of as the number of shifts (hours) a new worker *expects* to work.

schedule. Events each period proceed as follows. For each of the $S$ shifts, the firm learns of productivity shock $z$. If $z < n$, the firm removes $n - z$ of the workers. If $z > n$, the firm tries to fill the gap $(z - n)$ with its bench $(N - n)$. Then, production occurs and associated costs are incurred. After the shifts are complete, existing jobs and then regularly scheduled hours are destroyed with probabilities $\delta_w$ and $\delta_s$ respectively. Then, the firm chooses hours to fill ($Y_{fill}$), hours to give to existing workers ($Y_e$), and new hires ($H$), which pins down the next period workforce ($N'$) and workers per shift ($n'$).

The above describes the *baseline* environment. In what follows, we will consider additional environments, one of which forces the firm to offer all new hours ($Y_{fill}$) to existing workers before hiring new workers. In effect, this requires (3) to be a binding constraint. In order for this change to be meaningful, the firm must prefer to give existing workers fewer hours than they would like. We assume this is the case.

**Assumption 1** *In the solution to the baseline problem, existing workers do not get as many hours as they want:*

$$Y_e \ < \ h(Y_{fill}, (1 - \delta_w)N).$$

The firm's cost minimization problem in the baseline environment is:

$$\begin{aligned} V^b(n, N) \ = \ \min_{n', N', H} \Big\{ & S\phi_s \int_n^{\bar{z}} g(z - n, N - n) f(z) dz \\ & + S\phi_e \int_0^n (n - z) f(z) dz + \ H\kappa \ + \ \beta V^b(n', N') \Big\} \end{aligned} \tag{4}$$

subject to the new worker constraint (1). The firm uses its choices to balance the expected cost of staffing shortfalls (first term) and the expected cost of shift removals (second term). Note that we do not consider the constraints in (2) or (3) or the choice of $Y_{fill}$ because Assumption 1 renders it unnecessary.

### 3.2 FWW environment

Next, we consider multiple aspects of the FWW law that we split into two categories: penalizing short-notice schedule changes ("schedule changes" for short) and access to hours (ATH). We will eventually evaluate these two types of changes separately but we set up the firm problem below with both.

In the baseline environment, firms could add or remove workers from a particular shift without facing any financial costs (although they incur an effort cost $\phi_e$ upon removal). In the FWW environment, the firm must pay a worker $\pi_{add}$ if they take a shift on short notice and $\pi_{drop}$ if their shift is removed on short notice. As before, a bench worker cannot be forced to take a shift on short notice. Note that there is no longer an effort cost to removal ($\phi_e$), but we assume the financial penalty is bigger ($\pi_{drop} > \phi_e$).

Recall firms choose a mass of hours they want to fill and the workforce that remains after job destruction would accept a specified amount of them if offered. In the baseline environment, firms do not have to give existing workers all the hours they want, but in the FWW environment, they do because of the ATH provision.

The firm's cost minimization problem is:[11]

$$V^{fww}(n,N) = \min_{n',N',H,Y_e} \Big\{ S\int_n^{\bar{z}} \Big[ g(z-n,N-n)\phi_s + \big(1-g(z-n,N-n)\big)\pi_{add}(z-n)\Big] f(z)dz \\ + S\pi_{drop}\int_0^n (n-z)f(z)dz \; + \; H\kappa \; + \; \beta V^{fww}(n',N')\Big\} \tag{5}$$

subject to the new worker constraint (1), the total hours constraint (2), and a binding version of the new hours constraint for existing workers,

$$Y_e \;=\; h(Y_{fill},(1-\delta_w)N), \tag{6}$$

where $Y_{fill}$ is the difference between total hours next period and hours still occupied on the

[11]Note in (5) that if demand exceeds scheduled workers per shift, then the firm only pays for short-notice-added workers if it avoids a shortfall (with probability $1-g(z-n,N-n)$; see the first term). This is done for simplicity; in principle, it could hire some of the workers it needs and still have a shortfall.

current period's schedule after destruction:

$$Y_{fill} \;=\; Sn' \;-\; (1-\delta_w)(1-\delta_s)Sn. \tag{7}$$

## 3.3 Characterizing solutions to the firm problems

In this subsection, we characterize steady-state solutions to the firm problem in different environments. Each environment has two equations that dictate the choice of workforce ($N$) and workers per shift ($n$). We first compare equations in the baseline and "schedule-change" environments since the equations are similar. The schedule-change environment considers removal and add penalties, but not ATH. Then, we analyze the two equations for the full FWW environment: schedule-change penalties and ATH.[12]

The following equations describe the optimal choice of workers per shift ($n$) that balances the marginal costs (MC) and marginal benefits (MB) of increasing $n$. Equation (8) characterizes the optimal decision in the baseline environment and (9) in the schedule-change environment:[13]

$$\phi_e F(n) \;-\; \phi_s \int_n^{\bar{z}} g_2 f(z)dz \;=\; \phi_e \int_n^{\bar{z}} g_1 f(z)dz, \tag{8}$$

$$\underbrace{\pi_{drop} F(n) \;-\; \phi_s \int_n^{\bar{z}} g_2 f(z)dz}_{\text{MC of increasing } n} \;=\; \underbrace{\phi_e \int_n^{\bar{z}} g_1 f(z)dz \;+\; \pi_{add} \int_n^{\bar{z}} \big[(1-g) - (z-n)(g_1+g_2)\big] f(z)dz.}_{\text{MB of increasing } n} \tag{9}$$

On the left-hand side, the first terms capture the increased likelihood of removing workers from their scheduled shifts; this is more likely since workers per shift ($n$) is increasing. The term in (8) is an effort penalty, while the term in (9) is a financial penalty. As mentioned, we assume the financial penalty is more severe ($\phi_e < \pi_{drop}$). The second terms – which are costs

[12] Note there is a third equation dictating the steady-state mass of hires. Using the worker law of motion equation (1), which is the same across environments, $H = \delta_w N$. Intuitively, in a steady state, the mass of workers coming into the firm through hiring will equal the mass of workers leaving the firm through exogenous job destruction.

[13] Here, '$g_1$' and '$g_2$' are the derivatives of $g$ with respect to the first and second arguments (respectively) evaluated at $(z-n, N-n)$. Similarly, '$g$' is also evaluated at $(z-n, N-n)$. Note that we assume $g_2 < 0$ while $g_1 > 0$. For intuition behind these assumptions (and other assumptions on $g$ and $h$), see the appendix.

since $g_2 < 0$ – capture the decreased likelihood of avoiding shortfall due to a smaller bench $(N - n)$: as we increase workers per shift $(n)$ holding the workforce $(N)$ constant, the bench shrinks. On the right-hand side, the first terms – which are benefits since $g_1 > 0$ – reflect the increased likelihood of avoiding shortfall due to more workers per shift $(n)$. Additionally, (9) has a second term which captures that increasing $n$ will lower costs from add penalties.[14]

Similarly, the following equations express the optimal employment level $(N)$ that equates the MC and MB of increasing $N$; equation (10) for the baseline environment and in equation (11) for the schedule-change environment:

$$\frac{C_w}{S}\kappa = -\phi_s \int_n^{\bar{z}} g_2 f(z)dz, \tag{10}$$

$$\underbrace{\frac{C_w}{S}\kappa - \pi_{add}\int_n^{\bar{z}} (z-n) g_2 f(z)dz}_{\text{MC of increasing } N} = \underbrace{-\phi_s \int_n^{\bar{z}} g_2 f(z)dz.}_{\text{MB of increasing } N} \tag{11}$$

On the left-hand side, the first terms reflects the increased hiring costs associated with maintaining a larger workforce; the constant is $C_w \equiv \left[1/\beta - (1-\delta_w)\right]$. The bottom equation (11) has a second term which reflects the increased costs of avoiding shortfall. On the right-hand side, the sole terms reflect the benefit of having a larger bench $(N - n)$ to avoid a shortfall.[15]

Next, consider the full FWW environment, characterized by the baseline plus both short-notice schedule-change penalties and ATH. The two equations characterizing the steady state here – equations (12) and (13) – are different because the constraint on new hours to existing

[14]Note that in this integral, there are two terms. The first reflects that having to add workers on short notice (and, thus, incurring the penalty $\pi_{add}$) becomes less likely with higher $n$; this term is positive. The second reflects that the firm is more likely able to cover staffing gaps, which comes at a cost of $\pi_{add}$ per worker; this term is negative because $g_1 + g_2 > 0$. Assumption 2 in the appendix clarifies two points. First, the benefit of needing to cover smaller gaps on average to avoid staffing shortfalls (the first term) is bigger than the increased costs associated with avoiding the shortfall more often (the second term); i.e., the marginal benefit of increasing $n$ is positive in terms of short-notice add costs. Second, the firm will always prefer paying add penalties over incurring a staffing shortfall.

[15]For a fixed $n$, as the workforce increases, so does the bench $(N - n)$, which makes avoiding shortfall more likely. As avoiding shortfall becomes more likely, the firm also becomes more likely to pay add penalties. As mentioned in the previous footnote, Assumption 2 in the appendix ensures the firm will always prefer paying this penalty to incurring a shortfall. This implies the benefit of having a larger bench to avoid a shortfall dominates this cost of increased add penalties.

workers (3) is now binding by law. Equation (12) combines the constraints for total hours (2) and new hours to existing workers (3), and plugs in the equation for $Y_{fill}$ (7) and the steady state hiring value $H = \delta_w N$:

$$\gamma(n) \; = \; \delta_w N y_h \; + \; h\big(\gamma(n), (1-\delta_w)N\big). \tag{12}$$

where $\gamma(n) \equiv \big(\delta_w + \delta_s(1-\delta_w)\big)Sn$. Equation (13) equates the MC of hiring an additional employee (left-hand side) with its marginal benefits (right-hand side):[16]

$$\begin{aligned} & C_w C_{ws}(1-h_1)\kappa \; + \; \big[(1-\delta_w)h_2 + C_w y_h\big]\pi_{drop}F(n) \\ & \quad = \; \big[(1-\delta_w)h_2 + C_w y_h\big]\phi_s \int_n^{\bar{z}} g_1 f(z)dz \; + \; \Pi_a^{fww}(n,N) \\ & \qquad - \; \big[SC_{ws}(1-h_1) - (1-\delta_w)h_2 - C_w y_h\big]\phi_s \int_n^{\bar{z}} g_2 f(z)dz, \end{aligned} \tag{13}$$

where $C_{ws} \equiv \big[1/\beta - (1-\delta_w)(1-\delta_s)\big]$. The first term on the left-hand side captures the direct hiring cost, and the second captures the increased risk of needing to remove hours from workers. The first and third terms on the right-hand side reflect the lower shortfall risk from having more total worker-hours and a bigger bench, respectively. The second term – which is similar to the second term in (9) – captures that increasing the workforce will lower costs from add penalties ($\pi_{add}$).[17]

[16] Note that the two sides do not correspond to the exact marginal costs and benefits (respectively) of hiring one additional employee. Instead, they are both some multiple (in particular, the same multiple) of those amounts. Also note that '$h_1$' and '$h_2$' in (13) are the derivatives of $h$ with respect to the first argument evaluated at $(Y_{fill}, (1-\delta_w)N)$ where $Y_{fill} = \big(\delta_w + \delta_s(1-\delta_w)\big)Sn$.

[17] This term is defined as

$$\Pi_a^{fww}(n,N) \; \equiv \; \pi_{add} \int_n^{\bar{z}} \bigg(C_w y_h(1-g) \; - \; (z-n)\Big[C_w y_h g_1 - \big(SC_{ws}(1-h_1) - C_w y_h\big)g_2\Big]\bigg) f(z)dz.$$

It follows from Assumption 2 in the appendix that $\Pi_a^{fww}(n,N) > 0$; i.e., on net, hiring more workers avoids more costs from add penalties.

# 4 Results of Theoretical Model

This section overviews our main theoretical results, which are formally proved in Appendix A. First, we show that the removal penalty incentivizes firms to schedule fewer workers per shift but keep more workers in reserve. The add penalty does the opposite: it incentivizes firms to schedule more workers per shift, necessitating a smaller workforce to function as reserves. The ATH requirement of offering existing workers all newly-available hours unsurprisingly results in more hours per worker. This necessitates less hiring, which (in a steady state) shrinks the workforce. To offset having fewer workers in reserve, firms increase workers per shift.

## 4.1 Results: costly short-term schedule changes

In practice, under the NYC FWW law, the costs of removing a regularly scheduled shift on short notice ($\pi_{drop}$) are significantly higher than the costs of adding one ($\pi_{add}$). For example, within 24 hours, the add penalty is \$15 while the removal penalty is \$75 (DCWP 2023a). For this reason, we first consider the case where $\pi_{add} = 0$ and $\pi_{drop} > 0$. In this environment, we denote the optimal steady-state workforce, workers per shift, and hours per worker as $(N^d, n^d, y^d)$, and those from the baseline environment as $(N^b, n^b, y^b)$.

**Theorem 1** *If there is no add penalty ($\pi_{add} = 0$) and the removal penalty exceeds the effort cost from the baseline environment ($\pi_{drop} > \phi_e$), then the workforce is larger and workers per shift and hours are smaller relative to the baseline environment: $N^d > N^b$, $n^d < n^b$, $y^d < y^b$.*

The intuition behind this result is clear. If removing workers on short notice becomes more expensive, then the firm will have fewer workers per shift on the regular schedule (i.e., a lower $n$) and a larger workforce to fill shifts on short notice (i.e., a higher $N$). Moreover, with more workers and fewer total hours to go around, hours per worker will decrease. Before the legislation, relatively more risk of demand fluctuations falls on the workers. After the removal penalty is instituted, that risk shifts toward firms, and workers are compensated for short-notice changes to their schedule.

Next, we layer on the short-notice add penalty ($\pi_{add} > 0$) to the environment with a removal penalty, resulting in the schedule-change environment. Call the associated steady-state values $(N^{sc}, n^{sc}, y^{sc})$.

**Theorem 2** *Introducing an add penalty ($\pi_{add} > 0$) reduces the workforce and increases workers per shift and hours per worker: $N^{sc} < N^d$, $n^{sc} > n^d$, $y^{sc} > y^d$.*

Here, since adding workers on short notice becomes more expensive, the firm will *increase* workers per shift on the regular schedule and *reduce* the workforce. With fewer workers and more hours to go around, this increases hours per worker. Layering on this add penalty further shifts the risk of demand fluctuations away from workers and toward firms.

## 4.2 Results: access to hours

Next, we consider adding the access to hours (ATH) policy, to the *baseline* environment; i.e., without schedule-change penalties. In this ATH environment, denote the steady-state values as $(N^{ath}, n^{ath}, y^{ath})$.

**Theorem 3** *Relative to the baseline environment, access to hours decreases the workforce, and increases workers per shift and hours per worker: $N^{ath} < N^b$, $n^{ath} > n^b$, $y^{ath} > y^b$.*

As the firm is forced to offer all newly-available hours to existing workers, it will have fewer to offer new workers. Thus, it will hire fewer workers, which in the long run will lead to a smaller workforce. To compensate for having a smaller bench (which makes staff shortfall *more* likely, all else equal), it increases workers per shift (which makes shortfall *less* likely). With fewer workers and more total hours to go around, this increases hours per worker, which is the provision's intention.

### 4.3 Summary of results

Though these results add insight, the pertinent question is how the full FWW environment $(N^{fww}, n^{fww}, y^{fww})$ compares to the baseline $(N^b, n^b, y^b)$. After all, the environment for NYC fast food workers went from no schedule-change penalties and no ATH to both penalties and ATH.

As an intermediate question, consider the effect of both schedule-change penalties together: how $(N^{sc}, n^{sc}, y^{sc})$ compares to $(N^b, n^b, y^b)$. This comparison will most crucially depend on the relative sizes of the add and removal penalties ($\pi_{add}$ vs. $\pi_{drop}$). As noted, the removal penalty is significantly larger than the add penalty in the NYC law. Thus, the removal penalty effect is likely to dominate the add penalty effect in the schedule-change environment, which has both: $N^{sc} > N^b$, $n^{sc} < n^b$, $y^{sc} < y^b$. That is, introducing schedule-change penalties (with larger short-notice removal than add penalties) will likely increase the workforce but decrease workers per shift and hours per worker.

The fact that $\pi_{drop} > \pi_{add}$ suggests policymakers are more concerned with regular shifts being taken away on short notice than shifts being added on short notice. If $N^{sc} > N^b$, $n^{sc} < n^b$, $y^{sc} < y^b$ as posited, then the legislation would succeed in preventing more short-notice removals while compensating workers in expectation for the risks they bear. However, there will be fewer overall hours scheduled, and hours per worker will decrease.

On the other hand, the ATH effect is the opposite: relative to the baseline, $N^{ath} < N^b$, $n^{ath} > n^b$, $y^{ath} > y^b$. Thus, it seems likely that the two main parts of the NYC FWW law, schedule-change penalties and ATH, have opposing effects. Thus, the prediction from the FWW model for employment is ambiguous. If we observe that NYC fast-food employment increases after FWW, this suggests the removal penalty effect dominates. If we instead observe an employment decrease, this suggests that a combination of ATH and short-notice add costs dominates.

# 5 Empirical Design and Data

Our goal is to test the employment effects of NYC's FWW law for the fast-food industry. We contrast changing trends in NYC fast food against changes in two kinds of comparison groups: within fast food across other U.S. counties and within NYC across other industries. We refer to our analysis with these groups as the *within-industry* model and the *within-location* model, respectively. For each empirical model, we use synthetic difference-in-differences (SDID) analysis, which combines desirable properties of the synthetic control method and the difference-in-differences estimator (Arkhangelsky et al. 2021). Applying the empirical SDID model to employment data at the county-industry-quarter level from the QCEW yields estimated FWW effects. For interested readers, Appendix B provides more detail on SDID, including the equation we use to estimate treatment effects.

## 5.1 Data

The analysis focuses on quarterly employment at the county and six-digit industry level from the Quarterly Census of Employment and Wages (QCEW).[18] To measure workers affected by the regulation, we consider *limited-service restaurants* (NAICS code 722513) in the five counties that constitute NYC: Bronx, Kings, New York, Queens, and Richmond counties.

Though 722513 includes all NYC workers affected by the regulation, it also includes some unaffected workers. Supervisory jobs are not covered by the regulation, but those employees are included in 722513. Calculations from Wolfe et al. (2018) suggest more than 10% of 722513 NYC workers are unaffected by the legislation.[19] Table 1 demonstrates this

[18]The QCEW has a monthly employment measure. We obtain a quarterly measure by averaging employment from the three corresponding months. Though we would also like to analyze hours worked because our theoretical model gives relevant predictions, no such data exists in public sources. All industry codes are from the NAICS (North American Industry Classification System).

[19]In estimating the number of workers covered under the regulation, Wolfe et al. (2018) multiplies NYC 722513 employment by the share of non-supervisory workers in that industry at the national level. This share, 88.4%, is taken from 2016 Current Employment Statistics (CES) data. Also, to be covered, an employee must work in an establishment that "is part of a chain" and "is one of 30 or more establishments nationally, including as part of an integrated enterprise or as separately owned franchises" (DCWP 2023a). An unknown fraction of limited-service restaurant employees in NYC are not covered because of not meeting

| **county** | **estimate of covered workers** | **722513 employment** |
|---|---|---|
| Bronx | 6,260 | 7,081 |
| Kings | 11,684 | 13,218 |
| New York | 28,780 | 32,556 |
| Queens | 13,396 | 15,154 |
| Richmond | 2,289 | 2,589 |
| **Total** | **62,409** | **70,598** |

Table 1: Comparing 722513 employment with an estimate of covered workers

*Notes:* In our analysis, we use the NYC *limited-service restaurant* industry (NAICS code 722513) from the QCEW to proxy for the affected population of workers. This table compares an estimate of covered workers in 722513 to actual 722513 employment in 2016 by NYC county. The third column gives the average quarterly employment in 2016 data, and the second column estimates the number of workers that would be covered under the provision (if it had been effective in 2016). The second column is simply obtained by multiplying the third column by the non-supervisory share of 722513 employment in 2016 (88.4%); this share is taken from Wolfe et al. (2018), who uses a national estimate.

by comparing an estimate of covered workers in each county to its employment in 2016.[20] Thus, the QCEW provides a good proxy for changes in the affected population but not a perfect measure.

## 5.2 Empirical design

As mentioned, our two approaches for constructing comparison groups are the within-industry model and the within-location model. The within-industry control group is 722513 in *other* counties around the country – e.g., limited-service restaurants (722513) in Howard County, Maryland – and the within-location control group is other 6-digit industries in a *specific* NYC county – e.g., mattress manufacturing (337910) in Kings County, New York. The control groups are sizes 175 and 247, respectively, and the treatment group for both approaches is 722513 for NYC's five counties. For details on control group construction, see Appendix C.2. We also consider a third, *pooled* model which combines the control groups from the within-industry and within-location models.

these criteria. Unfortunately, the QCEW provides no data to help estimate this fraction. Following Wolfe et al. (2018), we will not adjust for this factor.

[20] In our analysis, we consider the log of employment, so that changes are proportional to levels. Further, we adjust for seasonality. For more details, see Appendix C.

Our analysis draws on data from 2014 Q1 to 2019 Q4. The FWW law became effective in November 2017, and we consider 2017 Q4 to be the first treatment period. Thus, there are 15 pre-policy quarters and 9 post-policy quarters, where "pre-policy" and "post-policy" are relative to the enactment date. We cut off analysis in 2019 Q4 to minimize the risk that COVID-19 disrupts the stable relationships from the control period that we rely on for estimating the counterfactual.

For inference in our SDID framework, we compute standard errors using the jackknife estimator. It computes quicker than other methods and has desirable properties under relatively mild assumptions (Arkhangelsky et al. 2021).[21]

Finally, we must control for minimum wage changes in our analysis (SDID allows for time-varying controls). Such changes may affect outcomes, and there are significant changes to relevant minimum wage policies during our period of analysis. We construct a quarterly county-level minimum wage dataset drawing on Vaghul and Zipperer (2022)'s public data of state- and sub-state-level minimum wages. The construction of this dataset is described in Appendix C.3.

For the within-industry approach, we report results from the model with and without a minimum wage control. We prefer the results with a minimum wage control because it changes in a way correlated with the policy of interest. For the within-location model, all industries in NYC except the fast-food industry follow the same minimum wage schedule. Thus, we can not separate the effect of the law from that of different minimum wage schedules using the within-location model. We also do not control for the minimum wage in pooled analysis for a similar reason.[22]

[21]The relevant theoretical result of Arkhangelsky et al. (2021) is to prove the estimator is asymptotically normal under assumptions that, "are substantially weaker than those used to establish asymptotic normality of comparable methods" (page 4107). Using these assumptions and assuming that the systematic component of the data-generating process is finite, the jackknife estimator yields conservative confidence intervals. Also, assuming that the treatment effect is constant and time weights are predictive enough on the exposed units, the jackknife yields exact confidence intervals. However, because we assume uniform time weights, this result is not established for our main specification. No similar results are established for the alternative estimators.

[22]Controlling for the minimum wage in the pooled model slants the synthetic control almost completely towards within-location control units. Thus, we have the same problem as in the within-location model.

| *Variable* | *Model* | | | |
|---|---|---|---|---|
| | Within-ind. (no mw cont.) | Within-ind. (mw cont.) | Within-location | Pooled |
| | (1) | (2) | (3) | (4) |
| Employment | 0.0063 | 0.0114 | -0.0014 | 0.002 |
| | (0.0319) | (0.0129) | (0.042) | (0.0362) |
| | [0.0031] | [0.0031] | [0.0028] | [0.0019] |

Table 2: Measuring the employment effect of NYC's FWW law on fast food workers

*Notes:* Four models are considered: (1) within-industry without a minimum wage control, (2) within-industry with a minimum wage control, (3) within-location, and (4) pooled (i.e., the within-industry and within-location control groups combined). Only (2) controls for minimum wage. For each specification, an estimate is given with the standard error in parentheses and the pre-intervention root mean squared prediction error (RMSPE) in brackets. The RMSPE is a standard measure of pre-policy fit for the synthetic-control method and its variants (Abadie 2021).

# 6 Empirical Results

This section describes our empirical results. First, we detail our main results on the employment effects of NYC's FWW law. Then, we summarize a robustness analysis from Appendix D.

Table 2 details employment results for each of our four specifications. No statistically significant employment effects are found at the 95% level for any of the four models.

Despite no significant effects, the role of the minimum wage control is worth considering. The estimate for specification (2) – the within-industry model with a minimum wage control – is between 0.5 and 1.2 log points higher than the other specifications. This is what we would expect given that: 1) the second specification is the only one that controls for the minimum wage; 2) the NYC fast-food minimum wage increased during the analysis period; 3) minimum wage increases have been linked to lower restaurant employment in some contexts (e.g., Karabarbounis et al. 2022).[23] Also, specification (2) is around 3 times more precise than the others. For these reasons, we consider the estimate in (2) – i.e., 1.2 log points with

[23]For 2), the relevant minimum wage increase can be seen in Figure C.1 in Appendix C.3, which plots the NYC and NYC fast-food minimum wages over our sample period (along with those for New York State). Further, because of 3), we expect a lower estimate even for the within-location model without a minimum wage control. Indeed, the fast-food minimum wage rose more quickly than that for other NYC industries (Vaghul and Zipperer 2022).

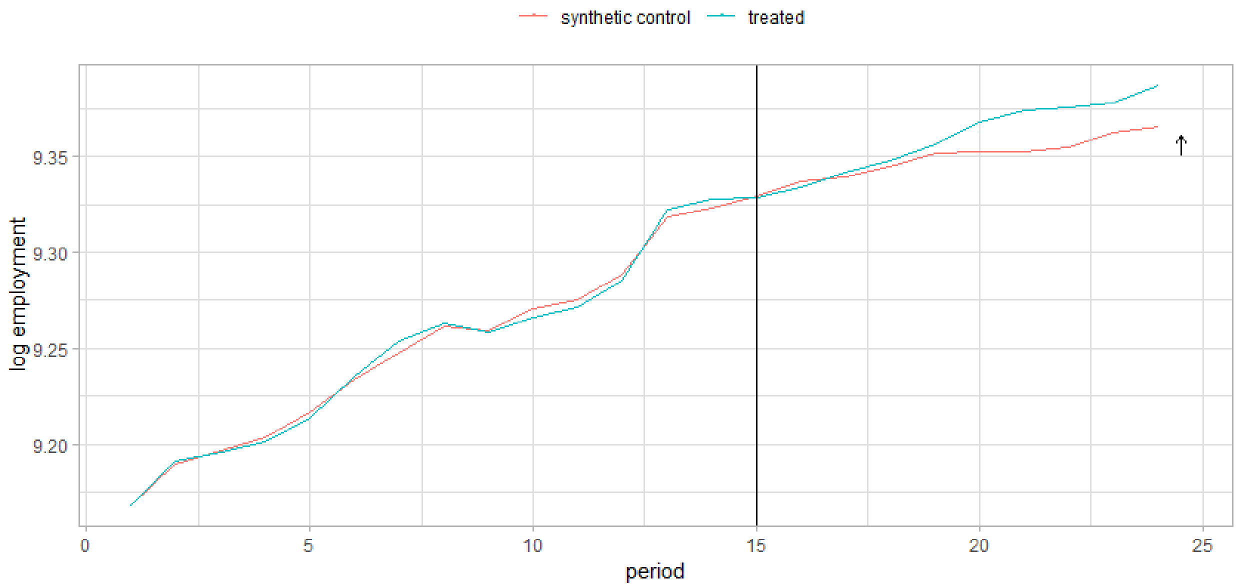


Figure 1: Visualizing the employment effect

*Notes:* The figure shows the second specification from Table 2 - the within-industry model with a minimum wage control. The x-axis is the period (quarter) in the corresponding sample, and the black line denotes the last pre-policy period. The sample spans from 2014 Q1 to 2019 Q4, and the last pre-policy period is 2017 Q3 (i.e., 15). The y-axis is in units of log employment. The blue line is the treatment group's log employment trend, and the red is that of the synthetic control. To better see the quality of the pre-policy fit, the synthetic control is shifted to have the same pre-policy average as the treatment group (but these averages are different in general). The black arrow at the end of the post-policy period denotes the measured effect of the law on employment. It points from the post-policy average of the synthetic control to that of the treatment group.

a 95% confidence interval (CI) of -1.4 to 3.7 – to be the most credible.

Figure 1 plots the pre- and post-policy trends of the treatment group and synthetic control for specification (2). There are two takeaways. First, the quality of the pre-policy fit is visually good. Second, there is a positive effect that emerges about a year after the law becomes effective and remains throughout the rest of the post-policy period. As the confidence interval dictates, this effect is not statistically significant.

Appendix D assesses the robustness of these results; we summarize its analysis here. To start, we discuss the role of our four different empirical models. Then, we attempt to gauge the potential role of different policy provisions within FWW using two tests. First, we estimate the effects of Oregon's FWW law on restaurant workers. Oregon's law is similar to NYC's but does not have an ATH provision. Second, we estimate the effects of NYC's

FWW law on *retail* workers; the provisions for retail workers do not include ATH or schedule-change penalties. Then, we consider the role of how time weights in the SDID algorithm are computed by estimating two alternate specifications. Results from these four tests are consistent with the above null results.

Next, we address a timing-related issue. Recall the legislation was passed and signed into law in May 2017, but did not become effective until November 2017. Since coming into compliance could take time for employers, anticipatory effects are possible.[24] Furthermore, such compliance efforts may have started before passage in May 2017. For example, Mayor Bill de Blasio announced his plans to curb unpredictable scheduling for fast-food workers on September 15, 2016 (Goldensohn 2016), so employers may have changed their behavior based on that signal. To account for the possibility of anticipatory compliance, we run two robustness exercises. The first considers treatment to start two quarters earlier (2017 Q2 as opposed to 2017 Q4) when the law was passed and signed into law. The second considers the treatment period to start five quarters earlier (2016 Q3) when the mayor announced his intentions. Both sets of results are consistent with the main results.

Lastly, we run a standard two-way fixed effects (TWFE) analysis. Though the TWFE model yields more positive estimates than SDID and two of the TWFE specifications are significantly positive, an event study reveals a positive pre-trend. TWFE assumes parallel trends in unobservables during treatment, so evidence that trends are not parallel before treatment reduces the credibility of this maintained assumption. While the TWFE model equally weights comparison units, the SDID alternative model chooses weights to minimize pre-treatment differences in unobservable trends. This motivates our use of the SDID method. For relevant details on the SDID method, see Appendix B.[25]

[24]For example, in a brief from an employer advisory organization, NYC fast food employers are advised to assess their scheduling and timekeeping practices, develop new scheduling policies, and train management before the effective date (Deakins 2017).

[25]Recall from footnote 19 that over 10% of our proxy for affected workers are likely supervisory workers and not affected by the legislation. Ideally, we would be able to assess robustness based on variation in this supervisory share across counties, but we do not know of data that would enable this. In addition to geography, we considered restrictions on other firm dimensions using QCEW variables, but did not find a fruitful way to proceed.

# 7 Integrating with Literature

In this section, we first relate our theoretical model to its most relevant counterpart in the literature: the model of McCrate et al. (2019). Next, we discuss the existing empirical literature on FWW laws' effects in labor markets and elsewhere.

To our knowledge, our paper is the first to theoretically model FWW provisions and their effects. In terms of theory, the most similar paper to ours is McCrate et al. (2019) who investigate the relationship between schedule instability and underemployment for hourly employees. In their model, uncertain demand motivates employers to offer incomplete contracts that do not specify hours or worker availability. Wages and competition for scarce hours motivate employees to be available during more times, although workers receive disutility from more availability. Ultimately, the firm chooses a wage to maximize worker availability per dollar spent on wages. As they point out, evidence from related literature suggests this sort of practice may exist and be profitable to firms in certain industries (Moss et al. 2004; Lambert 2015; Mani et al. 2015).

In our baseline environment, firms give a regular schedule specifying worker-shift combinations. This "schedule" functions as an incomplete contract since firms can add and remove workers on short notice without financial penalty (although removing workers comes with an effort penalty). Thus, this is similar to the incomplete contract environment of McCrate et al. (2019). Furthermore, just like firms in their model, firms in our model pass the risk of demand uncertainty on to workers.

Though our model is similar to theirs in these ways, the theories have different objectives. Their model focuses on the factors affecting worker availability and corresponding worker and firm strategies. In contrast, we do not model variance in worker availability. Instead, we focus on firm incentives for scheduling and workforce decisions in different legal environments. While they attempt to model a particular mechanism, we attempt to understand the employment effects of FWW laws and their different provisions.

McCrate et al. (2019) test their predictions using Canadian data. They find underemployment is significantly more likely among hourly workers on unstable schedules. Further, those initially underemployed who switch to unstable schedules receive fewer hours after the switch. Moreover, they find no evidence of compensating differentials for unstable schedules. In contrast, we analyze sector-level employment and find a null effect. In summary, though their work is related to ours, neither their theoretical mechanism nor empirical analysis are directly comparable. However, their empirical results suggest that FWW provisions, like schedule-change penalties and ATH, could significantly alter labor market outcomes for underemployed workers and workers with unstable schedules.

Our paper adds to a small literature on the labor market effects of FWW laws. Kwon and Raman (2023) study the recent laws in Philadelphia (effective April 2020), Chicago (July 2020), and Los Angeles (April 2023), each of which has schedule-change penalties and ATH. Using administrative shift-level data from multiple retailers, their analysis rules out common concerns over FWW laws, including a reduction in scheduled work, a reduction in worker hours, increased employee turnover, decreased hiring, and increased use of part-time employees. These null results coincide with our null employment result for NYC fast food workers. Further, while they find a decrease in short-notice shifts, they find null effects on several variables capturing work-schedule stability, suggesting the scheduling provisions did not have their intended effect. In “a model of cumulative disadvantage,” Choper et al. (2022) argue that unstable work schedules increase the likelihood of job separation. Using panel data from almost 2,000 U.S. hourly workers in retail and food service, they confirm schedule instability is a strong predictor of turnover, suggesting a well-designed and enforced scheduling law could decrease turnover. In a related literature, “just-in-time” scheduling has received some attention (Luce and Fujita 2012; Kamalahmadi et al. 2021; Lambert and Haley 2021; Harknett et al. 2022; Choper et al. 2022).

Yelowitz (2022) propose that one possible firm response to regulations that reduce scheduling flexibility is “playing it safe” by having fewer workers on a shift: when demand is low, firms avoid schedule-change penalties, and when demand is high, firms provide lower quality service or have the workers on shift exert more effort. This may result in *less* full-time and *more* part-time work, voluntary and involuntary; Yelowitz (2022) provides some evidence that this has occurred in jurisdictions that passed FWW laws. This mechanism is similar to the one in our model, except we do not consider the possibility of workers exerting more effort when demand is high.[26]

Our paper also relates to literature on the broader effects of schedule unpredictability and FWW laws. This includes a burgeoning sociological literature focusing on self-reported outcomes like well-being and sleep,[27] and a literature focused more on economic outcomes.[28]

Lastly, Pickens and Sojourner (2025) look at the 2021 expansion of NYC's FWW law that gives fast-food workers "just cause" protection after their first 30 days. Though they find null effects on the overall labor market, this hides heterogeneity across worker groups. In particular, they find the law makes it harder for younger workers to *achieve* stable employment.

# 8 Discussion

Above, we theoretically model and empirically analyze the effects of NYC's FWW laws. In this section, we offer a discussion of our empirical methods and put our null employment

[26]Corder and Yelowitz (2016) provide further evidence of this "playing it safe" mechanism. In a survey of possible firm responses to similarly proposed legislation in Washington D.C., half of the 100 employers surveyed say they would schedule fewer employees per shift. Moreover, McCrate et al. (2019) point to evidence that unstable hours can also motivate greater effort (Wharton 2008; Luce and Fujita 2012; Ikeler 2014).

[27]Using data from employee surveys and firm records, Henly and Lambert (2014) find that schedule unpredictability increases employee stress in several dimensions for hourly female workers, and employee input into scheduling alleviates some of these negative outcomes. In the context of the 2017 Seattle FWW law, Harknett et al. (2021) show that work-time uncertainty substantially affects workers' well-being, especially their sleep quality and economic security. In a study of 92 workers with young children, Ananat and Gassman-Pines (2021) find that unpredictable work schedule changes were associated with worse mood and sleep. In a separate study of 96 workers with young children, Ananat et al. (2022) find that the FWW law in Emeryville, California improved their work schedule predictability, well-being, and sleep.

[28]In studying 25 stores of a U.S. full-service restaurant chain, Kamalahmadi et al. (2021) find that the use of day-of schedules reduces server productivity by 4.4%. Further analysis suggests that providing more predictable work schedules can increase firm profits. Notably, this is at odds with the idea that just-in-time scheduling can increase firm efficiency. Analyzing data from the 1997 NLSY, Fugiel (2022) finds that workers are not compensated for scheduling risk through higher pay or job retention – a similar finding to McCrate et al. (2019) – and workers in unstable and unpredictable arrangements report lower job satisfaction.

effect finding in context.

**Assessing our empirical design:** There are a few caveats to our empirical analysis. First, the analysis ignores possible general equilibrium (i.e., spillover) effects. One would expect spillover to bias employment estimates toward greater magnitudes, *especially* in the within-location or pooled models. Indeed, if employees leave the fast-food industry after FWW takes effect, for example, they would presumably seek employment in other NYC industries, boosting those industries' employment. Some of these industries could be donor units to the fast-food industry's synthetic control. This would make the estimated employment effect more negative in this case. However, since estimates are not significant, spillover bias likely does not play a major role.[29]

Another caveat is that our empirical analysis relies on a close but imperfect proxy for affected employment that may attenuate or otherwise bias estimates. As mentioned, the NYC legislation does not apply to all workers in the limited-service restaurant industry, our proxy for the affected population. Thus, our analysis cannot precisely measure the employment effect. If the proxy were a constant proportion of the truth, then estimates in percentage terms would be unbiased. If the proxy is a white noise deviation from a constant proportion, then the estimate is attenuated.

**Relating empirical results to theoretical predictions:** Recall that our theoretical model makes an ambiguous prediction on the FWW law's employment effect. On one hand, it predicts the ATH provision will incentivize firms to *decrease* their employment: as firms are forced to offer all newly-available hours to existing workers, they will hire less, leading to a smaller workforce. On the other hand, it predicts the removal penalty will incentivize firms to *increase* their employment: they lessen workers per shift to reduce the expected removal penalty and want a bigger "bench" of workers who could fill in on short notice. Also, the

[29] Our theoretical analysis also excludes possible general equilibrium effects. Such effects could be considered by, for example, embedding our model into a two-sector framework where one sector is affected by the law and the other is not. When workforce size in the affected sector increases (because of removal penalties, for example), this could raise hiring costs, which may attenuate the workforce increase. Moreover, general equilibrium effects could be more important in a model that develops worker preferences over hours and schedule predictability and stability.

add penalty will incentivize a smaller workforce, although this effect is likely dominated by the larger removal penalty.

Unfortunately, we cannot separately identify effects from these different provisions in the NYC FWW law. Thus, our null empirical result suggests one of two scenarios. First, multiple provisions have sizable effects that cancel out, resulting in a null overall effect. Second, none of the provisions have a sizable effect, also resulting in a null overall effect. Further context helps us determine which of these two scenarios is more likely.

Given consistent robustness results, the estimated 95% confidence interval of -1.4 to 3.7 log points for employment in our preferred specification likely rules out large negative employment effects of the ATH provision. This suggests the second scenario is more likely: there are not *large* counteracting effects of schedule-change penalties and ATH for NYC fast food workers.

Since the estimate is positive, could a larger (statistically significant) positive employment effect from the removal penalty be muted by a smaller negative employment effect of ATH? Two of our robustness exercises suggest this is not the case. In measuring the effects of Oregon's FWW law on restaurant workers – which is similar to the NYC FWW law but does not have an ATH provision – we attempt to isolate the effect of schedule-change penalties. Further, to obtain a "control" estimate, we analyze the NYC law on retail workers, which does not have ATH or schedule-change penalties. Both robustness tests find null employment effects. This suggests that schedule-change penalties also have no sizable effects on employment.

In summary, while we cannot evaluate directly, large effects from any of the provisions seem unlikely. We next consider some reasons why this might be.

**Prevalence of schedule issues:** When contextualizing our null result, it is pertinent to understand how widespread schedule instability and unpredictability were among NYC fast food workers pre-FWW. Though specific measures do not exist (to our knowledge), anecdotal evidence suggests it was prevalent. First, existing surveys suggest scheduling issues are a widespread problem, particularly for food service workers. In a 2014 policy brief, Lambert et al. (2014) report that 41% of U.S. hourly workers learn about their schedule one or less weeks in advance. Further, 90% of hourly food service workers say their hours fluctuated in the last month. In a 2019 brief, Schneider and Harknett (2019) report that 80% of hourly workers have little or no input into their schedule, and 69% are required to keep their schedules "open and available" to work whenever needed by their employers. Further, 25% worked an on-call shift in the last month, and 50% worked clopening shifts.

Second, the NYC law had significant grassroots support, suggesting that many were affected by scheduling issues. Leading up to passage, 3,000 fast-food workers and their allies signed a petition in support of the legislation. Further, the law enjoyed widespread support from NYC unions and community groups (SEIU 2017). Third, there has been significant enforcement action since the law took effect, suggesting that scheduling issues were a problem pre-FWW. Indeed, between 2018 and 2021, the NYC DCWP secured millions in restitution for thousands of workers and opened hundreds of investigations. Investigations include major restaurant chains such as Subway, McDonald's, and Chipotle (ECM 2022).

Under the assumption that scheduling instability and unpredictability were prevalent pre-FWW, the null result begs a follow-up question: How widespread was enforcement and compliance after the law became effective? In particular, even though there has been significant enforcement action (in some cases, against prominent chains), this does not imply *widespread* enforcement.

**Enforcement and compliance:** Considering a number of factors, a serious lack of enforcement or compliance in the NYC fast-food industry seems possible, if not likely. Previous research on employment law makes clear that ensuring manager compliance is difficult. For example, using a survey of over 4,000 workers in low-wage industries from Chicago, Los Angeles, and NYC, Bernhardt et al. (2009) find that violations of well-known labor laws like the minimum wage and overtime pay are widespread. Given the complexity and novelty of a multi-provision scheduling regulation like NYC's FWW law, widespread non-compliance seems at least equally likely. This could make achieving policy goals (e.g., less involuntary part-time employment) through scheduling legislation difficult (Lambert and Haley 2021). Furthermore, in a report on how to improve labor standard enforcement, Weil (2010) identifies food service as a priority for strategic targeting because its workers are disproportionately vulnerable to violations and unlikely to submit a complaint on their own accord.

Lastly, since the regulation is *local* but many limited-service restaurants are part of large *national* chains, national management may not see it as worthwhile to change their systems to help ease compliance. Lambert and Haley (2021) interviewed 52 retail and food service managers in the months leading up to Seattle's FWW law (*Secure Scheduling Ordinance*) to study enforcement and compliance challenges at the local level. Some of the managers from "very large chains" indicated their firms were leaving it to them to figure out compliance. Even vendors of scheduling apps that employees use to swap shifts conveyed similar concerns: it might not be worth it to customize their product for a single municipality.

On the other hand, there is some reason to believe the NYC law could measurably change employer behavior. First, as mentioned, there has been significant enforcement action since the law became effective in 2017. Second, Lambert and Haley (2021) conclude their study with "cautious optimism" that the Seattle scheduling law can substantially impact employer behavior; the same optimism may be warranted for NYC's law. Third, NYC fast food workers may be relatively empowered to file complaints. The NYC law creates a complaint system where NYC authorities can find an employer guilty without further action from the worker, like acquiring legal representation (DCWP 2023a). In addition to enforcing the law, the DCWP regularly conducts outreach to workers, so NYC workers may be relatively well-informed of their rights. Further, the law explicitly offers the same rights and protections regardless of immigration status (DCWP 2023a). In general, immigrants may perceive themselves to be in a weaker position and could be less likely to file a complaint; employers could take advantage of this. This could lead to less compliance in a high-immigrant industry like fast food. However, the explicit protection of immigrants and education campaigns by the

DCWP could empower immigrants to stand up for their rights, leading to more compliance from firms.

In the end, evidence on both sides is anecdotal, so we cannot take a definitive stance on the level of enforcement and compliance. Further, we cannot say whether enforcement and compliance started immediately or grew in intensity over time. For example, it is possible that many employers did not take enforcement seriously until Chipotle was sued by the DCWP in 2019 (ECM 2022), or another high-profile action was taken.

**Involuntary part-time work:** Though measuring and accounting for enforcement and compliance is difficult, there is a simpler factor we can help clarify, specifically for the ATH provision: how many workers might be affected by the provision if it were properly enforced? Microdata from the Current Population Survey (CPS) can shed light on this question (IPUMS 2024).

In the U.S., part-time workers are more prevalent in the restaurant industry and are more likely to be part-time because they cannot find a full-time job. Indeed, in the two years after the NYC FWW law went into effect (2018-2019), in the "restaurants and other food services" industry – the finest superset of the fast-food industry in the CPS – workers were twice as likely to be part-time as in the entire workforce (43% vs 22%). Further, during this same period, 6.6% of part-time restaurant workers said their main reason for being part-time was they "could only find part-time work" compared to 4.4% for all part-time workers. This suggests that the restaurant industry is more susceptible to the ATH employment-decreasing mechanism.

Despite this relative susceptibility, only 2.8% ($\approx$ 43% $\times$ 6.6%) of restaurant workers are part-time *and* reported not being able to find a full-time job. Given this small percentage, it seems difficult for the mechanism in the law and the model to translate into a statistically significant effect.[30]

[30] In an early evaluation of San Francisco's FWW law, Yelowitz and Corder (2016) provide support for this view. A key premise of the legislation is that many part-time workers had insufficient hours and scheduling laws would fix that problem. This study gives evidence against that assumption.

Perhaps a significant effect is more likely if the law is passed in a place with more involuntary part-time workers. Recall that the above statistics are national. So if involuntary part-time workers are more prevalent *where* a law is passed, there may be a bigger effect. Additionally, *when* the law became effective is likely important. The two years after it went into effect (2018-2019) coincided with a period of relatively tight labor markets. Perhaps in a period of slacker labor markets, more workers would be involuntarily part-time, and the ATH mechanism could have more of an effect.

In a 5-year period after the Great Recession (2010-2014), the fraction of restaurant workers who were part-time *and* reported not being able to find a full-time job averaged 5.5% (47% were part-time and 11.7% of those part-time "could only find part-time work"). This is double the 2.8% figure reported for 2018-2019. Thus, it seems plausible that effects would be larger in a slacker labor market.

**Underemployment:** As a counterpoint, a problem with these "involuntary part-time" statistics is they may not capture all part-time workers who want additional work. The relevant CPS survey question only captures those who are part-time because they could only find part-time work. Some part-time workers may want more hours without being full-time.

Golden and Kim (2020) attempt to address this deficiency by analyzing data from the 2016 U.S. General Social Survey. In examining the "subjective underemployment rate" – the fraction of workers who report wanting more hours – they find that 40% of part-time workers want more hours. This dwarfs the involuntary part-time statistics mentioned above.

Subjective underemployment rates are higher for low-income individuals (54%), hourly workers (47%), and service occupations (50%). Since these are common characteristics of fast-food workers, it seems that ATH policies may be especially effective in that industry. Moreover, rates are higher for workers whose hours are decided by the employer (45%) and those with variable schedules or schedules decided on short notice by the employer (47%).

Ex-ante, one may assume those with fewer hours are more likely to want more hours.

However, limited evidence from Golden and Kim (2020) suggests this may not be the case. While the subjective underemployment rate for part-time workers is 40%, it is almost the same for *all* workers: 38%. While this statistic does not tell the whole story of worker preferences in our context, we decide to have constant worker preferences in the theoretical model. In particular, as mentioned in footnote 9, the amount of hours existing workers would accept is independent of how much they are already working. This decision simplifies the model and should not alter the main theoretical predictions.

# 9 Conclusion

In the last decade, several U.S. jurisdictions have passed fair workweek (FWW) laws giving hourly workers rights around scheduling issues. One common provision penalizes firms for making schedule changes on short notice, aiming to increase the stability and predictability of workers' schedules. Another common provision – access to hours (ATH) – gives existing workers the right of first refusal on newly-available hours, aiming to reduce the prevalence of involuntary part-time work.

To clarify employers' incentives and potential reactions under these common provisions, we develop a theoretical model. It generates predictions for how removal penalties, add penalties, and ATH will affect firm decisions. We test these predictions on NYC's FWW law for fast-food workers.

Because different provisions have opposing effects, the overall predictions of the law are ambiguous. Moreover, we cannot directly measure the effects of specific provisions. Nevertheless, a careful, robust empirical analysis finds a null overall employment effect on NYC fast food workers and suggests that none of the provisions alone had a sizable effect.

In providing context for this null result, we consider a few factors. First, given the findings of previous work, a serious lack of enforcement or compliance seems possible. Second, we analyze the share of restaurant workers who are involuntarily part-time. The share is quite small nationally, suggesting limited scope for ATH policy effects (though these shares will vary locally). As a counterpoint, a problem with involuntarily part-time statistics is they do not capture all workers wanting more hours. *Underemployment* statistics from Golden and Kim (2020) suggest a larger scope of ATH effects.

Our analysis invites several avenues of future research. First, to better understand the effects of FWW provisions, one could rigorously exploit differences in provisions across jurisdictions and industries. Second, one could analyze how different demographic groups are affected by the provisions.[31] Third, with individual- or shift-level data, one could more precisely measure employment effects and other effects. As more U.S. jurisdictions consider and pass FWW legislation, understanding the effects of each provision on labor market outcomes is critical.

[31] The Quarterly Workforce Indicators dataset offers breakdowns of worker demographic categories (sex-age, sex-education, and race-ethnicity) by county-industry level (Census 2019).

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# Appendices

## A Details and proofs for theoretical model

This appendix complements and completes the theoretical analysis described in Sections 3 and 4. To start, we list the assumptions on key functions ($g$ and $h$) and primitives along with the associated intuition. Next, we prove Theorem 1: removal penalties increase the workforce and decrease workers per shift and average hours. Then, we prove Theorem 2: add penalties decrease the workforce and increase workers per shift and average hours. Lastly, we prove Theorem 3: ATH decreases the workforce and increases workers per shift and average hours. In proving each of these theorems, we build up notation and establish intermediate results.

### A.1 Assumptions on functions

Assumptions on $g : [0, \bar{z}] \times \mathbb{R}_+ \to [0, 1]$:

- $g \in \mathcal{C}^2 \;\longrightarrow\;$ $g$ and its first and second derivatives are continuous
- $g(0, y) = 0 \;\longrightarrow\;$ if there is no gap, there is no chance of a shortfall
- $g_1 > 0 \;\longrightarrow\;$ a shortfall is more likely with a larger gap
- $\lim_{x \to 0^+} g_1(x, y) = 0 \;\longrightarrow\;$ the chance of being able to cover a very small gap is high
- $g_{11} > 0 \;\longrightarrow\;$ the effect of adding one worker to the gap is larger for a bigger existing gap
- $g_2 < 0 \;\longrightarrow\;$ a shortfall during a shift is less likely when you have more workers on the bench
- $g_{22} > 0 \;\longrightarrow\;$ the effect of having one more worker on the bench diminishes in the size of the bench

- $g_{12} < 0 \longrightarrow$ the effect of adding one worker to the gap is smaller when the bench is larger; alternatively, the effect of having one more worker on the bench increases in the size of the gap

- $\frac{\partial}{\partial n} g(z-n, N-n) = -g_1 - g_2 < 0 \longrightarrow$ increasing workers per shift decreases the chance of shortfall

- $\frac{\partial}{\partial^2 n} g(z-n, N-n) = g_{11} + 2g_{12} + g_{22} > 0 \longrightarrow$ the effect of increasing workers per shift is decreasing in the existing mass of workers per shift

- $\frac{\partial}{\partial n \partial N} g(z-n, N-n) = -g_{12} - g_{22} > 0 \longrightarrow$ the effect of increasing workers per shift is smaller when the existing workforce is larger; the effect of adding one to the existing workforce is smaller when workers per shift is larger

- In the following equation, the second derivatives $g_{12}$, $g_{11}$, and $g_{22}$ are all evaluated at $(z-n, N-n)$ in the integrals. Also, there is no straightforward intuition for this assumption.

$$\left( \int_n^{\bar{z}} g_{12} f(z) dz \right)^2 < \left( \int_n^{\bar{z}} g_{11} f(z) dz \right) \left( \int_n^{\bar{z}} g_{22} f(z) dz \right) \tag{A.1}$$

Assumptions on $h : \mathbb{R}_+^2 \to [0, 1]$:

- $h \in \mathcal{C}^2 \longrightarrow h$ and its first and second derivatives are continuous

- $h_1 > 0 \longrightarrow$ more hours offered yields more hours accepted by existing workers

- $h_{11} < 0 \longrightarrow$ diminishing returns to offering more hours

- $h_2 > 0 \longrightarrow$ more existing workers yields more hours accepted by existing workers

- $h_{22} < 0 \longrightarrow$ diminishing returns to having a bigger existing workforce

- $h_{12} > 0 \longrightarrow$ offering one more hour has a bigger effect if there are more existing workers; alternatively: having one more existing worker has a bigger effect if the firm is trying to fill more hours

- $h_1 < 1 \longrightarrow$ offering one more hour yields less than one more hour taken (in expectation)

**Assumption 2** *Firms will always want to avoid shortfalls:*

$$\phi_s \; > \; \pi_{add}\bar{z}.$$

*That is, the penalty of a shortfall ($\phi_s$) is larger than paying the add penalty ($\pi_a$ per worker) for the largest possible gap ($\bar{z}$). Further, recall equation (9). In terms of add penalties, the marginal benefit of increasing workers per shift ($n$) is always positive:*

$$\pi_{add} \int_n^{\bar{z}} \big[(1-g) - (z-n)(g_1+g_2)\big] f(z)dz \; > \; 0.$$

## A.2 Proving Theorem 1

**Theorem 1** *If there is no add penalty ($\pi_{add} = 0$) and the removal penalty exceeds the effort cost from the baseline environment ($\pi_{drop} > \phi_e$), then the workforce is larger and workers per shift and hours are smaller relative to the baseline environment: $N^d > N^b$, $n^d < n^b$, $y^d < y^b$.*

Define the following functions/constants:

$$
\begin{aligned}
\Omega(n, N) &\equiv -\phi_s \int_n^{\bar{z}} g_2 f(z) dz, \\
\Lambda_b(n, N) &\equiv \phi_s \int_n^{\bar{z}} g_1 f(z) dz - \phi_e F(n), \\
\Lambda_d(n, N) &\equiv \phi_s \int_n^{\bar{z}} g_1 f(z) dz - \pi_{drop} F(n), \\
\Psi_b &\equiv \frac{C_w}{S}\,\kappa, \quad \Psi_d \equiv \frac{C_w}{S}\,\kappa, \quad \text{for convenience} \quad \Psi \equiv \Psi_b = \Psi_d, \\
\lambda_b(n) \quad &\text{to satisfy} \quad \Omega(n, \lambda_b(n)) = \Lambda_b(n, \lambda_b(n)), \\
\lambda_d(n) \quad &\text{to satisfy} \quad \Omega(n, \lambda_d(n)) = \Lambda_d(n, \lambda_d(n)), \\
\psi_b(n) \quad &\text{to satisfy} \quad \Omega(n, \psi_b(n)) = \Psi, \\
\psi_d(n) \quad &\text{to satisfy} \quad \Omega(n, \psi_d(n)) = \Psi.
\end{aligned}
$$

Note that $\psi_b(n) = \psi_d(n)$ for every $n$; we will use $\psi \equiv \psi_b = \psi_d$ for convenience. Also note that $(N^b, n^b)$ satisfy $N^b = \lambda_b(n^b) = \psi(n^b)$ and $(N^d, n^d)$ satisfy $N^d = \lambda_d(n^d) = \psi(n^d)$. The proof of Theorem 1 uses two intermediate results and a corollary.

**Lemma 1** *For every $n$, $\lambda_b(n) > \lambda_d(n)$.*

**Proof of Lemma 1:** To start, we claim that $\frac{\partial}{\partial N}\Lambda_b(n, N) < \frac{\partial}{\partial N}\Omega(n, N)$:

$$
\begin{aligned}
\frac{\partial}{\partial N}\Lambda_b(n, N) &= \phi_s \int_n^{\bar{z}} g_{12} f(z) dz \\
&< -\phi_s \int_n^{\bar{z}} g_{22} f(z) dz \qquad [\text{using } g_{12} + g_{22} < 0] \\
&= \frac{\partial}{\partial N}\Omega(n, N).
\end{aligned}
$$

The following holds for every $n$:

$$
\Omega(n, \lambda_d(n)) = \Lambda_d(n, \lambda_d(n)) > \Lambda_b(n, \lambda_d(n)),
$$

where the inequality relies on $\pi_{drop} > \phi_e$ and Assumption 2 (so the third term subtracts a positive number). Using that $\frac{\partial}{\partial N}\Lambda_b(n,N) < \frac{\partial}{\partial N}\Omega(n,N)$, we must go up from $\lambda_d(n)$ to find the $\lambda_b(n)$ such that $\Omega(n,\lambda_b(n)) = \Lambda^b(n,\lambda_b(n))$. Since the $n$ was arbitrary, t follows that $\lambda_b(n) > \lambda_d(n)$ for every $n$. ■

**Lemma 2** *The optimal choice of shifts per worker in the baseline environment ($n^b$) is such that*

$$\forall n < n^b, \quad \psi(n) < \lambda_b(n) \qquad \forall n > n^b, \quad \psi(n) > \lambda_b(n)$$

**Proof of Lemma 2:** Since the functions $f$ and $g$ are sufficiently regular (i.e., $\mathcal{C}^2$), the derivatives of $\psi$ and $\lambda_b$ exist and are continuous. To find $\psi'(n)$, we use $\frac{\partial}{\partial n}\Omega(n,\psi(n)) = \frac{\partial}{\partial n}\Psi$, which holds by the definition of $\psi$. This equation is simplified because $\Psi$ is a constant and, therefore, the right-hand side is 0. Expanding and simplifying, this yields

$$\psi'(n) \;=\; \frac{\int_n^{\bar{z}}(g_{12}+g_{22})f(z)dz}{2\int_n^{\bar{z}} g_{22}f(z)dz}. \tag{A.2}$$

Using that $(g_{12}+g_{22}) < 0$ and $g_{22} > 0$, it follows that $\psi'(n) < 0$

Similarly, to find $\lambda_b'(n)$, we use $\frac{\partial}{\partial n}\Omega(n,\lambda_b(n)) = \frac{\partial}{\partial n}\Lambda_b(n,\lambda_b(n))$, which holds by the definition of $\lambda_b$. Expanding and simplifying, this yields

$$\lambda_b'(n) \;=\; \frac{\phi_e f(n) \;+\; \phi_s\int_n^{\bar{z}}(g_{11}+2g_{12}+g_{22})f(z)dz}{2\phi_s\int_n^{\bar{z}}(g_{12}+g_{22})f(z)dz}.$$

Using that $(g_{11}+2g_{12}+g_{22}) > 0$ and $(g_{12}+g_{22}) < 0$, it follows that $\lambda_b'(n) < 0$. Further using $g_1 > 0$ and $\lambda_b'(n) < 0$,

$$\lambda_b'(n) \;<\; \frac{\int_n^{\bar{z}}(g_{11}+2g_{12}+g_{22})f(z)dz}{2\int_n^{\bar{z}}(g_{12}+g_{22})f(z)dz}. \tag{A.3}$$

Recall the assumption on $g$ in (A.1). Adding the same terms to both sides of this equation,

$$\left(\int_n^{\bar{z}} g_{12} f(z) dz\right)^2 + 2\int_n^{\bar{z}} g_{12} f(z) dz \int_n^{\bar{z}} g_{22} f(z) dz + \left(\int_n^{\bar{z}} g_{22} f(z) dz\right)^2$$
$$< \int_n^{\bar{z}} g_{11} f(z) dz \int_n^{\bar{z}} g_{22} f(z) dz + 2\int_n^{\bar{z}} g_{12} f(z) dz \int_n^{\bar{z}} g_{22} f(z) dz + \left(\int_n^{\bar{z}} g_{22} f(z) dz\right)^2$$

Simplifying:

$$\left(\int_n^{\bar{z}} (g_{12} + g_{22)} f(z) dz\right)^2 < \int_n^{\bar{z}} g_{22} f(z) dz \int_n^{\bar{z}} (g_{11} + 2g_{12} + g_{22}) f(z) dz$$

Since $(g_{12} + g_{22}) < 0$, this assumption implies

$$\frac{\int_n^{\bar{z}} (g_{11} + 2g_{12} + g_{22}) f(z) dz}{2\int_n^{\bar{z}} (g_{12} + g_{22}) f(z) dz} < \frac{\int_n^{\bar{z}} (g_{12} + g_{22}) f(z) dz}{2\int_n^{\bar{z}} g_{22} f(z) dz} \tag{A.4}$$

hold for every $(n, N)$.

Using the inequality in (A.3),

$$\lambda_b'(n) < \frac{\int_n^{\bar{z}} (g_{11} + 2g_{12} + g_{22}) f(z) dz}{2\int_n^{\bar{z}} (g_{12} + g_{22}) f(z) dz}$$

holds at $(n, N) = (n, \lambda_b(n))$ for every $n$. The equation for $\lambda_b'(n)$ in (A.2) holds at $(n, N) = (n, \psi(n))$ for every $n$. So the above inequality, (A.2), and (A.4) all hold at $(n^b, N^b)$ since $N^b = \psi(n^b) = \lambda_b(n^b)$. Therefore, it follows that $\lambda_b'(n^b) < \psi'(n^b)$.

Since $\lambda_b'(n)$ and $\psi'(n)$ are continuous, $\lambda_b(n^b) = \psi(n^b)$, and $\lambda_b'(n^b) < \psi'(n^b)$, $\exists \delta > 0$ such that:

$$\forall n \in (n^b - \delta, n^b), \psi(n) < \lambda_b(n); \qquad \forall n \in (n^b, n^b + \delta), \quad \psi(n) > \lambda_b(n).$$

Suppose there was a $n_0 > n^b$ such that $\psi(n_0) \leq \lambda_b(n_0)$. Then, since $\psi$ and $\lambda_b$ are both continuous, there must exist a $n_1 \in (n^b, n_0]$ such that $\psi(n_1) = \lambda_b(n_1)$; without loss of generality, assume $n_1$ was the smallest such point. Then, as for $n^b$, $\frac{\partial}{\partial n}\lambda_b(n_1) < \frac{\partial}{\partial n}\psi(n_1)$. But then, $\exists \delta_1 > 0$ such that $\forall n \in (n_1 - \delta_1, n_1)$, $\psi(n) < \lambda_b(n)$. Since $\lambda_b$ and $\psi$ are continuous and $\forall n \in (n^b, n^b + \delta), \psi(n) > \lambda_b(n)$, the intermediate value theorem implies that there is a $n_2 \in (n^b, n_1)$ such that $\psi(n_2) = \lambda_b(n_2)$. This contradicts the assumption that $n_1$ was the smallest. Therefore, $\forall n > n^b, \psi(n) > \lambda_b(n)$. The proof of the other part of the lemma – $\forall n < n^b,\ \psi(n) < \lambda_b(n)$ – is analogous. ■

**Corollary 1** *The optimal choice of shifts per worker under the removal penalty ($n^d$) is such that*

$$\forall n < n^d, \quad \psi(n) < \lambda_d(n); \qquad \forall n > n^d, \quad \psi(n) > \lambda_d(n).$$

**Proof of Corollary 1:** The proof is exactly analogous to the proof of Lemma 2. This is because $\lambda'_d(n)$ is the same as $\lambda'_b(n)$ except $\phi_e$ is replaced with $\pi_{drop}$ so the key inequality in (A.3) still holds for $\lambda'_d(n)$. ■

**Proof of Theorem 1:** Using that $\psi(n^d) = \lambda_d(n^d)$ and that $\psi(n') < \lambda_d(n')$ for any $n' < n^d$, it follows that $\psi(n) \leq \lambda_d(n)$ for any $n \leq n^d$. Also, at $n \leq n^d$, $\lambda_d(n) < \lambda_b(n)$ by Lemma 1. Therefore, $\psi(n) < \lambda_b(n)$ for any $n \leq n^d$. Since $\psi(n^b) = \lambda_b(n^b)$, it must be that $n^b > n^d$.

Since $N^d = \psi(n^d)$, $N^b = \psi(n^b)$, $\psi'(n) < 0$, and $n^d < n^b$, it follows that $N^b < N^d$. Finally, using $Sn = Ny$, both $n^b > n^d$ and $N^b < N^d$ give that $y^b > y^d$. ■

## A.3 Proving Theorem 2

**Theorem 2** *Introducing an add penalty ($\pi_{add} > 0$) reduces the workforce and increases workers per shift and hours per worker: $N^{sc} < N^d$, $n^{sc} > n^d$, $y^{sc} > y^d$.*

Define the following functions:

$$\Lambda_{sc}(n,N) \equiv \phi_s \int_n^{\bar{z}} g_1 f(z)dz - \pi_{drop}F(n) + \pi_{add}\int_n^{\bar{z}} \big[(1-g)-(z-n)(g_1+g_2)\big]f(z),$$
$$\Psi_{sc}(n,N) \equiv \frac{C_w}{S}\,\kappa - \pi_{add}\int_n^{\bar{z}}(z-n)g_2 f(z)dz,$$
$$\lambda_{sc}(n) \quad \text{to satisfy} \quad \Omega(n,\lambda_{sc}(n)) = \Lambda_{sc}(n,\lambda_{sc}(n)),$$
$$\psi_{sc}(n) \quad \text{to satisfy} \quad \Omega(n,\psi_{sc}(n)) = \Psi_{sc}(n,\psi_{sc}(n)).$$

Note that $(N^{sc}, n^{sc})$ satisfies $N^{sc} = \lambda_{sc}(n^{sc}) = \psi(n^{sc})$. The proof of Theorem 2 uses two intermediate results.

**Lemma 3** *For every $n$, $\psi_d(n) > \psi_{sc}(n)$.*

**Proof of Lemma 3:** To start, we claim that $\frac{\partial}{\partial N}\Omega(n,N) < \frac{\partial}{\partial N}\Psi_{sc}(n,N)$. Using that $g_{22} > 0$:

$$\begin{aligned}
\frac{\partial}{\partial N}\Omega(n,N) &= -\phi_s \int_n^{\bar{z}} g_{22} f(z)dz \\
&< -\pi_{add}\,\bar{z}\int_n^{\bar{z}} g_{22} f(z)dz \qquad \text{[by Assumption 2 and using } g_{22}>0\text{]} \\
&< -\pi_{add}\int_n^{\bar{z}}(z-n)g_{22} f(z)dz \qquad \text{[since } \bar{z} > z-n\text{, for every } z \text{ and } n\text{]} \\
&= \frac{\partial}{\partial N}\Psi^{sc}(n,N)
\end{aligned}$$

Since $g_2 < 0$, $\Psi_d(n,N) < \Psi_{sc}(n,N)$ for every $(n,N)$. Using this and the definition of $\psi_d(n)$, we get that for every $n$,

$$\Omega(n,\psi_d(n)) = \Psi_d(n,\psi_d(n)) < \Psi_{sc}(n,\psi_d(n)).$$

Further using that $\frac{\partial}{\partial N}\Omega(n,N) < \frac{\partial}{\partial N}\Psi_{sc}(n,N)$, we have to go down from $\psi_d(n)$ to find $\psi_{sc}(n)$ where

$$\Omega(n,\psi_{sc}(n)) = \Psi_{sc}(n,\psi_{sc}(n)).$$

It follows that $\psi_d(n) > \psi_{sc}(n)$. ■

**Lemma 4** *For every $n$, $\lambda_d(n) < \lambda_{sc}(n)$.*

**Proof of Lemma 4:** Recall from the proof of Lemma 1 that $\frac{\partial}{\partial N}\Lambda_b(n,N) < \frac{\partial}{\partial N}\Omega(n,N)$. Noting that $\frac{\partial}{\partial N}\Lambda_d(n,N) < \frac{\partial}{\partial N}\Lambda_b(n,N)$, it follows that $\frac{\partial}{\partial N}\Lambda_d(n,N) < \frac{\partial}{\partial N}\Omega(n,N)$.

By Assumption 2, the third term of $\Lambda_{sc}(n,N)$ is positive; therefore, $\Lambda_d(n,N) < \Lambda_{sc}(n,N)$. For any $n$, using this inequality and the definition of $\lambda_d(n)$:

$$\Omega(n,\lambda_d(n)) \;=\; \Lambda_d(n,\lambda_d(n)) \;<\; \Lambda_{sc}(n,\lambda_d(n)).$$

Since $\frac{\partial}{\partial N}\Lambda_d(n,N) < \frac{\partial}{\partial N}\Omega(n,N)$, we have to go up from $\lambda_d(n)$ to find the $\lambda_{sc}(n)$ such that

$$\Omega(n,\lambda_{sc}(n)) \;=\; \Lambda_{sc}(n,\lambda_{sc}(n)).$$

It follows that $\lambda_d(n) < \lambda_{sc}(n)$. ■

**Proof of Theorem 2:** Recall from the proof of Theorem 1 that for any $n \le n^d$, $\lambda_d(n) \ge \psi_d(n)$. Using this and the previous two lemmas, for any $n \le n^d$,

$$\lambda_{sc}(n) \;>\; \lambda_d(n) \;\ge\; \psi_d(n) \;>\; \psi_{sc}(n).$$

Since $\lambda_{sc}(n) > \psi_{sc}(n)$ for all $n \le n^d$ and $\lambda_{sc}(n^{sc}) = \psi_{sc}(n^{sc})$, it follows that $n^d < n^{sc}$.

Using that $\psi_d'(n) < 0$ (from the proof of Corollary 1) and Lemma 3 again,

$$N^d \;=\; \psi_d(n^d) \;>\; \psi_d(n^{sc}) \;>\; \psi_{sc}(n^{sc}) \;=\; N^{sc}.$$

Finally, using that $Sn = Ny$, $n^d < n^{sc}$ and $N^d > N^{sc}$, we get that $y^d < y^{sc}$. ■

## A.4 Proving Theorem 3

**Theorem 3:** *Relative to the baseline environment, access to hours decreases the workforce and increases workers per shift and hours per worker:* $N^{ath} < N^b$, $n^{ath} > n^b$, $y^{ath} > y^b$.

Define the following functions:

$$\begin{aligned}
\Lambda_a(n,N) \;&\equiv\; C_w C_{ws}\kappa \;-\; \Gamma_h(n,N)\;\Psi_b(n,N), \\
\eta_h(n,N) \;&\equiv\; (1-\delta_w)\frac{h_2}{1-h_1} + C_w\frac{y_h}{1-h_1}, \\
\Psi_a(n,N) \;&\equiv\; \delta_w N y_h \;+\; h\big(\gamma(n),(1-\delta_w)N\big), \\
\lambda_a(n) \quad &\text{to satisfy} \quad \big[SC_{ws} - \eta_h(n,N)\big]\;\Omega(n,\lambda_a(n)) \;=\; \Lambda_a(n,\lambda_a(n)), \\
\psi_a(n) \quad &\text{to satisfy} \quad \gamma(n) \;=\; \Psi_a(n,\psi_a(n)).
\end{aligned} \tag{A.5}$$

Note that $(N^a, n^a)$ satisfies $N^a = \lambda_a(n^a) = \psi(n^a)$. The proof of Theorem 2 uses two intermediate results.

**Lemma 5** *The derivative of $\psi_a$ is positive: $\psi_a'(n) > 0$.*

**Proof of Lemma 5:** To compute the derivative of $\psi_a$, we use that $\frac{\partial}{\partial n}\gamma(n) = \frac{\partial}{\partial n}\Psi_a(n,\psi_a(n))$. This yields that

$$\psi_a'(n) \;=\; \frac{\gamma'(n)(1-h_1)}{2\big[\delta_w y_h + (1-\delta_w)h_2\big]},$$

where $\gamma'(n) = \big(\delta_w + \delta_s(1-\delta_w)\big)S > 0$. Since $h_1 \in (0,1)$ and $h_2 > 0$, it follows that $\psi_a'(n) > 0$. ■

**Lemma 6** *The functions $\psi_b$ and $\lambda_a$ are such that:*

$$\psi_b(n^b) = \lambda_a(n^b); \qquad \forall n < n^b, \quad \psi_b(n) < \lambda_a(n); \qquad \forall n > n^b, \quad \psi_b(n) > \lambda_a(n).$$

**Proof of Lemma 6:** Recall that at $n^b$, $\psi_b(n^b) = \lambda_b(n^b) = N^b$ and, hence, $\Omega(n^b, N^b) = \Psi =$

$\Lambda(n^b, N^b)$. So at $(n^b, N^b)$,

$$-\phi_s \int_n^{\bar{z}} g_2 f(z) dz \ = \ \phi_s \int_n^{\bar{z}} g_1 f(z) dz - \phi_e F(n) \ = \ \frac{C_w}{S} \ \kappa.$$

Plugging this in to $\Lambda_a(n, N)$, we see that at $(n^b, N^b)$,

$$\left[ SC_{ws} - \eta_h(n^b, N^b) \right] \ \Omega(n^b, N^b) \ = \ \Lambda_a(n^b, N^b).$$

By the definition of $\lambda_a$, it follows that $\lambda_a(n^b) = N^b$ and (hence) $\lambda_a(n^b) = \psi_b(n^b)$.

Now consider any $n > n^b$. By the definition of $\psi_b$, $\Omega(n, \psi_b(n)) = \Psi$. Since $\psi_b(n) < \lambda_b(n)$ (by Lemma 2) and $\frac{\partial}{\partial N}\Omega(n, N) < 0$, it follows that

$$\Omega(n, \lambda_b(n)) \ > \ \Psi. \tag{A.6}$$

By the definition of $\lambda_b$, $\Omega(n, \lambda_b(n)) = \Lambda_b(n, \lambda_b(n))$. Since $\psi_b(n) < \lambda_b(n)$ (by Lemma 2) and $\frac{\partial}{\partial N}\Omega(n, N) > \frac{\partial}{\partial N}\Lambda_(n, N)$, it follows that

$$\Omega(n, \psi_b(n)) \ > \ \Lambda_b(n, \psi_b(n)). \tag{A.7}$$

Starting from $(n, \lambda_b(n))$ and going down:

$$\begin{aligned}
&\left[ SC_{ws} - \eta_h(n, \lambda_b(n)) \right] \ \Omega(n, \lambda_b(n)) \\
&\quad = \ SC_{ws}\Omega(n, \lambda_b(n)) - \eta_h(n, \lambda_b(n)) \ \Lambda_b(n, \lambda_b(n)) \quad [\text{since } \Omega(n, \lambda_b(n)) = \Lambda_b(n, \lambda_b(n))] \\
&\quad > \ SC_{ws}\frac{C_w}{S}\kappa - \eta_h(n, \lambda_b(n)) \ \Lambda_b(n, \lambda_b(n)) \quad [\text{using inequality in (A.6)}] \\
&\quad = \ \Lambda_a(n, \lambda_b(n)).
\end{aligned}$$

Starting from $(n, \psi_b(n))$ and going up:

$$\begin{aligned}
&\big[SC_{ws} - \eta_h(n, \psi_b(n))\big]\ \Omega(n, \psi_b(n)) \\
&\quad = \ SC_{ws}\frac{C_w}{S}\kappa - \eta_h(n, \psi_b(n))\ \Omega(n, \psi_b(n)) \quad [\text{since } \Omega(n, \psi_b(n)) = \Psi] \\
&\quad < \ C_{ws}C_w\kappa - \eta_h(n, \psi_b(n))\ \Lambda_b(n, \psi_b(n)) \quad [\text{using inequality in (A.7)}] \\
&\quad = \ \Lambda_a(n, \psi_b(n)).
\end{aligned}$$

To summarize:

$$\begin{aligned}
\text{at } (n, \lambda_b(n)), \quad \big[SC_{ws} - \eta_h(n, \lambda_b(n))\big]\ \Omega(n, \lambda_b(n)) \ &> \ \Lambda_a(n, \lambda_b(n)) \\
\text{at } (n, \psi_b(n)), \quad \big[SC_{ws} - \eta_h(n, \psi_b(n))\big]\ \Omega(n, \psi_b(n)) \ &< \ \Lambda_a(n, \psi_b(n)).
\end{aligned}$$

Since everything is continuous, we can use the intermediate value theorem to find a $N^* \in (\lambda_b(n), \psi_b(n))$ such that

$$\big[SC_{ws} - \eta_h(n, N^*)\big]\ \Omega(n, N^*) \ = \ \Lambda_a(n, N^*).$$

This $N^*$ is $\lambda_a(n)$. It follows that $\lambda_b(n) < \lambda_a(n) < \psi_b(n)$; in particular, $\psi_b(n) > \lambda_a(n)$.

An analogous proof can show that for every $n^b$, $\psi_b(n) < \lambda_a(n)$. ■

**Proof of Theorem 3:** Recall that the constraint on hours for existing workers is not binding in the baseline by Assumption 1. This implies that

$$\gamma(n^b) \ < \ \Psi_a(n, \psi_b(n^b)).$$

However, this constraint is binding at $(n, \psi_a(n^b)$. Since $\frac{\partial}{\partial N}\Psi_a > 0$, it follows that

$$\psi_b(n^b)) \ > \ \psi_a(n^b)). \tag{A.8}$$

Consider any $n \leq n^b$:

$$\begin{aligned}
\psi_a(n) &\leq \psi_a(n^b) && \text{[since } \psi_a'(n) > 0 \text{ by Lemma 5]} \\
&< \psi_b(n^b) && \text{[using the inequality in (A.8)]} \\
&\leq \psi_b(n) && \text{[since } \psi_b'(n) < 0 \text{ (shown in the proof of Lemma 2)]} \\
&\leq \lambda_a(n). && \text{[by Lemma 6]}
\end{aligned}$$

So $\psi_a(n) < \lambda_a(n)$ for every such $n \leq n^b$. At $n^a$, $\psi_a(n^a) = \lambda_a(n^a)$. Therefore, it cannot be that $n_a \leq n_b$, and so $n_b < n_a$.

Using $\psi_b'(n) < 0$ and Lemma 6 again along with $n_b < n_a$,

$$N^b \;=\; \psi_b(n^b) \;>\; \psi_b(n^a) \;>\; \lambda_a(n^a) \;=\; N^a.$$

Thus, $N^b > N^a$. Using $Sn = Ny$, we also get that $y_b < y_a$. ■

# B Details on the SDID method

For each empirical model, we use a synthetic difference-in-differences (SDID) estimator from Arkhangelsky et al. (2021) which combines desirable properties of the synthetic control method (SCM) and the difference-in-differences (DID) estimator. The standard DID estimator employs a two-way fixed effect regression to control for unit and time fixed effects. The synthetic difference-in-differences (SDID) estimator adds unit and time weights to make this regression "local" in the sense that it puts more weight on units and periods that are most similar to treated units (pre-policy) and treatment periods, respectively. These weights both remove bias and improve precision by reducing the influence of units or periods that significantly differ from treated units and post-policy periods.

DID requires a parallel trends assumption: that the pre-policy difference between control and treated units would remain approximately constant over time but for treatment. For this assumption to be credible, the control unit(s) has to retain a constant gap from the treated unit(s) in the pre-policy period. Finding such a control unit(s) can be difficult in practice. In contrast, the unit weights in SDID are chosen to maximize the credibility of the parallel trends assumption. Indeed, the unit weights are those that minimize the variance of the gap between the synthetic control and treated unit(s) over the pre-policy period.

The standard SCM similarly deals with concerns about parallel trends because it sets unit weights to (almost) exactly match pre-policy outcomes of the synthetic control and the treatment group. In contrast, the SDID allows there to be a gap between the synthetic control and treatment group that is constant in pre-policy periods. This flexibility makes SDID invariant to additive unit-level shifts (like DID).

The first step of the SDID algorithm is to choose these unit and time weights. As mentioned, unit weights are chosen to ensure parallel trends. In the minimization problem, a penalty term is employed to increase the dispersion and ensure the uniqueness of the weights. Using a similar idea, the time weights are chosen so that the difference in time-weighted average pre-policy and post-policy values is approximately the same across units. Again, a penalty term is used to ensure uniqueness. After these weights are obtained, the SDID treatment effect is estimated as a weighted DID where the weight on each observation is the unit weight multiplied by the time weight.[1]

Lastly, the SDID framework can adjust for time-varying exogenous covariates. It does this by first regressing the outcome variable on the covariates and then applying SDID to the residuals. We use this in our analysis when we control for minimum wage changes.

The analysis in our paper uses the *synthdid* package (Hirshberg 2019) to implement the SDID estimator. For additional details on SDID, see Arkhangelsky et al. (2021); specifically, their description of Algorithm 1 in the introduction and Section I.A.

[1] Arkhangelsky et al. (2021) outline a few methods to obtain standard errors of the estimates. We use the jackknife variance estimate because it is the least computationally complex, and the authors prove that, under some assumptions, the standard error has desirable properties in the limit. See their Theorem 2.

## B.1 Notation for our application

In this subsection, we describe the equation used to calculate the treatment effect for our empirical design. For convenience, we closely follow the notation of Arkhangelsky et al. (2021).

Consider a balanced panel with $N$ units and $T$ time periods where $Y_{it}$ is log employment for unit $i$ in period $t$. Assume the first $N_{co}$ units are never exposed to treatment while the last $N_{tr} = N - N_{co}$ are. Let $W_{it}$ be the binary treatment variable where an observation is treated if $i$ is the fast food industry in a NYC county and $t > T_{pre}$; $T_{pre}$ is the last pre-policy period. For all our main specifications, $T = 24$ and $N_{tr} = 5$; $N$ and $N_{co}$ depend on the number of control units in the specification. The first period ($T = 1$) corresponds to 2014 Q1, the last pre-policy period ($T_{pre} = 15$) corresponds to 2017 Q3, and the last quarter corresponds to 2019 Q4. The optimization problem used to obtain the treatment effect $\hat{\tau}^{sdid}$ is the following:

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}, \tag{B.1}$$

where $\alpha_i$ are unit fixed effects, $\beta_t$ are time fixed effects, $\mu$ is the gap between the synthetic control and treatment group (discussed above), $\hat{\omega}_i^{sdid}$ are unit weights, and $\hat{\lambda}_t^{sdid}$ are time weights. As is standard in the synthetic control literature, the unit weights "align pre-exposure trends in the outcome of unexposed units with those for the exposed units ... $\sum_{i=1}^{N_{co}} \hat{\omega}_i^{sdid} Y_{it} \approx \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it}$ for all $t = 1, ..., T_{pre}$" Arkhangelsky et al. (2021); see their paper for further details. As for time weights, our main specification sets them to be uniform: $\hat{\lambda}_t^{sdid} = 1/T$. However, we consider robustness exercises where time weights are chosen differently; see Appendix D for details.

# C Data appendix

## C.1 Background on the QCEW

As mentioned, we use the Quarterly Census of Employment and Wages (QCEW) in our analysis. The QCEW provides aggregate employment and earnings measures at the industry-by-county level, deriving from each state's unemployment insurance (UI) accounting system. All private-sector employers and government employers covered under the UI program submit quarterly reports on employment and wages, which the QCEW aggregates. In addition to this administrative data, the QCEW conducts surveys to verify the main business activity, physical location, employment, and wages of certain businesses.

The employment measure from the QCEW is monthly, not quarterly. In particular, it is the sum of the counts of people employed in each of the firms in the county-industry at any time during the month. We obtain a quarterly measure by averaging employment from the three corresponding months. During the pre-policy period (2014 Q1 to 2017 Q3), the average employment in NYC's limited restaurant industry – our proxy of the affected population – is 68,699.

## C.2 Exclusions from control groups

Recall that our two main approaches are the within-industry model, which takes other fast-food industries around the country as a control group, and the within-location model, which takes other NYC county-industry pairs as the control group.

We make several restrictions on these control groups. For the within-industry approach, the control group is restricted to Census-designated "central counties" in metro areas with more than 1,000,000 people in the 2020 Census.[2] There are 257 such counties, excluding NYC's 5 counties. In addition to this, the county (or a city within the county) must not

[2]The populations of metro areas (i.e., Metropolitan Statistical Areas) and the designation of counties as central (as opposed to outlying) come from datasets on the Census Bureau website (Census 2020; Census 2023c).

have implemented a FWW law for fast-food workers before 2019 Q4 (the last post-policy quarter in our analysis of NYC's law) with either short-notice schedule-change penalties or ATH. This exclusion strategy is similar to Allegretto et al. (2018) who when analyzing the effect of minimum wage changes, compare affected counties to other counties that did not have a change in their minimum wage policy and are in a metropolitan area with an estimated population of at least 200,000 in the fourth quarter of 2009.

The locations to implement FWW with either short-notice schedule-change penalties or ATH for fast-food workers before 2019 Q4 were: San Francisco, California in December 2014; San Jose, California in March 2017; Emeryville, California in July 2017; Seattle, Washington in July 2017; and Oregon (statewide) in July 2018 (Wolfe et al. 2018; NWLC 2019). Therefore, we exclude the corresponding counties from the within-industry control group: San Francisco County, California; Santa Clara County, California; Alameda County, California; King County, Washington; and all counties from Oregon (respectively). Two other cities passed such FWW laws before 2019 Q4 – Philadelphia (December 2018) and Chicago (July 2019) – but the laws did not become effective until after 2019 Q4 – January 2020 and July 2020, respectively. We exclude the corresponding counties from the within-industry control group to be safe (Philadelphia County, Pennsylvania, and Cook County, Illinois, respectively).

In the within-location model, we also exclude industries affected by the NYC FWW law for retail workers. In particular, we exclude all 6-digit industries that start with 44 or 45.

Further, we exclude units (counties in the within-industry model and county-industry pairs in the within-location model) that have average quarterly employment below 2000 across our period of analysis. We also exclude units that have any blank or zero values for variables over the period we consider. In the end, we have 175 control units (i.e., counties) for the within-industry model and 247 control units (i.e., county-industry pairs) for the within-location model.

## C.3 Minimum wage dataset details

Since our period of analysis coincides with substantial minimum wage changes, we construct a quarterly county-level minimum-wage dataset to span the period (2014 Q1 to 2019 Q4). We draw on Vaghul and Zipperer (2022)'s public data of quarterly state-level minimum wages and sub-state minimum wages.

For each quarter, we consider the minimum wage to be its value on the first day of the quarter. To incorporate substate changes into our county-level dataset, we take the population-weighted average of the minimum wage at the beginning of the quarter. In particular, weights are based on city and county-level population estimates from the 2020 Census (Census 2023a; Census 2023b). Thus, weights are fixed over time. As an example, consider the minimum wage changes in Flagstaff, Arizona that began in 2018. Flagstaff is located in Coconino County, and in 2020, it made up 53% of the population in the county. Over our period, 2014 Q1 to 2019 Q4, the minimum wage in Coconino County outside Flagstaff coincided with the Arizona state minimum wage, which underwent annual increases. In 2018, the minimum wage in Flagstaff rose above that in the rest of Coconino County, increasing each year to stay above the Arizona minimum wage. By 2019 Q4, the Flagstaff minimum wage was \$12, though the Arizona minimum wage was \$11. For 2018 Q1 and after, we take the minimum wage in Coconino County to be 0.53 times the Flagstaff minimum wage plus 0.47 times the Arizona state minimum wage. For example, in 2019 Q4, this was \$11.53.

The minimum wage data also accounts for special fast-food minimum wages that exceed the typical minimum wage. According to Vaghul and Zipperer (2022), there are only these special wages in New York State. We assume that this higher minimum wage applies to all workers in the limited-service restaurant industry, our proxy of the affected population. No other industries in New York State have these special minimum wages in the Vaghul and Zipperer (2022) data. Figure C.1 plots the NYC and NYC fast-food minimum wages over our sample period (along with those for New York State).

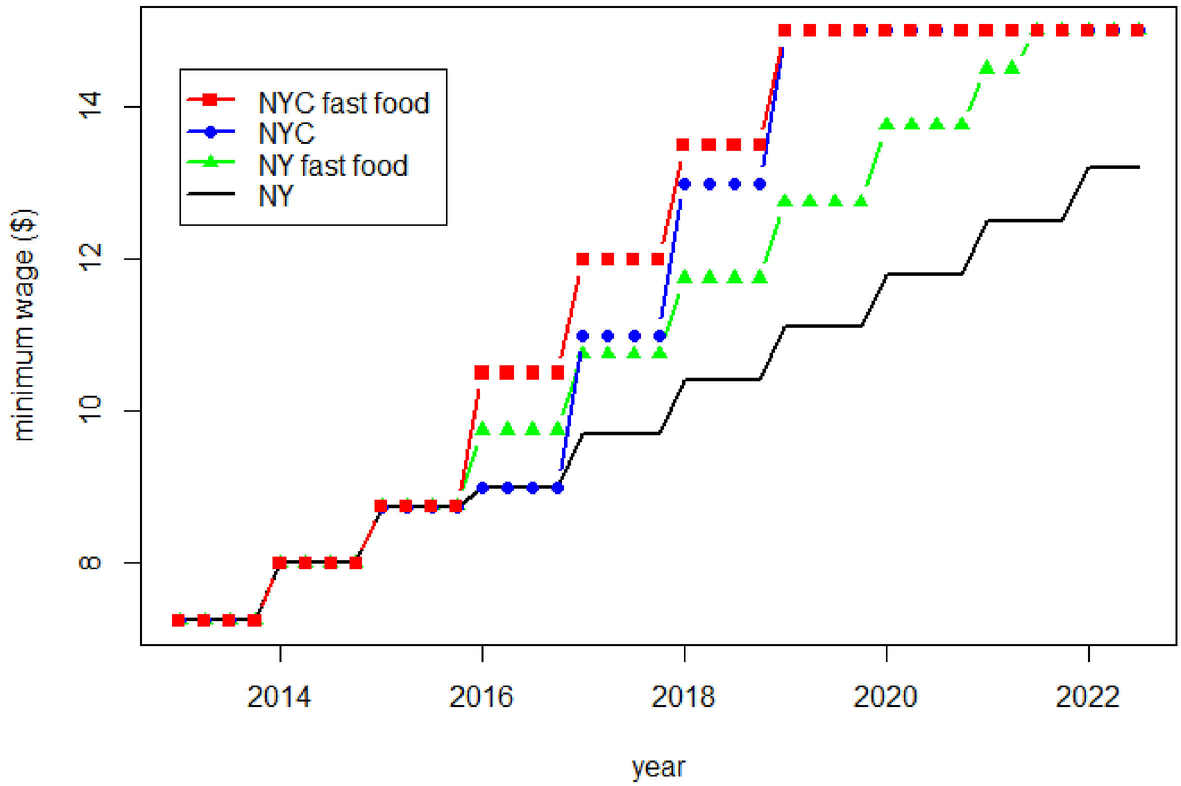



Figure C.1: Evolution of the minimum wage in New York

*Notes:* The graph plots the evolution of the minimum wages over our sample period for: (1) the NYC (New York City) fast-food industry; (2) the non-fast-food NYC industries; (3) the fast-food industry in the rest of NY (New York) state; and (4) the non-fast-food industries in the rest of NY state. Note that (4) does not apply to the New York counties of Nassau, Suffolk, and Westchester which had separate (non-fast-food) minimum wage evolutions.

# D Robustness

This appendix discusses and tests the robustness of our empirical results. To start, we discuss the role of our four different empirical models. Next, we attempt to gauge the different roles of schedule-change provisions and ATH with two tests. First, we estimate the effects of Oregon's FWW law for restaurant workers. Oregon's law is similar to NYC's but does not have an ATH provision. Second, we estimate the effects of NYC's FWW law on *retail* workers; the provisions for retail workers do not include ATH or schedule-change penalties.

Then, we consider the role of how time weights in the SDID algorithm are computed by generating "low-penalty" and "high-penalty" estimates. Next, we address the possibility of anticipatory compliance with two alternative treatment start times. Lastly, we obtain results from a standard two-way fixed effects regression.

The results for all five robustness checks are detailed in Table D.1. Details on the Oregon law and the NYC retail law and methodological differences in how we evaluate them are discussed in Appendix D.1 below.

**Conflicting estimates across models:** The purpose of having multiple models is to assess robustness. The two baseline approaches - the within-industry and within-location models - are susceptible to different kinds of bias. If there were a common shock to NYC industries around the same time as the legislation but unrelated to it, the within-industry estimates would be biased, though the within-location model would be less prone to such bias.[3] If there were a shock common to the U.S. fast-food industry, the within-location estimates would be biased and the within-industry model would be less prone.

For our employment estimates, the within-industry (without the minimum wage control) and the within-location models - specifications (1) and (3), respectively - are approximately similar. Looking at Table 2, the estimates for (1) and (3) are 0.6 (3.2) and 0.3 (4.4) log point,s respectively. Given that the estimates are only 0.3 log points apart and both standard errors are above 3 log points, it is unlikely that the estimates are biased by a within-NYC or a within-fast-food common shock.[4]

**Gauging effects of different provisions:** Recall that our empirical analysis cannot separately identify effects of the different NYC FWW provisions; it can only capture the law's overall effect. However, we can exploit variation in FWW laws across different industries and locations to gauge the role of certain provisions. In what follows, we analyze two other FWW laws: Oregon's FWW law, which has no ATH, and NYC's FWW law for retail workers, which

[3]Note that such a shock would not have to affect *all* NYC industries to alter estimates. If the shock affected a few industries that are significant donor units to the synthetic control, this could introduce bias.

[4]Though it is possible that these shocks are in the same direction and of a similar magnitude, it does not seem likely.

| *Robustness test* | *Model* | | | |
|---|---|---|---|---|
| | Within-ind. (no mw cont.) (1) | Within-ind. (mw cont.) (2) | Within-location (3) | Pooled (4) |
| Employment | 0.0063<br>(0.0319)<br>[0.0031] | 0.0114<br>(0.0129)<br>[0.0031] | -0.0014<br>(0.042)<br>[0.0028] | 0.002<br>(0.0362)<br>[0.0019] |
| Oregon restaurant industry | -0.0099<br>(0.0188)<br>[0.0034] | -0.0078<br>(0.0169)<br>[0.0036] | | |
| NYC retail industry | 0.002<br>(0.0212)<br>[0.0042] | 0.003<br>(0.0103)<br>[0.0042] | -0.0383<br>(0.0243)<br>[0.01] | -0.0164<br>(0.0204)<br>[0.0076] |
| low-penalty time weights | 0.0069<br>(0.0135)<br>[0.0032] | 0.0114<br>(0.0138)<br>[0.0032] | 0.0016<br>(0.0172)<br>[0.004] | 0.004<br>(0.0147)<br>[0.0027] |
| high-penalty time weights | 0.0055<br>(0.0176)<br>[0.0032] | 0.0097<br>(0.0123)<br>[0.0032] | -0.0017<br>(0.0197)<br>[0.0028] | 0.0018<br>(0.017)<br>[0.0019] |
| alt. treatment start: 2017 Q2 | 0.0109<br>(0.0328)<br>[0.0033] | 0.0141<br>(0.0154)<br>[0.0033] | -0.0059<br>(0.0433)<br>[0.0027] | -0.0019<br>(0.0374)<br>[0.0019] |
| alt. treatment start: 2016 Q3 | 0.0255<br>(0.0348)<br>[0.0027] | 0.0323<br>(0.024)<br>[0.0025] | 0.0176<br>(0.0419)<br>[0.0022] | 0.0222<br>(0.0367)<br>[0.0015] |
| two-way fixed effects | 0.0204*<br>(0.0074) | 0.0283*<br>(0.0082) | 0.0255<br>(0.0228) | 0.0234<br>(0.0181) |

Table D.1: Results of robustness exercises

*Notes:* This table summarizes the employment effect from our robustness exercises. The first row repeats the main results for reference. The second row measures the effect of Oregon's FWW law on restaurant workers. The third row measures the effect of NYC's FWW law on retail workers. The fourth and fifth rows rerun the main analysis for NYC fast food workers but use low- and high-penalties, respectively, to calculate time weights (in place of uniform time weights). The sixth and seventh rows rerun the main analysis considering alternate treatment starts: 2017 Q2 and 2016 Q3. The last row runs a standard two-way fixed effects model for NYC fast food workers; note these estimates have no RMSPE values. A star (*) denotes statistical significance at the 95% level.

has no ATH or schedule-change penalties.

Oregon's law – the *Fair Work Week Act*, effective July 1, 2018 – applies to hourly employees of retail, hospitality, and food service firms (Wolfe et al. 2018). We focus on Oregon's *restaurant and other eating places* industry, the four-digit superset of the *limited-service restaurant* industry used in our main analysis. Analysis proceeds in an analogous way to Section 5. Details on the law's provisions and methodological differences are discussed in Appendix D.1, but note that we only use the within-industry approach – models (1) and (2). Consistent with our conclusions for NYC's FWW law on fast food workers, we find no significant employment effects.

Similar to the Oregon law, we run an analysis on the NYC retail labor market that is largely analogous to that in Section 6. Provisions on the retail law and methodological alterations are also discussed in Appendix D.1, but note that we run all four models, not just the first two. Estimates again show no significant effects, but note that the within-location and pooled estimates are lower than the within-industry estimates.

**Changing how time weights are computed:** Though the details of the SDID method are outlined in Appendix B, one technical issue deserves further attention. The SDID algorithm chooses unit and time weights for the synthetic control. Time weights are chosen so that the difference in the time-weighted average of pre- and post-policy values is approximately the same across units, and a penalty term on the time-weight vector is used to ensure uniqueness. Similarly, a penalty term is used when computing the unit weights. However, the regularization term in the penalty (i.e., the default in Arkhangelsky et al. 2021) is much larger for unit weights than for time weights.[5]

In our main specifications, we depart from the default in Arkhangelsky et al. (2021) and give equal weight to all pre-policy periods;[6] this is similar to Karabarbounis et al. (2022). To address the effects of this change, we report results using a "low-penalty" term (i.e., the

[5]For time weights, the weight is $10^{-6}$, and for unit weights, it is at least 1.

[6]In our experience, without equal weights, time weights are often strongly biased toward the last pre-policy period or the last few pre-policy periods; it was common for all weight to be put on the last pre-policy period.

default in Arkhangelsky et al. 2021) and a "high-penalty" term (i.e., we set the regularization term for time weights to be the same as that for unit weights). Presumably, this high-penalty specification would spread the time weights across pre-policy periods.

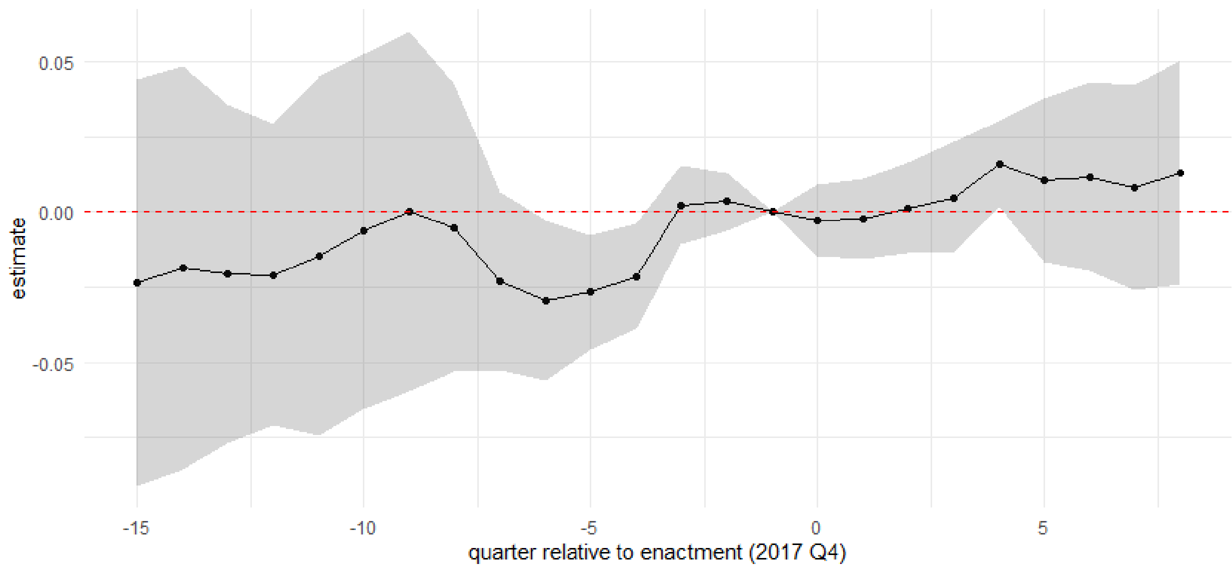
The pattern of results for the low-penalty specification is consistent with those from Section 6: no significant effects, but the specification with the minimum wage control yields a higher estimate. The same is true of the high-penalty specification.

**Alternate treatment start:** Recall the legislation was passed and signed into law in May 2017, but did not become effective until November 2017. Since coming into compliance could take time for employers, anticipatory effects are possible. Furthermore, such compliance efforts may have started before passage in May 2017. In particular, Mayor Bill de Blasio announced his plans to curb unpredictable scheduling for fast-food workers on September 15, 2016. It is plausible that employers responded to this announcement by changing their behavior.

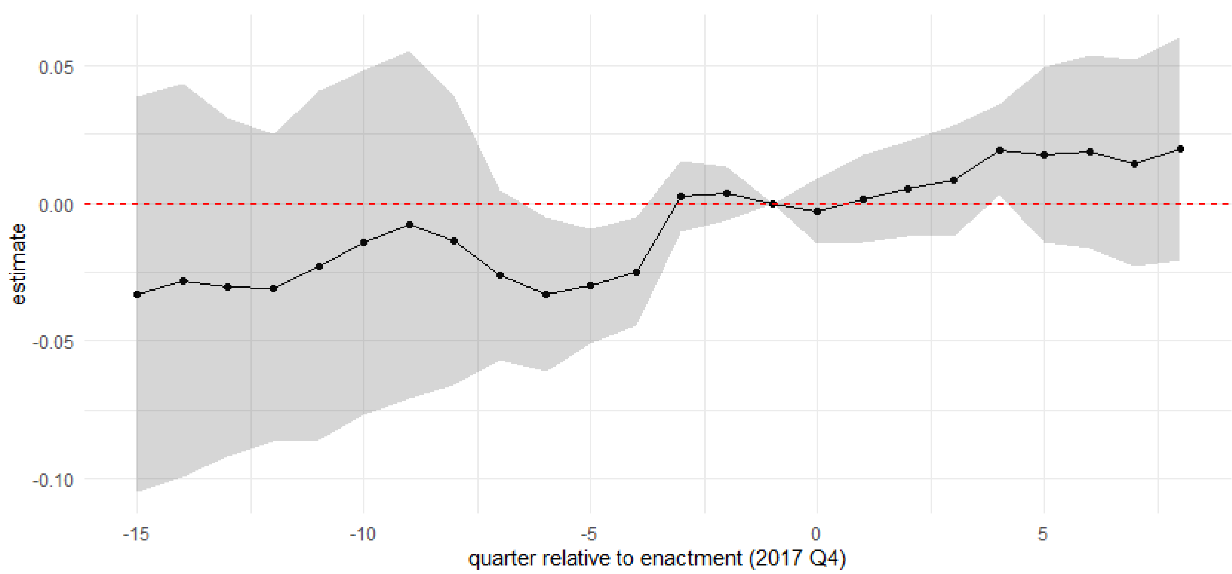
To account for the possibility of anticipatory compliance, we run two robustness exercises. The first considers the treatment period to start two quarters earlier (2017 Q2) when the law was passed and signed into law. The second considers the treatment period to start five quarters earlier (2016 Q3) when the mayor announced his intentions. Both sets of results are consistent with the main results.

**Two-way fixed effects model:** A more basic approach than the SDID we use in our main analysis is a two-way fixed effects regression. That is, a panel regression where log employment is the dependent variable, being treated (i.e., the limited-service restaurant industry in NYC between 2017 Q4 and 2019 Q4) is the independent variable, and there are time and unit fixed effects. A "unit" is a county in the within-industry model and a county-industry pair in the within-location model.

All four specifications yield employment estimates between 2 and 3 log points. These are higher than all other estimates in the paper. Furthermore, both within-industry estimates are statistically significant at the 95% level. However, looking at an event study for these




(a) within-location model (no minimum wage control)




(b) within-location model (with minimum wage control)

Figure D.1: Event study plots for two-way fixed effect models

*Notes:* The x-axis of both plots is relative to the first post-policy period (2017 Q4). The leftmost point ($x = -15$) corresponds to 2014 Q1 and the rightmost point ($x = 8$) corresponds to 2019 Q4. The y-axis is the estimate on log employment relative to the last pre-policy period (2017 Q3).

specifications casts doubt on the method's validity.

Figure D.1 shows the event study plots for the two specifications with a statistically significant result: the within-location model without and with a minimum wage control, respectively. Both plots show a positive pre-trend, and the estimates 6, 5, and 4 quarters before the effective date are significantly negative (relative to the quarter before the law went into effect). This casts doubt on the parallel trends assumption necessary for two-way fixed effects analysis. This, in turn, motivates the use of SDID, which satisfies parallel trends by construction. For relevant details on the SDID method, see Appendix B.

## D.1 Additional legal and methodological details

Here, we briefly overview the provisions of Oregon's FWW law and NYC's FWW law for retail workers, and how our methodology for evaluating them differs from Section 5. The information for Oregon's law comes from Wolfe et al. (2018) and that for NYC's law for retail workers comes from DCWP (2023b).

**Oregon's law:** The statewide *Fair Work Week Act* applies to hourly employees of retail, hospitality, and food service firms. The law's provisions are as follows: employers must provide workers with an approximate schedule before they start employment; two weeks' notice is required before schedule changes, otherwise, a premium must be paid; employers cannot make last-minute shift additions without the worker's consent; employers have the right to rest 10 hours between shifts; employees are protected from retaliation when they request scheduling accommodations. This is very similar to the NYC FWW law for fast-food workers but there is no ATH.

Similar to the NYC law, smaller firms are excluded: the law applies to establishments with 500 or more employees worldwide. However, unlike the NYC law, the Oregon law applies to all food service firms, not just fast-food establishments. Thus, we use the relevant 4-digit industry – 7225, restaurants and other eating places – as opposed to the six-digit industry for fast-food workers.

We perform an analysis of Oregon's FWW law that is largely analogous to the analysis in Section 5. However, there are a few distinctions. First, though the law affects all Oregon counties, we only consider those that met the criteria for our control group. Most significantly, a county must be a Census-designated central county in a metro area with more than 1,000,000 people in the 2020 Census; see Appendix C for details on this and other restrictions. These restrictions give us a treatment group of three Oregon counties: Clackamas, Multnomah, and Washington. Second, we only use the within-industry approach and not the within-location approach; i.e., our analysis includes models (1) and (2), but not (3) and (4). Since the Oregon law applied to more industries, a within-location approach (and, hence, a pooled approach) would be more difficult. Third, consistent with the methodology in Section 5, we remove NYC's five counties from the control group.

**NYC's law for retail workers:** Though our paper focuses on how the NYC *Fair Workweek Law* affects fast-food workers, a separate part of the law applies to retail workers. The provisions for retail workers are as follows: employers must provide employees with a work schedule at least 72 hours before the first shift on the schedule; *on-call shifts*[7] are prohibited; employers cannot require employees to "check in" within 72 hours of a scheduled shift to find out if they need to report for the shift; workers can reject additional hours less than 72 hours before a shift starts (if they accept, consent must be in writing); and with some exceptions, employers cannot reduce or cancel a shift less than 72 hours before it starts. While some of the provisions are similar to the law for fast-food workers (described in Section 2), there are no schedule-change penalties and no ATH.

These provisions apply to any retail business that: (1) has 20 or more employees at one or more stores in NYC and (2) engages primarily in the sale of consumer goods. *Consumer goods* are those "primarily used for personal, household, or family purposes" (DCWP 2023b). A business is considered to engage "primarily" in the sale of consumer goods if 50% or more of their sales transactions during the previous 12 months were of consumer goods sold to retail consumers.

Given our data limitations, these criteria make it difficult to separate retail employers

[7] "Occurs when a worker is required to be ready and available to work at the employer's call for a period of time, regardless of whether the worker actually works or is required to report to a work location" (DCWP 2023b).

subject to the law and those who are not. To proceed, we isolate four-digit retail industries where *it seems* most of the firms within those industries are subject to the law (i.e., based on our judgment). Of the 24 four-digit retail industries, we exclude the following 4 industries: 4441 Building Material and Supplies Dealers; 4572 Fuel Dealers; 4594 Office Supplies, Stationery, and Gift Retailers; and 4599 Other Miscellaneous Retailers. Our opinion is that firms in these industries are likely to be (or could be) making most of their sales transactions to other businesses rather than consumers. We consider the other 20 four-digit retail industries to be our *treatment group*.[8]

For the within-industry approach, our *control group* is comprised of the *two-digit* industry "44-45 Retail Trade" in other counties around the country. These counties must meet the same restrictions detailed in Appendix C.2 to be included in the control group. For the *treatment group*, the five counties are considered separately but the aforementioned 20 four-digit retail industries (within a county) are considered together. So there are five treated units, each being the sum of the 20 four-digit industries in that county.

For the within-location approach, the *control group* is comprised of non-retail *four-digit* industries in NYC. The *treatment group* comes from the 20 four-digit retail industries but these industries are now considered separately. To be included in the control group *or the treatment group*, the NYC industry must meet the same restrictions detailed in Appendix C.2; one exception is that the average quarterly employment cutoff is raised to 5,000 from 2,000 since four-digit industries are bigger than six-digit industries on average. The four retail industries that are excluded from the treatment group, and the restaurant and other eating places industry are also excluded from the control group.

[8]These industries are: 4411 Automobile Dealers; 4412 Other Motor Vehicle Dealers; 4413 Automotive Parts, Accessories, and Tire Retailers; 4442 Lawn and Garden Equipment and Supplies Retailers; 4451 Grocery and Convenience Retailers; 4452 Specialty Food Retailers; 4453 Beer, Wine, and Liquor Retailers; 4491 Furniture and Home Furnishings Retailers; 4492 Electronics and Appliance Retailers; 4551 Department Stores; 4552 Warehouse Clubs, Supercenters, and Other General Merchandise Retailers; 4561 Health and Personal Care Retailers; 4571 Gasoline Stations 4581 Clothing and Clothing Accessories Retailers; 4582 Shoe Retailers; 4583 Jewelry, Luggage, and Leather Goods Retailers; 4591 Sporting Goods, Hobby, and Musical Instrument Retailers; 4592 Book Retailers and News Dealers; 4593 Florists; and 4595 Used Merchandise Retailers.