The Effects of Inconsistent Work Schedules on Employee Lateness and Absenteeism

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Abstract

Problem Definition: Employee lateness and absenteeism pose challenges for businesses, particularly in the retail industry, where punctuality is vital for optimal store operations and customer service. This paper relates employee lateness and absenteeism with inconsistent work schedules. We address three questions: (1) How common is employee lateness and absenteeism at the shift level? (2) How prevalent are inconsistent work schedules? (3) Is there a causal relationship between inconsistent work schedules and employee lateness and absenteeism?

Methodology/Results: Analyzing more than 28 million shift level timecards from two major retail chains covering more than 135,000 employees across 1,000 store locations, we empirically analyze the causal effects of inconsistent work schedules on employee lateness and absenteeism. We focus on two mutually exclusive types of inconsistent work schedules: (i) shifts that are scheduled on a day of the week (e.g. Monday) that the employee did not work the prior week, and (ii) shifts that are scheduled on a day of the week that the employee did work the prior week, but with a start time that differs by more than one hour. We first document that lateness or absenteeism, as well as inconsistent work schedules, are highly prevalent in our data. They occur in approximately 4.6 million (16%) and 10.7 million (37%) shifts, respectively. Following the identification strategies of Lu et al. (2022) and Bergman et al. (2023), we find that inconsistent work schedules significantly increase the probability of lateness and absenteeism at the shift level. Heterogeneous effects analyses show that these results are primarily driven by the behavior of full-time employees, who may value schedule consistency more than their part-time counterparts.

Managerial Implications: We provide causal evidence of the adverse effects of inconsistent work schedules on employee lateness and absenteeism, which have plausible connections to store performance. Inconsistent work schedules are prevalent in our data, which could reflect the need for flexible and short-notice scheduling practices in the retail industry. Consequently, our findings may assist managers in evaluating the trade-offs of inconsistent work schedules, especially when they are necessary due to fluctuations in demand or disruptions in labor supply.

*Disclaimer:** This paper makes use of proprietary administrative data on various companies. The conclusions drawn from the data are those of the researchers and do not reflect the views of any companies examined in this paper. These companies are not responsible for, had no role in, and were not involved in analyzing or developing the hypotheses or results reported herein. The corresponding author has received financial compensation for consulting work from some suppliers to the companies examined in the paper. He has not consulted for, or received compensation from, the companies examined in this paper.

1 Introduction

Employee lateness and absenteeism present significant challenges for businesses, particularly within the retail industry, where employee punctuality is critical for optimal store operations. When employees are late or absent, it directly affects the performance of the store by reducing customer service levels. Additionally, such occurrences can have spillover effects on coworkers, who may be required to work longer hours or exert additional effort to compensate for the labor shortage. The costs associated with unexpected lateness or absenteeism are estimated to be substantial. According to analyses conducted by Circadian, a workforce solution company, unscheduled absenteeism costs approximately $3,600 per year for each hourly worker and $2,660 per year for salaried employees (Circadian, 2005). Furthermore, a Gallup-Sharecare Well-being Index survey estimates that the annual cost of lost productivity due to absenteeism amounts to approximately 84 billion dollars (Folger, 2013).

Despite the large potential costs associated with employee lateness and absenteeism (or equivalently, schedule inadherence), few papers have empirically examined the causal drivers of employee schedule inadherence. The lack of empirical research of potential drivers leaves a knowledge gap that may hinder the development of effective strategies to increase employee schedule adherence. This knowledge gap may be particularly concerning in retail, where inconsistent work schedules may frequently emerge as managerial responses to customer demand shocks and labor supply shocks (Kamalahmadi et al., 2021; Kwon and Raman, 2023a,b; Lu et al., 2022). In this paper, we provide novel evidence that inconsistent work schedules are a significant driver of shift level lateness and absenteeism rates.

Retail is a particularly suitable context for studying the scheduling drivers of employee lateness and absenteeism for several reasons. First, the direct interaction between employees and customers in retail clearly underscores the importance of schedule adherence: A reduction in service levels resulting from a late or absent worker can result in depressed sales, for example, because a customer may not be able to find the product they were looking to buy (Fisher et al., 2021). Second, clearly defined shift schedules (i.e. a predetermined start and end time), which are typical in retail, allow for accurate tracking and measurement of schedule adherence. In other industries where start and end times are systematically variable (i.e., trade-related work and medicine), it may be challenging to infer schedule adherence by simply comparing realized versus scheduled clock-in and clock-out times. Third, given retail's status as a major employment sector (10.5% of all non-farm employees in 2021 according to the Bureau of Labor Statistics), adjustments to scheduling practices that result in modest reductions in the rates of lateness and absenteeism across stores, all else equal, may have substantial aggregate effects within the economy. Fourth, given the potential need for flexible scheduling practices in the retail industry (Kamalahmadi et al., 2021; Kesavan et al., 2022; Kwon and Raman, 2023a; Lu et al., 2022), understanding the potential costs of these scheduling practices may help managers better weigh their associated costs and benefits more accurately. For example, managers may need to adjust schedules based on unanticipated demand shocks (e.g., news of good weather) or labor supply shocks (e.g., unanticipated employee turnover) in a way that increases inconsistent work schedules. Accordingly, understanding how inconsistent work schedules affect schedule adherence may help managers anticipate potential operational disruptions and address them proactively. Finally, the diversity of employees and roles within retail, ranging from sales to management, from inexperienced to experienced, provides important variation at the employee level to study how drivers of schedule adherence can be heterogeneous based on employee characteristics. Understanding heterogeneous effects may also be important when developing scheduling strategies that account for different employee needs, experiences, and behaviors (e.g., part-time versus full-time employees).

In this paper, we empirically analyze the link between inconsistent work schedules and employee lateness and absenteeism. For this purpose, we analyze more than 28 million shift level timecards from two independent retail chains: a grocery chain and a durable goods chain. In total, this dataset covers more than 135,000 employees across more than 1,000 brick-and-mortar store locations over a 5-year period. Our sample is unredacted and includes *all* shift-based employees at all store locations. We combine these data with contextual information of the scheduling processes across all stores along with two additional datasets. The first dataset provides granular human resource related variables for each shift-based employee, such as their tenure, gender, and status (i.e., part-time versus full-time). This particular dataset is critical for managerial implications as we examine whether the effects of inconsistent work schedules on schedule adherence vary according to employee characteristics. The second dataset contains information on the temporary absences of all employees that result from paid time off requests. As we describe below, we use this particular dataset as part of our identification strategy, which mimics the approach of Bergman et al. (2023).

Using these datasets, we study the causal effects of inconsistent schedules on shift level rates of employee lateness and absenteeism. Following Lu et al. (2022), we focus on two mutually exclusive types of schedule inconsistency: day-of-the-week inconsistency and start-time inconsistency. We define the former as shifts that are scheduled on a day of the week (e.g., Monday) the employee did not work the previous week, and the latter as shifts that are scheduled on a day of the week that the employee did work the prior week, but with a start time that differs by more than one hour. Our shift level data reveal that these two types of shifts are very common, with over 37% of shifts (i.e., 10.7 million shifts) exhibiting either of these two characteristics. Furthermore, schedule inadherence is also a significant issue, with 10% and 6% of shifts being marked absent or late (by 10 minutes), respectively (a combined total of more than 4.6 million shifts).

Why might inconsistent work schedules increase shift-level rates of lateness and absenteeism? To formulate our hypotheses, we leverage insights from past research in Operations Management and Management (discussed in Section 2). Based on these studies, we posit that inconsistent shifts likely increase the probability of lateness and absenteeism for three primary reasons. First, when managers disregard employees' preferences or availability by scheduling them inconsistently, employees may prioritize other existing commitments or personal obligations. Second, the inconsistency of such schedules can disrupt employees' regular routines, from sleep patterns to daily activities, making punctuality and attendance more challenging. Finally, inconsistent schedules can erode employee morale and job satisfaction. The ensuing feelings of job insecurity and a diminished sense of loyalty to the company may cause employees to express their discontent through lateness or absenteeism, which can be seen as a form of quiet protest or disengagement.

Based on these hypotheses, we use our data to empirically examine the causal effects of inconsistent schedules on schedule inadherence. The identification challenge in our empirical context is that inconsistent shifts are not randomly assigned to employees. For instance, inconsistent shifts may be predominantly distributed to newer employees, who may have systematically higher rates of schedule inadherence. Additionally, inconsistent shifts may only be distributed after managers verify that the receiving employee can commit to them. To address the potential endogeneity between schedule adherence and inconsistent work schedules, we closely mimic the approaches of Lu et al. (2022) and Bergman et al. (2023). We do so to ensure that our estimates are closely comparable to theirs and because their empirical context and identification concerns are similar to ours. Following the approach of the former, we estimate various fixed effects models that control for a range of variables that may be correlated with our two measures of schedule inconsistency and the propensity to be late or absent. A key difference in our approach, however, is that given the size and granularity of our data, we can include more granular fixed effects, interacting store $\times$ worker $\times$ year $\times$ week to account for important unobserved factors that remain constant within these sets of observations, such as employees' abilities, commitments, and relationships with management and co-workers. We make further improvements to their approach by incorporating additional shift and store-specific controls such as: (i) the amount of advance notice provided for each shift, and (ii) stores' forecasted demand and operating duration. In Section 4.1, we explain why our fixed effects and controls are important. However, despite the added controls and fixed effects, we argue that this approach may still yield biased estimates due to the possibility of omitted variables that vary within our granular set of fixed effects.

To get closer to causal estimates, we follow Bergman et al. (2023) and take advantage of the quasirandom variation in the labor supply of stores resulting from employees taking paid time off. Specifically, we isolate short-term negative shocks to labor supply in a given store by examining the number of employees who are unavailable due to *voluntary* paid time off requests. We instrument the two types of inconsistent shifts (separately) with the fraction of employees who are unavailable due to temporary paid time off. The key identifying assumption here is that an employee's time off affects their coworkers' likelihood of being late or absent solely through its impact on their schedules. We extrapolate the arguments made previously by Bergman et al. (2023) to argue for the plausibility of this assumption in our empirical context. With this approach, we find that scheduling an employee on a day of the week they did not work on in the previous week increases the probability of being late by at least 10 minutes or being absent by 12.1 and 7.4 percentage points, respectively. Furthermore, scheduling an employee on a day of the week that they *did* work on in the previous week, but starting more than 1 hour later, increases the probability of being late and absent by 21.3 and 32.9 percentage points, respectively. Given that the mean shift level rates for lateness and absenteeism are 5.9% and 9.7%, respectively, these estimates are large. Due to our inclusion of fixed effects and controls, these findings are not explained by a multitude of critical factors including intrinsic employee commitment or ability, relationships with management or management practices, weekly work distributions, local labor market conditions, weekly fluctuations in store demand or foot traffic, or changes in store demand expectations. Finally, exploring heterogeneous effects, we find that the impacts of inconsistent shifts on schedule adherence are significantly greater for newer employees and are primarily driven by full-time workers. We discuss how these heterogeneous effects shape managerial implications in Section 5.5.

In sum, we provide direct evidence at the shift level that inconsistent work schedules can increase rates of employee lateness and absenteeism, factors that are intrinsically linked to store performance. Previous studies have rigorously demonstrated the causal effects of work schedule characteristics on worker productivity and employee turnover (e.g., Lu et al. (2022), Kesavan et al. (2022), Kamalahmadi et al. (2021), and Bergman et al. (2023)). Our paper advances this growing literature by showing that inconsistent work schedules also causally affect a key intermediate outcome: schedule adherence. We argue that given the prevalence of lateness and absenteeism in our data, incorporating schedule inadherence is critical in any empirical analysis that relates scheduling practices with performance metrics. Overall, understanding the impact of work schedules on this intermediate variable can provide managers with a more nuanced and comprehensive understanding of how these inconsistent work schedules ultimately affect other crucial outcomes such as productivity and turnover.

Literature Review

This article intersects with three distinct strands of literature. The first strand examines the empirical relationship between scheduling practices and store or worker performance. Our study directly speaks to this relationship, as we argue that inadherence to employees' schedules, potentially triggered by inconsistent work schedules, can adversely impact store performance. We initially refer to Fisher and Raman (2010) for a comprehensive overview of the relationship between store execution, performance, and labor scheduling. In the following, we cite and review specific papers pertinent to this relationship.

A large body of empirical evidence shows that labor scheduling decisions are critical for store performance. For example, Netessine et al. (2010) and Perdikaki et al. (2012) highlight the importance of matching labor with store traffic for optimal performance, noting the diminishing returns on sales with increased traffic. Fisher et al. (2021) and Mani et al. (2015) suggest that retailers often understaff, resulting in suboptimal sales and profitability, which can be improved by adjusting staffing levels based on queuing theory. Furthermore, Kesavan et al. (2022) demonstrate the positive effects of ”responsible” on store performance, and Kamalahmadi et al. (2021) show that short-notice scheduling practices can boost worker productivity. We add to this body of work by showing how inconsistent schedules can negatively impact store performance by increasing shift level rates of lateness and absenteeism, which can exacerbate the labor understaffing documented by Fisher et al. (2021) and Perdikaki et al. (2012).

The second strand of literature connects to the extensive body of work in Management and Sociology that investigates employee lateness and absenteeism. We initially refer to Goodman and Atkin (1984), Mowday et al. (1982), and Harrison and Martocchio (1998), all of which offer comprehensive reviews of the literature that summarize the theory and empirical evidence on the drivers and impacts of lateness and absenteeism among employees. Regarding drivers, Staw and Oldham (1978) argue that absenteeism represents a form of withdrawal from stressful work situations. Furthermore, job satisfaction is frequently cited as a central driver of absenteeism (Blau and Boal, 1987; Tharenou, 1993; Zaccaro et al., 1991). Other causes of absenteeism are attributed to inherent characteristics of the employee, with factors associated with the personality, demographics, and attitudes of the employees that play a role in driving absenteeism (Garrison and Muchinsky, 1977a,b; Harrison and Martocchio, 1998; Johns, 1997; Porter and Steers, 1973). Regarding impacts, Goodman and Atkin (1984) propose that absenteeism can have effects at the individual level (e.g., loss of pay and experience), the coworker level (e.g. additional work to compensate for the late or absent employee) and the organizational level (e.g. productivity). Our work contributes to this literature by identifying a novel driver of lateness and absenteeism among employees: inconsistent work schedules.

The third stream of literature to which this paper contributes is related to the effects of inconsistent work schedules on employees. A growing body of empirical work has documented that unpredictable and volatile work schedules correlate with diminished mental and physical health, as well as economic prosperity (Ananat et al., 2022; Ben-Ishai, 2015; Harknett et al., 2021; Henly and Lambert, 2014; Lambert et al., 2019). By causally associating inconsistent work schedules with reduced rates of schedule adherence, we contribute to this literature by demonstrating a link between inconsistent work schedules and the consequential negative effects on both employees and businesses.

We conclude this review of the literature with a discussion of three papers that are most closely related to ours in both context, spirit, and purpose. First, Lu et al. (2022) demonstrates, in the context of a grocery retailer, that schedule consistency can positively affect cashier productivity. Specifically, they draw on transaction level scanner data that include more than 1.2 million shopping baskets processed by 126 cashiers over a 2-year period. They find that hour-of-the-day consistency (which corresponds to our start-time consistency measure) and day-of-the-week consistency boost cashier productivity by 0.95% and 1.63%, respectively. Second, Bergman et al. (2023) shows that, in the context of home healthcare care, volatile work scheduling practices can lead to employee turnover. Finally, Wang and Gupta (2014) use data on nurses in two hospitals to estimate correlations between workload and absenteeism of nurses to estimate a structural model that investigates the impact of demand and absentee rate variability on the performance of staffing plans. The estimated correlations are used to propose and test several heuristics to identify near-optimal staffing strategies.

Although this paper relates to all the aforementioned papers in this literature review, the insights and analyses of Lu et al. (2022) and Bergman et al. (2023) are particularly integral to this paper in terms of hypothesis development and the construction of a sound empirical strategy that has already been vetted to some extent. We view our work as building on their earlier work in the following ways. First, we consider the effects of inconsistent scheduling practices on employee schedule adherence, which has yet to be examined and which is a major concern in retail. Second, our data are substantially larger, covering two independent retail chains and consisting of more than 1,000 stores and 135,000 employees over a five-year period. This is a much larger sample than Lu et al. (2022), which analyzes 126 cashiers in two grocery stores during a two-year period, and Bergman et al. (2023), which covers 2,100 full-time and 1,000 part-time registered nurses during a three-year period. The large sample size in our study provides us with additional statistical power and allows us to examine how our effects differ based on observable employee characteristics such as gender, wage, and tenure. Finally, due to the large sample size, we can control for store time-invariant unobservables within store $\times$ worker $\times$ period groups of observations, which we argue in Sections 4.2 and 4.3 capture important sources of confounding unobservables.

2 Theoretical Motivation

In this section, we draw on past research in management, operations management, and sociology to discuss (i) why businesses and managers may care about employee schedule inadherence and (ii) why a relationship between inconsistent work schedules and schedule inadherence is both plausible and expected.

2.1 Employee Schedule Inadherence: An Organizational Concern

We first discuss why addressing employee lateness and absenteeism may be an important priority for managers, and why identifying their scheduling drivers may be a fruitful empirical exercise. To begin, we refer the reader to Goodman and Atkin (1984) who provide a comprehensive overview of some of the negative effects of employee absenteeism on the individual (i.e., the absent employee), their colleagues, their family, the organization, and society (see Table 7.1 on page 280 of their article). This overview is mostly based on theory, but some discussions are also based on empirical findings from surveys. Although their focus is on absenteeism, many of their arguments also apply to employee lateness. Below, we briefly go over some of their arguments to motivate our discussion of the empirical link between inconsistent work schedules and employee schedule inadherence.

Managers may wish to reduce schedule inadherence because, at the individual level, schedule inadherence can harm employees through a loss of pay, increased disciplinary actions, a loss of experience and human capital, and workplace accidents. Furthermore, as Goodman and Atkin (1984) points out, a less obvious consequence of schedule inadherence is the potential for altered job perceptions (Mowday et al., 1982; Nicholson and Johns, 1985). Specifically, absenteeism can lead to the development of negative beliefs about the job or work environment, which may not accurately reflect the reality of their work situation. These negative beliefs can have detrimental effects on the individual and may lead to decreased job satisfaction, performance, and turnover. Accordingly, reducing schedule inadherence may be one mechanism by which managers can help develop a committed and engaged workforce.

The effects of schedule inadherence are not only limited to the individual, but may also affect their coworkers. For instance, one employee's lateness and absenteeism may spillover onto their coworkers as other employees may need to work longer or exert more effort to make up for the reduction in labor. Consequently, these spillover effects can result in higher workloads and more erratic schedules for other employees that may reduce job satisfaction and performance.

Finally, the aforementioned effects on employees and co-workers may aggregate to the store level. Specifically, late or absent employees may be detrimental to store performance due to the direct effects of the loss of labor resulting from the late or absent employee and the spillover effects resulting from fatigued coworkers that may work longer or exert more effort to make up for the reduction in labor. As discussed in the literature review, Fisher et al. (2021) and Mani et al. (2015) suggest that retailers often understaff, resulting in suboptimal sales and profitability, which can be improved by adjusting staffing levels based on queuing theory. Overall, due to the effects of schedule inadherence at the individual, coworker and store levels, the works of Goodman and Atkin (1984) and Mowday et al. (1982) and the references therein provide compelling reasons for managers to better understand the drivers of employee lateness and absenteeism.

2.2 Inconsistent Schedules and Schedule Inadherence

The discussion in the previous subsection provides several incentives for managers to reduce the rates of lateness and absenteeism in their workforce, as they may have negative effects at the individual, co-worker, and store levels. In this subsection, we focus our discussion on some of the drivers of schedule inadherence that relate to scheduling practices. Our focus on scheduling practices is motivated by recent papers that have drawn similar empirical links between inconsistent work schedules and employee productivity and turnover (Bergman et al., 2023; Lu et al., 2022). In the following discussion, we provide three empirical pathways by which inconsistent work schedules can be linked to inadherence to work schedules.

The first pathway concerns the challenges that inconsistent work schedules pose to employees' external commitments, affecting their decision to adhere to their assigned shifts. Specifically, schedules that lack consistency create challenges in planning and committing to activities associated with employees' family or social life (Cauthen, 2021), which can have detrimental effects on their health and mental well-being (Schneider and Harknett, 2019). Additionally, employees may also have multiple forms of employment, and inconsistent work schedules from one place of employment may interfere with their ability to fulfill obligations at their other jobs. Accordingly, inconsistent schedules can contribute to schedule inadherence based on choice: The underlying employee who is subject to an inconsistent work schedule may simply opt not to adhere to their scheduled shift to tend to other work or commitments. This hypothesis is consistent with a recent and ongoing trend called the "Great Resignation" (Sull et al., 2022) in which employees have voluntarily resigned from their place of employment for a variety of reasons, including the inability to "...choose when to put in their hours" (Parker and Horowitz, 2022).

The second pathway relates to the relationship between inconsistent scheduling practices and the increased stress they induce, leading to higher rates of absenteeism as employees seek to withdraw from stress-filled job situations. Past research has shown that absenteeism of employees may be a form of withdrawal from job-stress situations (Goodman and Atkin, 1984; Staw and Oldham, 1978), and there is a large literature that demonstrates a link between unpredictable and unstable scheduling practices on employee stress, health, and well-being. For example, Henly and Lambert (2014) find that women employees in low-skilled retail jobs whose work schedules are unpredictable report greater stress and work-life conflict than their counterparts with more predictable work schedules. Another example is Ben-Ishai (2015), who find that scheduling instability leads to increased income instability, which can contribute to increased stress because it is harder for workers to create an accurate budget and make ends meet. Finally, Harknett et al. (2021) show using the passing of Seattle's Fair Workweek Law that uncertainty about work schedules has harmful effects on worker happiness, sleep quality, and material hardship.

The third pathway by which inconsistent schedules can give rise to increased rates of lateness and absenteeism is based on the relationship between inconsistent schedules and disruptions to employees' sleep, which can detrimentally affect their daily (circadian) and weekly (circaseptan) rhythms. There is a large literature that documents the relationship between sleep schedules, work schedules, productivity, and work-life balance (see Bedrosian (2008); Lu et al. (2022); Walsh (2004) the references therein). According to Kessler et al. (2011), estimates of annual costs related to insomnia at work due to absence, reduced productivity, and workplace accidents and injuries in the US civilian workforce range between $15 and $92 billion dollars. In short, irregular work schedules that are characterized by varying dates (across weeks) and start times may negatively impact the consistency of employees' sleep schedules, which can make (among other things) present challenges in making it on time to work.

3 Empirical Context, Data and Defintions

In this section, we provide an overview of our data sources and present summary statistics and stylized facts on the rates of employee lateness and absenteeism in our sample. Our empirical analysis uses unredacted administrative scheduling and HR data from more than 1,000 brick and mortar locations, covering more than 135,000 employees across the two retail chains in our sample. Here, 1,000 is a lower bound on the number of stores. As we describe below, our data are not only comprehensive but also precise. Specifically, we observe the work schedules of all shift-based employees, and these work schedules are meticulously tracked by a workforce scheduling software that archives work schedules. As we describe later, this software allows us to easily merge timecards with planned work schedules, which allows us to measure employee lateness and absenteeism at the shift-level.

3.1 Focal Retailers

Our analyses focus on two independent retailers operating in the United States. By independent retailers, we refer to retailers that are not part of the same larger corporate entity or chain. The first retailer is a grocery chain and the second is a retail chain that sells durable goods. Combined, our sample has good coverage throughout the United States, with stores in more than 10 states and more than 500 cities. To preserve the anonymity of both retailers, we refrain from revealing the exact geographical distribution of the stores in our sample or the exact figures related to the sample size of stores and employees. However, we have obtained complete and unredacted datasets that contain the full work schedules of all shift-based workers in both retail chains. In addition to the unredacted administrative datasets, we also possess detailed information about labor scheduling processes between stores, including information on the workforce scheduling software that is used in each store between both retail chains. We provide more details about the scheduling algorithm in the Online Appendix (A.1).

3.2 Definitions of Work Schedule Inconsistency

We now present our definitions of "inconsistent" work schedules. Following Lu et al. (2022), we focus on two variables that capture schedule inconsistency.

1. **Day-of-the-week Inconsistency**: Shifts that are scheduled on a day of the week (e.g. Monday) that the employee did not work the prior week.
2. **Start-time Inconsistency**: Shifts that are scheduled on a day of the week that the employee did work the previous week, but with a start time that differs by more than one hour.

It is important to note that by design, our two measures are mutually exclusive. For example, start-time inconsistency implies that the employee worked on the same day of the week in the previous week, which would imply that the underlying shift is characterized by the day-of-the-week inconsistency (and vice versa). Additionally, for new hires, we assume that their shifts in their first week of employment are *not* subject to either type of inconsistency.

These metrics are similar in spirit (but not identical) to the measures utilized in Lu et al. (2022). Their approach features analogous metrics such as day-of-the-week and start-time consistency measures. However, their measures for shift inconsistency are functions of the focal employee's schedules in the past four weeks. Although this approach is valid, it presents a drawback: It requires four weeks of historical data to ensure comparability across the cross section and time series of employees. However, the retail sector is characterized by significant turnover rates, as is evident in our context. That is, our sample includes a notable number of employees who have worked for a relatively short period of time. Consequently, some employees in our sample lack sufficient observations to compute these measures (as per their definition), and we would also have to disregard four weeks of observations for employees who have an adequate number of observations.

3.3 Data and Summary Statistics

In this subsection, we outline the two data components that we observe between the two retail companies. We describe the information contained in the data component and their purpose in our analysis.

Employee Shifts and Timecards

Our primary data set includes the planned work schedules for *all* shift-based employees in both companies, defined here as specific time intervals assigned for work, including any potential breaks, dedicated to a particular worker for a given day. This dataset is unredacted and contains all stores, employees, and shifts. With more than 28 million shift observations scheduled across more than 1,000 retail stores in the US, this dataset spans a 5-year duration from 2018 through 2023.

Our main outcome variables capture shift-level lateness and absenteeism. We construct these variables by merging planned schedules with employee timecards that document the actual start and end times of every shift (conditional on not being absent). We categorize an employee as absent if they did not clock-in during their scheduled shift. Similarly, lateness is defined as an employee who clocks in later than their scheduled start time. The accuracy of our lateness and absenteeism measurements is ensured by managers' proactive actions, such as shift cancellations or adjustments, if they are aware of a potential absence or delay in advance. For example, if an employee informs his or her manager about impending sick leave, his or her planned shifts would be deleted or reassigned to another employee. There are private incentives for managers to take these corrective actions, as both punch-cards and planned work schedules are sent to payroll for wage processing.

Human Resource Data

Our second dataset contains human resource records that describe all shift-based employees in stores. For each employee, we observe their wage, hire date, full name, gender, termination date (if it exists), what tasks they can work on, their availability to work on each day of the week, and whether they are a full-time or part-time worker. We observe multiple observations for an employee if, for example, their wage changed, if they previously worked at the company before, or if they were promoted.

This dataset becomes relevant when exploring heterogeneous effects. For example, through our first identification strategy (see Subsection 4.2 below), we analyze how the impacts of key indicators of schedule inconsistency can differ based on various employee characteristics, such as tenure, gender, and full-time or part-time status. This underscores the importance of considering individual employees when evaluating the benefits and drawbacks of flexible scheduling practices, as there may not be a "one size fits all" optimal strategy for scheduling labor.

3.4 Final Sample and Summary Statistics

Our final sample for analysis contains more than 28 million shifts that cover over 135,000 employees in more than 1,000 stores. Table 13 presents detailed summary statistics that describe our sample. This table provides a perspective of our data across various levels: shift, store-week, store (cross-sectional), worker-week, and worker (cross-sectional) outcomes. The information is divided into five panels, each representing a specific level.

Panel A focuses on shift level outcomes. With more than 28 million shifts present in the sample, the average scheduled minutes per shift is around 440 minutes with a standard deviation (SD) of approximately 85 minutes, indicating some variability between shift lengths. Most of this variability comes from shifts that are half the length (i.e., 4 hours or 240 minutes, instead of 8 hours). Among all shifts, about 36% are worked by men, and the average employment tenure of workers is approximately 1,186 days (or approximately 3.24 years), although the high standard deviation (1681 days) suggests a significant dispersion around this average, driven by the significant rates of employee turnover observed in the data. Furthermore, the average wage is $15.28 per hour. On average, employees receive 20.53 days of notice for their shifts. Due to the potential correlation between schedule inconsistency and shift-advance notice, we include the (log) number of days that the employee received for their shift as a control variable in all specifications.

Regarding the scheduling inconsistency measures described in Section 3.2, we find that 24% of the shifts are scheduled on different days-of-the-week and 13% have different start times than the previous week. Approximately 27% of the shifts are scheduled on a date when a coworker is on paid time off. In this subset of shifts, the mean, median, and standard deviation of the number of coworkers on paid time off is 1.23, 1.00, and 0.51, respectively. As we describe in Section 4.3, the number of employees on paid time off is utilized in our empirical strategy.

Finally, we find that schedule inadherence, in the form of lateness (by 10 minutes or more) and absenteeism, is substantial, with the former and the latter occurring in 6% and 10% of shifts, respectively.

The latter three panels (B, C, D, and E) are based on aggregations of our shift level data. Panel B presents the store-week level outcomes, featuring nearly 191,000 records. The average number of scheduled minutes per store-week is around 66,870, and there are an average of 152 shifts per store-week. The percentage of shifts on different workdays and start times are 24% and 13%, respectively. The lateness and absenteeism rates mirror those found at the shift level, both around 6% and 10%, respectively. In Panel C, we present statistics at the worker level. The average number of scheduled minutes and shifts per worker is significantly large, indicating a considerable amount of work time for each worker. The percentages of different workdays, different start times, lateness, and absenteeism are quite similar to those found in the shift and store-week level data. Panel D shows the worker-week-level results from more than 7 million records. The average number of scheduled minutes and shifts per worker-week are around 1,730 and 4 respectively. The statistics concerning different start times, lateness, and absenteeism follow patterns similar to those found in the other panels. Finally, Panel E provides another view of worker-level outcomes, this time with more than 133,000 records. The average number of scheduled minutes per worker is about 95,654, with an average of 217 shifts per worker.

4 Empirical Methodology

The goal of this paper is to estimate the causal effect of inconsistent work schedules on shift level lateness and absenteeism rates of employees. As discussed earlier in Section 2.2, our hypothesis is that such schedules can lead to higher shift-level rates of lateness and absenteeism due to potential disruptions in work-life balance, heightened stress, conflicts with other job and personal commitments, and adverse effects on sleep patterns.

To identify this effect, we must address a key identification challenge: Work schedules are not randomly distributed to employees, and managers may incorporate dynamic information about the employee (that is unobserved to us), such as their intrinsic commitment and ability, and personal obligations outside of work when crafting work schedules. To address this challenge, we follow the identification strategies of Lu et al. (2022) and Bergman et al. (2023), who have examined the effect of inconsistency in the work schedule on other key outcomes related to operational performance (e.g., worker productivity and turnover).

4.1 Empirical Models

We examine the impact of scheduling practices on the likelihood of an employee being late (by at least 10 minutes) or absent at the shift level. To do this, we estimate variants of the following linear probability model:

$$y_{i,j,t} = \boldsymbol{\beta} \cdot \mathbf{X}_{i,j,t} + \psi \cdot \Psi_{i,j,t} + \lambda_t \times \alpha_i \times \nu_j + \varepsilon_{i,j,t} \tag{1}$$

where $y_{i,j,t}$ on the left-hand side of the equation is a binary variable that equals 1 if employee j at store i was late (by at least 10 minutes) or absent on their scheduled shift on date t (and zero otherwise). Henceforth, when we describe an employee being "late" in subsequent discussions, it implies lateness by at least 10 minutes. Our preference for a linear model, as opposed to nonlinear models like logit or probit, stems from our identification strategy that leverages within store-worker-year-week group observations. Nonlinear models are less suitable in our scenario because they discard observation groups (due to fixed effects) when there is no variation in the dependent variable. Such an exclusion is significant, as it is not rare for employees to fully comply with their weekly schedules, even when assigned inconsistent shifts.

On the right-hand side of Equation 1, $\boldsymbol{X}_{i,j,t}$ contains our two measures of schedule inconsistency described in Section 3.2 (day-of-the-week and start time inconsistency), $\Psi_{i,j,t}$ are characteristics that vary with time (the amount of advance notice provided for the shift, the operating duration, and the demand forecast at the store date level), λ_t is a fixed time effect, α_i is a fixed store effect, and ν_j is an employee fixed effect. As we describe below, our preferred specification is a saturated one where employee, store, and time fixed effects are fully interacted to account for unobservables that may be correlated with both $\boldsymbol{X}_{i,j,t}$ and $y_{i,j,t}$. Our coefficient of interest is $\boldsymbol{\beta}$, which captures the average effect of our scheduling inconsistency variables ($\boldsymbol{X}_{i,j,t}$) on the shift-level probability of lateness or absenteeism. For statistical inference of $\boldsymbol{\beta}$, we cluster our standard errors at the worker and year-week levels.

A primary challenge in identifying the effects in our study arises from the non-random allocation of work schedules to employees. For instance, longer tenured employees may receive more consistent schedules due to seniority, and they could inherently exhibit lower rates of schedule inadherence. Lower rates of schedule inadherence for longer tenured employees may be plausible if frequent lateness or absenteeism are factors for termination. On the other hand, there may be inconsistent schedules among employees who voluntarily take on additional shifts for extra income. Employees with these incentives may be less likely to be late or absent. Both empirical patterns could bias our coefficient $\boldsymbol{\beta}$ towards a null effect. Additionally, managerial scheduling decisions can be influenced by unobserved, private communications about employee availability. If we operate under the assumption that managers are averse to schedule inadherence, this would once again skew our estimates towards zero. In the following subsections, we present two identification strategies that attempt to provide unbiased estimates of $\boldsymbol{\beta}$, given these concerns.

4.2 Empirical Strategy: Approach 1

Our first approach follows Lu et al. (2022) closely. As discussed in Section 3.2, they use similar measures of schedule inconsistency to study its effects on worker productivity. They estimate fixed effects models using OLS to identify the effects of such schedules on worker productivity. We follow their approach and estimate Equation

1 after including store × worker × year × week fixed effects. This approach controls for all omitted variables that do not vary within these granular set of fixed effects. We discuss some of these omitted variables below.

Static Employee-level Characteristics Managers may condition on the innate characteristics of employees, such as their general punctuality, motivation, and reliability when scheduling labor. Consequently, managers may distribute work schedules that are more (or less) inconsistent for employees who are innately more punctual and dedicated. Employee fixed effects (as part of our full set of interacted fixed effects) addresses these concerns.

Dynamic Employee-level Characteristics Changes in an employee's circumstances or behavior over time can also affect work schedules and schedule adherence. For example, if an employee improves their reliability or acquires new skills, they may be scheduled for more desirable or consistent shifts. Simultaneously, their improved reliability could also reduce lateness or absenteeism. Conversely, if an employee develops health problems or other personal challenges, they may require more flexible or inconsistent schedules and may also be more prone to lateness or absences. Our employee × year-week fixed effects addresses these concerns.

In addition, these fixed effects capture dynamic worker-level characteristics such as their tenure, wage, and schedule workload (these variables do not variable considerably within our interacted fixed effects). Tenure, for example, is an important factor that can influence both scheduling practices and employee punctuality. As an employee gains experience and establishes their reliability, they may receive more desirable shifts or more predictable schedules. At the same time, their increased familiarity with the job and commitment to the organization may reduce their propensity to be late or absent. Similarly, wage rates can also affect both scheduling and punctuality. Employees with higher wages may be considered more valuable and hence be given more consistent schedules. Higher wages could also incentivize employees to be more punctual and less likely to be absent (i.e. act similarly to "efficiency wages").

Finally, these fixed effects importantly capture the schedule workload for each employee for each week. While our scheduling variables are constructed at the shift level, the inconsistency (or lack of) of their overall work schedule in a given week may influence the effects of an inconsistent shift on a particular day. For example, the effects of an inconsistent shift on a given day may be amplified if the schedule in a given week contains multiple inconsistent shifts.

Static Store-level Characteristics Store's inherence characteristics can shape the schedules of its employees and affect their punctuality. For example, stores in busy city centers may have extended operating hours, requiring schedules that some employees may find challenging, potentially leading to increased tardiness or absenteeism. Stores with a supportive culture and efficient management, on the other hand, could be better at creating balanced schedules that consider employee needs, which could result in lower lateness and absenteeism rates. Our store fixed effects addresses these concerns.

Dynamic Store-level Characteristics Changes in store characteristics over time can also affect employee scheduling and adherence to schedules. For example, if a store increases its operating hours or starts opening on days it was previously closed, employees may find their schedules changing. Such changes can disrupt employee routines, potentially leading to increased lateness or absences. Another important dynamic factor that our fixed effects control is the staffing roster in the store. Changes in the staffing roster through hirings, terminations, or time off may affect the frequency and magnitude of inconsistent schedules in the store. Our store $\times$year-week fixed effects addresses these concerns.

Employee-Manager Interactions Finally, our fixed effects also capture the overall effect of store management teams on scheduling practices and adherence to schedules. The relationship between an employee and their store or manager can influence both the employee's work schedule and their lateness or absenteeism. For example, an employee who works well with his or her manager may receive more favorable schedules, and his or her positive relationship could also make the employee more committed to being on time and present for his shifts. Our employee $\times$ store $\times$ year-week fixed effects addresses these concerns.

Overall, our approach here is based on Lu et al. (2022), with two key differences. First, our specification includes more granular fixed effects that may be correlated with scheduling practices and employees' schedule adherence. Many of the omitted variables above would not be controlled for if we did not interact the fixed effects associated with the store, employee, and time. Second, we conduct our inference on β using standard errors that are clustered at both the worker and year-week levels. In contrast, Lu et al. (2022) conduct inference after assuming that errors are Gaussian and independent across observations.

Clustering errors at the employee level accounts for correlations due to persistent, unobservable individual characteristics (some of which are described above). For instance, an employee's propensity to be late may be influenced by inherent traits such as their personal work ethic, leading to correlated errors for that individual over time. Additionally, clustering errors at the year-week level captures common influences that may affect multiple employees in the same way during a specific week. This includes external factors such as weather events, public holidays, and other global or local events, as well as internal changes such as store policies, management decisions, or store environment shifts. These influences can influence rates of lateness and absenteeism across employees for that particular time frame. By double clustering at both the employee and year-week levels, we aim to account for both individual persistent tendencies and time-specific external or internal shocks, ensuring our inferences are robust against these potential sources of error correlation.

4.3 Empirical Strategy: Approach 2

Our primary concern with the first approach using OLS is that there may still exist an unobservable, $\xi_{i,j,t}$, that captures an employee's time-varying availability. This variable can capture anything about an employee's availability that may affect their ability to make it to a shift on time. For example, this variable may reflect an employee's child-care responsibilities (e.g., picking up their child from school) or other important events such as a doctor's appointment. Consequently, if managers are conditioning on $\xi_{i,j,t}$ when distributing work schedules (which is likely if we assume that managers dislike schedule inadherence), then our OLS estimates are likely to be conservative and biased towards zero.

As an alternative approach, we adopt the empirical strategy of Bergman et al. (2023) and utilize the paid time off days of other employees as an instrument for inconsistent shifts. The intuition here is that when employees take paid time off, it can cause the number of inconsistent shifts for their coworkers to increase. Our hypothesis is that when employees take paid time off, the regularity and predictability of shifts for their coworkers may be disrupted. This is because managers may need to reallocate work hours, often on short notice, to ensure that all tasks are covered. This sudden need to adjust and redistribute work hours may lead to shifts that deviate from an employee's usual routine, which may be captured by our two shift inconsistency measures. Accordingly, this disruption can be seen as a negative shock to the manager's available labor supply.

The key identifying assumption for this approach is that the instrument (i.e., the occurrence of paid time off days by other employees) affects the outcome of interest (i.e., lateness or absenteeism) only through its effect on the endogenous variable (i.e., our two shift inconsistency variables). In other words, we are assuming that the occurrence of paid time off days by other employees has no direct effect on the individual employee's likelihood of lateness or absenteeism, and any effect it does have is fully mediated through changes in the individual employee's work schedule.

We argue that this assumption is plausible for four reasons. First, the decision to take time off is typically personal and independent, usually influenced by factors such as health, family needs, or vacation, which should not directly affect the punctuality or attendance of other employees. Second, the direct link between the instrumental variable (the occurrence of paid time off days) and the outcome variable (lateness or absenteeism) would imply a level of interdependence between employees that extends beyond their work schedules. This would require that employees are so attuned to each other's personal schedules and choices that one's decision to take paid time off could directly influence another employee's work ethic or personal life decisions. This level of interdependence is not typically observed in most workplace settings. Third, company privacy policies often restrict the dissemination of specifics regarding an employee's reasons for leave, reducing the likelihood of other employees being directly influenced by this information. Fourth, there is generally no financial incentive for an employee to modify their attendance behavior based on the paid time off decisions of their colleagues.

Two Stage Least Squares Model

We estimate the effects of inconsistent shifts on schedule adherence in two stages. In the first stage, we (separately) relate our measures of inconsistent scheduling practices with the percentage of employees who are on paid time off on a given date. This percentage is constructed by simply dividing the number of employees on paid time off at store i on date t with the sum of the total number of employees scheduled during the week of t and the number of employees on paid time off. This denominator is meant to proxy the labor supply of the store. However, we note that our results are more conservative when using the raw counts of employees or when taking the log transform after adding 1 to account for the possibility that no employee is on paid time off on a given day (we present these results in a robustness test).

Our first stage specification is given by:

$$X_{i,j,t} = \delta \cdot N_{i,t} + \lambda_t \times \alpha_i \times \nu_j + \psi \cdot \Psi_{i,j,t} + \varepsilon_{i,j,t} \tag{2}$$

where all the variables and fixed effects here are the same as in Equation 1, except for $N_{i,t}$, which is the the percentage of employees that are away on paid time off at store i on date t. Based on the exclusion restriction, we assume here that $\mathbb{E}[N_{i,t} \cdot \xi_{i,t,j}] = 0$.

We expect the coefficient δ in Equation 2 to be positive for both our schedule inconsistency measures. As mentioned above, when an employee takes time off, managers may need to adjust the schedules of the remaining staff to compensate for this sudden reduction in available labor. These adjustments can cause inconsistencies in work schedules as managers make adjustments to fill in the gaps left by employees on paid time off.

In the second stage, we use the instrumented values in Equation 2 to separately estimate the effect of each scheduling variable on lateness and absenteeism. Specifically, we estimate:

$$y_{i,j,t} = \beta \cdot \widehat{X_{i,j,t}} + \lambda_t \times \alpha_i \times \nu_j + \psi \cdot \Psi_{i,j,t} + \varepsilon_{i,j,t} \tag{3}$$

where $\widehat{X_{i,j,t}}$ are the instrumented values from Equation 2. As is the case in the first stage, we include all control variables and fixed effects from Equation 1. Accordingly, we identify β by studying the variation in $X_{i,t,j}$ stemming from $N_{i,t}$ only within employee-store-year-week groups of observations.

5 Empirical Results

In this section, we report our estimates from Section 4 that attempts to link inconsistent work schedules with shift-level rates of employee lateness and absenteeism. Examining both the OLS and IV estimates, we find that both of measures of schedule inconsistency have considerable effects on the adherence to employees' work schedules.

5.1 OLS Results (Approach 1)

Table 1 presents our OLS estimates associated with Equation 1, which is closely aligned with the approach of Lu et al. (2022). As described in Subsection 4.2, the inclusion of our interacted store $\times$ worker $\times$ time fixed effects eliminates a broad set of time-varying omitted variables that include the innate commitment of the worker, management practices, and factors driven by seasonality, including weather and demand. The regression results in Table 1 present estimates using three response variables: Instances where an employee was absent or late by at least 10 minutes (column 1), instances where an employee was absent (column 2), and instances where an employee was late by at least 10 minutes (column 3). The independent variables of interest are our two scheduling measures described in Section 3.2, i.e, a binary variable equal to 1 if the shift is scheduled on a day of the week that they did not work on the previous week, and a binary variable equal to 1 if the start time of the shift did not match the start time of the shift that they worked on in the same day of the week in the previous week.

Here, the results indicate a positive association between the difference in the start time and the likelihood of an employee being late by at least 10 minutes or absent (0.015, p-value < 0.001), just absent (0.011, p-value < 0.001) or late by more than 10 minutes (0.005, p-value < 0.001), which implies that changes in start times are associated with higher rates of lateness or absence. Relative to their sample means (0.151, 0.097, and 0.059, respectively), these estimates reflect a 9.96%, 11.3% and 8.43% increase, respectively.

The results also indicate a positive association for shifts that are scheduled on a day of the week (e.g., Monday) that the employee did not work in the previous week. Specifically, we estimate increases of 0.011, 0.010, and 0.003 for our three outcomes (late by at least 10 minutes or absent, just absent, and just late by at least 10 minutes), respectively. Relative to their sample means (0.151, 0.097, and 0.059, respectively), these estimates reflect a 7.30%, 10.3%, and 5.06% increase, respectively.

In summary, our OLS estimates reveal a sizeable and statistically significant reduction in punctuality and attendance when shifts are characterized by start time or day of the week inconsistency.

5.2 Instrumental Variable Results (Approach 2)

In this section, we present the results of our estimation of instrumental variables (IV). As previously mentioned in the description of our IV approach in Section 4.3, an important concern arises from the presence of unobservable factors (denoted earlier by $\xi_{i,j,t}$) that vary in time within the worker $\times$ store $\times$ year-week observations that influence both scheduling practices and the occurrences of lateness and absenteeism. For example, managers may possess private information on employee availability and their ability to adhere to inconsistent work schedules that vary within the week. Specifically, managers may systematically choose to give inconsistent work schedules to employees they believe will make it to these shifts. Consequently, our OLS estimates may be biased towards zero. To address this issue, we employ the methodology utilized earlier by Bergman et al. (2023), where we use the percentage of employees who are on paid time off as an instrument for inconsistent work shifts. Here, we present our first-stage and reduced-form estimates, followed by our second-stage estimates.

First-Stage and Reduced Form Estimates

We begin by presenting evidence on the relevance of the instrument. Specifically, we test whether inconsistent schedules increase on days when there are higher percentages of employees on paid time off by estimating our first-stage specification (Equation 2). Table 2 presents these estimates. Again, both columns include the full set of interacted fixed effects and control variables, in addition to the excluded endogenous regressor (i.e., for start time inconsistency, we include the day of the week inconsistency measure as a control, and vice versa). Dropping the excluded endogenous regressor has no material effects on our estimates.

Based on our estimates in columns (1) and (2) of Table 2, we find that a 10 percentage point increase in the number of employees on paid time off (on a given store and date) increases the likelihood of a shift scheduled on a different start time and day of the week by 0.8 and 2.5 percentage points, respectively. In addition, consistent with our intuition that inconsistent schedules may arise from unanticipated shocks to stores' staffing rosters, we also find that the likelihood of inconsistent shifts decreases with the amount of advance notice provided for each shift.

A potential concern for our IV approach is the problem of weak instruments. It is widely recognized that a weak first stage can lead to unreliable IV estimates and inferences. To address this concern, the standard protocol is to examine the first-stage F-statistic. However, since our empirical model employs double clustered standard errors, we employ statistics associated with Kleibergen-Paap's test for weak instruments (see Kleibergen and Paap (2006)), which is the robust equivalent of the Cragg-Donald F statistic. These statistics, referred to as the Wald (1st stage), are presented in the second to last row of Table 2. Our robust F statistics range from 243.950 to 1163.239, suggesting that our IV approach does not suffer from weak instruments.

Finally, we present our reduced form estimates in Table 3. Here, our findings reveal that schedule adherence is decreasing in the percentage of employees on paid time off within a store on a given week. Specifically, a 10 percentage point increase in the percentage of employees on paid time off corresponds to a 0.42, 0.30, and 0.19 percentage point increase in being late or absent, just absent, and just late, respectively. Compared to their means, these estimates correspond to an increase of 2.79%, 3.14%, and 3.14%, respectively.

5.3 Second Stage Estimates

Our reduced form estimates, presented in Table 3, indicate a negative effect of paid time off requests on schedule adherence (being late by at least 10 minutes or absent). However, these estimates do not provide a quantification of the impact on schedule inadherence that is attributed to our two inconsistent scheduling measures. To quantify these effects, we rely on our second stage estimates, which are reported in Tables 4 and 5. Each table presents the IV estimate associated with one of our inconsistent scheduling variables ($\boldsymbol{X}_{i,j,t}$), while controlling for the excluded scheduling variable, the entire set of control variables, and fixed effects.

Consistent with our hypothesis, we find that both of our shift level inconsistency measures result in statistically significant increases (at the level 1%) of shift level rates of absenteeism and lateness, as evidenced by the sample averages of these variables. Table 4 indicates that scheduling an employee on consecutive days of the week (e.g. Monday) with start times differing by more than 1 hour leads to an increase of 32.9 percentage points in absenteeism and 21.3 percentage points in lateness. Next, in Table 5, we find that scheduling an employee on a day-of-the-week that they did not work the previous week results in an increase of 12.1 percentage points in absenteeism and 7.4 percentage points in lateness, respectively. Taken together, we find that start-time inconsistency has larger effects on schedule adherence than day-of-the-week inconsistency.

Comparing our IV estimates in Tables 4 and 5 with our OLS estimates in Table 1, we find that the IV estimates are several orders of magnitude larger (more than 10 times). For example, our IV estimate for day-of-the-week inconsistency for absenteeism is 0.121, which is much higher than its corresponding OLS estimate of 0.010 (more than 10 times).

Our IV estimates suggest that start-time inconsistency may have a larger adverse effect on absenteeism and lateness than day-of-the-week inconsistency. One potential reason could be related to the natural circadian rhythms of the human body, a notion previously highlighted by Lu et al. (2022). Although we cannot make definitive claims due to the absence of specific data, our hypothesis posits that inconsistencies in start times, especially when differing by more than an hour, may disrupt these rhythms. This could lead to challenges in sleep patterns, which could affect an employee's readiness for work. Conversely, changing the day an employee works may introduce conflicts with other work or personal commitments, but it may not carry the same potential physiological impact as a pronounced shift in start time.

Finally, we examine the robustness of our results by presenting our second stage estimates when using two alternate definitions of our instrument: (i) the raw number of employees on PTO, (ii) and one plus the raw number of employees on PTO. These results are presented in Tables 14 and 15. Comparing the estimates in these two tables with our IV estimates when using $N_{i,t}$, we find that our preferred instrument measure is conservative (i.e. smaller, but still retaining the 1% significant level).

5.4 Comparing OLS and IV Estimates

The substantial difference observed between our OLS and IV estimates warrants closer examination. This discrepancy may stem from unobserved variables that fluctuate within store-worker-year-week clusters of observations or it may be a result of the "local" nature of our IV estimates, which captures the Local Average Treatment Effect (LATE) for some subpopulation of employees. Regarding the former, based on our understanding of the scheduling processes across stores in our sample, we hypothesize that managers are likely to be conditioning on various time-varying factors of employee availability, and may even verify or confirm with the employee that they can make the shift that is inconsistent. And because managers have private incentives to decrease store-level rates of employee lateness and absenteeism, it is likely that they distribute inconsistent work schedules to employees whom they believe are both available and are likely to make the shift on time. Consequently, our OLS estimates are likely to be conservative and biased towards a null effect. This hypothesis is consistent with the fact that our OLS estimates are much smaller than our IV estimates.

Regarding the latter, an important question that emerges is whether our IV estimates predominantly reflect the experiences of a specific subset of workers who are disproportionately subject to inconsistent scheduling when their coworkers avail time off. For instance, these could be part-time employees who are more likely to receive additional or irregular shifts in order to compensate for coworkers' absences. If this were true, then some of the differences in our OLS and IV estimates would result from the fact that our IV estimates are not representative of the entire population of employees in our sample, but instead reflect the effects of inconsistent schedules on schedule inadherence for, say, part-time workers. Accordingly, the difference in our IV and OLS estimates may fully be explained by the localness of our IV estimates, and our OLS estimates may in fact be unbiased.

Understanding whether our effects predominantly reflect a "LATE" is also important in our context for managerial takeaways. If our IV estimates depict the experiences of a particular subset of workers, such as part-time employees, this information becomes important when considering changes to scheduling practices. For example, if managers rely on inconsistent scheduling practices to optimize store performance (e.g., scheduling short-notice inconsistent shifts based on the revelation a demand or supply shock), then understanding which subpopulation of employees are more (or less) likely to be late or absent for such shifts may benefit managers. If, however, we do not find strong evidence that our IV estimates are driven by some subpopulation of employees, then the difference in our IV and OLS estimates would be largely explained by the bias associated with $\xi_{i,j,t}$.

We directly investigate whether our IV estimates, as presented in Tables 4 and 5, primarily reflect a LATE for certain types of employees based on their characteristics. To do so, we re-estimate our first stage (Equation 2) after interacting our instrument with employee characteristics (i.e., tenure, gender, and whether they are a part-time employee), and dropping employee fixed effects (elaborated on below). Specifically, we estimate:

$$\begin{aligned} X_{i,j,t} = {} & \delta_1 \cdot N_{i,t} + \delta_2 \cdot N_{i,t} \times \text{Part-Time}_i + \delta_3 \cdot N_{i,t} \times \text{Female}_i + \delta_4 \cdot N_{i,t} \times \log(\text{Tenure}_{i,t}) \\ & + \lambda_t \times \alpha_i + \psi \Psi_{i,j,t} + \varepsilon_{i,j,t} \end{aligned} \tag{4}$$

Here, the coefficients δ_2 through δ_4 capture the interaction effects of our instrument and our employee-specific covariates on our two inconsistency variables.

We note that because we dropped employee fixed effects, Equation 4 is not identical to our main first stage (Equation 2). We omit employee fixed effects because our goal is to identify *which* type of employees are more likely to receive inconsistent work shifts when their coworkers are on paid time-off. Specifically, Equation 4 aims to answer the question, "Which employees, based on their characteristics, receive relatively more (or fewer) inconsistent shifts when their coworkers avail paid time off?". By contrast, if we had included employee fixed effects, the question would then be "How does an individual's response to changes in $N_{i,t}$ differ from their average response, factoring in their gender." For example, the interaction $N_{i,t} \times$ Female would not directly provide information on how women as a group could differ from men. Instead, it would assess how the interaction between $N_{i,t}$ and $X_{i,j,t}$ for an individual female differs from her own average response over time.

Table 12 provides estimates for a series of regression models investigating the impact of our instrument (percentage of employees on paid time off) on our two scheduling variables when the effect of our instrument can vary based on employee characteristics. Beginning with our first stage estimates on the effects on differential start times (column 1), we find that these effects of $N_{i,t}$ on our two measures of shift inconsistency vary significantly depending on tenure and status (part-time). The effects also vary by gender, but only for its effect on shifts scheduled on different days of the week. Specifically, we find that for a fixed level of $N_{i,t}$, its effects on differential start times decrease by 4.1 percentage points for every 1% increase in tenure. Additionally, we find that its effects on differential start times are 42.4 percentage points larger for part-time employees. Both interaction effects are statistically significant at the 1% level. Finally, based on our small (-0.017) and statistically insignificant interaction effect (at the 10% level) on the Female dummy, we do not find evidence that women are scheduled for shifts with differential start times more often than men. Overall, our estimates show that, holding all other variables fixed, the employees who are scheduled for shifts with differential start times are more likely to be newer, considerably more likely to be part-time employees, but are on average, spread equally between male and female employees.

We find similar effects for shifts scheduled on different days of the week (presented in column 2 of Table 12).Specifically, we find that the likelihood of being scheduled for such shifts are decreasing in tenure (3.6 percentage point decrease for every 1% increase in tenure) and is significantly larger for part-time employees

(75.3 percentage point increase). In contrast to our results on differential start times, we find that women are more likely to be scheduled for such shifts, albeit with a relatively small magnitude of 3.1 percentage points. All the interaction effects estimated here are statistically significant at the 1% level. Consistent with the results in column 1 (different start times), employees who are scheduled for shifts with differential start dates are more likely to be newer, part-time employees. However, a difference here is that these shifts are more likely to be distributed to female employees.

Overall, we find evidence that our second-stage estimates do not, in fact, reflect the average effect across all employees in our sample but more closely reflect the effects of part-time and lower-paid employees. Consequently, our results may reflect the behavior of employees who, say, have weaker ties to the store (due to their tenure). Despite this limitation, these estimates still retain some value, especially in the context of high turnover in the retail industry, where there may be a significant number of lower-tenured and low-paid employees in a store, making our findings relevant to a substantial portion of the workforce. We conclude by noting that an important limitation of our results is that we do not know how much of the difference in our OLS and IV estimates is attributed to the bias resulting from $\xi_{i,t,j}$ versus the "LATE"-ness of our IV estimates.

5.5 Heterogeneous Effects

Finally, we examine how the impacts of our inconsistent scheduling practices vary across different employee characteristics, some of which were previously used to characterize the "compliers" in our first stage estimates. Examining heterogeneous effects across different employee characteristics (e.g., gender) is crucial in our context for at least two reasons. First, we know from our complier analysis that our IV estimates weigh certain subpopulations of employees more heavily (e.g., part-timers). Therefore, a heterogeneous effects analysis allows us to unpack the second stage estimates based on employee characteristics. Second, because inconsistent shifts for workers may sometimes be unavoidable (due to unforeseen events like employee illness), recognizing which employees are most impacted (e.g., those more likely to be late or absent) may help managers better schedule their labor around these events to mitigate disruptions.

We study heterogeneous effects using two approaches. First, we interact both our measure of scheduling inconsistency and our instrument with the following characteristics: (i) Gender (Female and Male), (ii) Status (part-time versus full-time), (iii) Tenure, and (iv) Advance notice. We then re-estimate our first and second stages based on these interactions, after dropping employee fixed effects (for the same rationale as in our complier analysis). Here, we assume (and test for) the relevance of our expanded set of instruments (i.e., $N_{i,t}$ and $N_{i,t} \times E_{i,t,j}$), but also assume that $\mathbb{E}[N_{i,t} \cdot \varepsilon_{i,t,j} | E_{i,t,j}] = 0$, which is necessary for our exclusion restriction to hold. Here, $E_{i,t,j}$ is our employee characteristic, which may not vary across j or t for some characteristics (e.g., gender). This assumption ensures that after conditioning on the employee's characteristic ($E_{i,t,j}$), our exclusion restriction remains valid. In words, this condition implies that the effect of $N_{i,t}$ on lateness or absenteeism, channeled through $\boldsymbol{X}_{i,j,t}$, does not vary according to the characteristic of the employee. For our second approach, we subsample our data based on employee characteristics. The tradeoff with this approach is statistical power for the full set of employee $\times$ store $\times$year $\times$ week fixed effects.

Gender Based on the potential differences in their: (i) roles outside of work (such as care responsibilities), and (ii) preferences for work-life balance, we hypothesize that the effects of inconsistent shifts on schedule adherence may differ between males and females. Tables 6 and 7 presents our estimates when exploring the potential heterogeneous effects of differential start times and day-of-the-week based on gender. Due to the small and statistically insignificant (at the 10% level) coefficient on the interaction term, we do not find evidence that the effects of inconsistent work schedules on schedule adherence vary based on gender in our sample. The null heterogeneous effects based on gender are also confirmed with our second approach, where we estimate β (using our instrument) after splitting the subsample between men and women (Tables 16 and 17). We make this conclusion by noting that the 95% confidence intervals of the estimated coefficients overlap with each other.

Full-time versus Part-time Next, we investigate the potential heterogeneous effects according to status (that is, part-time versus full-time employees). A priori, it is unclear whether full or part-time employees would more adversely affected by inconsistent shifts. On the one hand, full-time employees may depend more heavily on their job for their livelihood, so they may be more affected by inconsistent scheduling practices because of the potential impact on their income and stability. On the other hand, part-time employees may have other commitments (such as school or another job) that make them more sensitive to scheduling inconsistencies, or they may be more flexible and less affected by inconsistent schedules.

Tables 8 and 9 presents our estimates when exploring the potential heterogeneous effects of differential start times and day-of-the-week based on part-time status. Here, we find that significant differences in effects for part-time status employees. Specifically, we find that the interaction effect (for part-time status) is negative and statistically significant at the 1% level. For both inconsistency measures, the interaction effect is approximately double (slightly less) than the main effect, which indicates that inconsistent work schedules predominantly affect full-time employees. We confirm this finding when splitting the sample between full-time and part-time employees, and find that the positive effect of inconsistent work schedules on schedule inadherence is *fully* driven by full-time employees. Specifically, Tables 18 and 19 show that the IV estimates for full-time employees are much larger than the IV estimates for part-time employees. Interestingly, the effect for part-timers is, in fact, positive (and significant at the 1% level), which implies that part-time employees are *more* likely to adhere to inconsistent shifts.

There are several plausible hypotheses for the observed differences in effects according to full-time versus part-time status. First, part-time workers can possess greater flexibility of the schedule, allowing them to adjust more easily to different start times and days. Second, they may be more accustomed to inconsistent work schedules, as evidenced by higher rates of such schedules compared to their full-time counterparts. Third, full-time workers often have established routines surrounding work, such as childcare, elder care, or other family responsibilities. Disruptions to these routines, due to inconsistent scheduling, can precipitate challenges leading to lateness or absenteeism. Fourth, part-time employees typically encounter a greater proportion of inconsistent shifts than full-time employees, suggesting that they are already accustomed to such variability. Lastly, the motivations of part-time workers may differ; some may be seeking to supplement income or acquire work experience, rather than considering their job as their primary livelihood. As such, they could be more inclined to adhere to shifts, even if they are inconsistently scheduled. These varied motivations may be the cause for different responses to irregular work schedules between full-time and part-time employees.

Tenure Next, we investigate potential heterogeneous effects by tenure. Employees with longer tenure may be more accustomed to scheduling practices in their store and may have developed coping mechanisms to handle inconsistency. On the other hand, they may also have higher expectations for consistent scheduling given their commitment and loyalty to the store, so they may be more affected by inconsistent schedules. On the contrary, employees with shorter tenure may be more flexible or may be less affected because they have lower expectations.

Tables 10 and 11 present our estimates when interacting our scheduling inconsistency measures by the log of the focal employee's tenure. For both measures, we find the interaction effects to be statistically significant (at the 1%) and negative, indicating that the effect sizes are larger for newer employees. Finally, we note that our results are statistically significant and convey the same message when creating a dummy variable that equals 1 for employees that are above their store's median tenure.

5.6 Discussion of Results

Taking stock, our OLS and IV estimates suggest that our two variables that capture two different forms of schedule inconsistency strongly predict shift level rates of lateness (by at least 10 minutes) and absenteeism. We also show that these effects are larger for full-time and shorter tenured employees.

Through our analyses, we highlight a significant econometric challenge that pertains to empirical studies investigating the association between scheduling practices and worker-shift level outcomes, such as productivity. Specifically, we emphasize the potential presence of a collider variable when examining scheduling policies. This occurs when policies impact both schedule adherence and worker-shift level outcomes concurrently. For instance, if a researcher aims to investigate the effects of scheduling practices on worker productivity at the shift level, it becomes crucial to consider that the scheduling practices may concurrently influence both schedule adherence and productivity. Specifically, let θ, x, and y, represent a scheduling policy, a binary indicator variable indicating schedule adherence, and a measure of productivity. Here, x is a collider variable since it simultaneously affects both θ and y. In other words, there is a curated sample of employees who appear (on time) based on the scheduling policy θ, which may have systematic differences in productivity. Furthermore, θ can also have a direct effect on productivity. Given that schedule inadherence in our sample, which contains two large retail chains, is greater than 15%, we argue that the effects of such a collider bias may be substantial. Accordingly, accounting for lateness and absenteeism may be critical in any study that examines the relationship between a scheduling policy and worker or store-level outcomes.

6 Conclusion

This paper studies the causal effects of inconsistent work schedules on shift-level rates of lateness and absenteeism in the retail sector. By examining more than 28 million shifts and timecards from two separate retail chains, we empirically show that inconsistent schedules are a significant driver of employee punctuality and presence. Our findings are two-fold. First, we find that inconsistent shifts, such as unpredictable day-of-the-week and start times, significantly contribute to increased rates of lateness and absenteeism. This is a potentially important insight, as punctuality and presence have direct implications for store performance and customer service levels.

Second, we highlight the importance of considering the characteristics of the employees when examining the effects of inconsistent scheduling. We found that the impact of scheduling inconsistency varies based on factors such as tenure and job status (i.e., full-time or part-time). For example, we find that our effects are driven by full-time employees, which may suggest that such workers have more established routines around their work schedules and hence have greater desires for work schedule stability. Overall, the heterogeneous effects that we find emphasize the need for employers to consider the diverse needs and commitments of their workforce when developing and implementing scheduling policies.

Our research adds to the growing body of literature that emphasizes the need for consistency and predictability in scheduling practices. While flexibility is important for managers to adapt to short-term fluctuations in demand and labor supply, our findings stress that this flexibility may come at the expense of employee well-being and job satisfaction (proxied by schedule adherence). Given the apparent connection between inconsistent scheduling and increased lateness and absenteeism rates, a focus on creating stable and predictable schedules could be a beneficial strategy to reduce these issues.

Although our study offers some novel insights on the effects of inconsistent schedules on shift-level rates of schedule adherence, it also carries certain limitations. The external validity of our findings could be limited, as the data used were exclusively from the retail sector, limiting generalizability to other industries with different scheduling practices and work environments. Further research could explore how these scheduling effects translate into other sectors and investigate additional factors such as the role of employee engagement and job satisfaction in reducing employee lateness and absenteeism.

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Table 1: OLS Results for Schedule Consistency

	Absent or Late > 10 Mins. (1)	Absent (2)	Late > 10 Mins. (3)
Diff. Start Time	0.015***	0.011***	0.005***
	(0.0003)	(0.0002)	(0.0002)
Diff. Day-of-the-Week	0.011***	0.010***	0.003***
	(0.0002)	(0.0002)	(0.0001)
Observations	28,401,423	28,401,423	25,670,637
Adjusted R^2	0.318	0.365	0.216
Store-Worker-Year-Week FEs	✓	✓	✓

Notes: The estimates above correspond to fixed effects regression where binary indicator variables that represent either absenteeism or lateness (by at least 10 minutes) are regressed on schedule in-consistency variables. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 2: First Stage Estimates

	Diff. Start Time (1)	Diff. Day-of-the-Week (2)
Pct. PTO	0.088***	0.250***
	(0.006)	(0.007)
log(1+ Days Notice)	-0.055***	-0.071***
	(0.0003)	(0.0003)
log(Store Operating Duration)	-0.094***	-1.18***
	(0.003)	(0.004)
log(Algo Forecast)	0.003***	-0.147***
	(0.001)	(0.001)
Diff. Week-of-the-Day	-0.250***	
	(0.0002)	
Diff. Start Time		-0.418***
		(0.0002)
Observations	28,401,423	28,401,423
Adjusted R^2	0.274	0.229
Wald (1st stage)	243.950	1,163.239
Store-Worker-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our first stage fixed effects regression where our schedule inconsistency variables are regressed on our fixed effects and control variables. The unit of observation is at the shift level. The Wald (1st stage) statistic is the cluster-robust F statistic (Kleibergen and Paap, 2006). Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 3: Reduced Form Estimates

	Absent or Late > 10 Mins. (1)	Absent (2)	Late > 10 Mins. (3)
Pct. PTO	0.042***	0.030***	0.019***
	(0.006)	(0.005)	(0.004)
log(1+ Days Notice)	0.005***	0.010***	-0.005***
	(0.0002)	(0.0002)	(0.0002)
log(Store Operating Duration)	0.025***	0.029***	0.002
	(0.002)	(0.002)	(0.002)
log(Algo Forecast)	-0.021***	-0.027***	0.002**
	(0.001)	(0.0009)	(0.0008)
Observations	28,401,423	28,401,423	25,670,637
Adjusted R^2	0.318	0.365	0.216
Store-Worker-Year-Week FEs	✓	✓	✓

Notes: The estimates above correspond to fixed effects regression (for our reduced form equation) where binary indicator variables that represent either absenteeism or lateness (by at least 10 minutes) are regressed on our instrument, Pct. PTO, which is the percentage of employees that are on paid time off. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 4: Second Stage Estimates for Different Start Times

	Absent or Late > 10 Mins. (1)	Absent (2)	Late > 10 Mins. (3)
Diff. Start Time	0.462***	0.329***	0.213***
	(0.072)	(0.058)	(0.051)
Observations	28,401,423	28,401,423	25,670,637
Store-Worker-Year-Week FEs	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 5: Second Stage Estimates for Different day-of-the-week

	Absent or Late > 10 Mins. (1)	Absent (2)	Late > 10 Mins. (3)
Diff. Day-of-the-Week	0.169***	0.121***	0.074***
	(0.024)	(0.019)	(0.017)
Observations	28,401,423	28,401,423	25,670,637
Store-Worker-Year-Week FEs	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different week of the day. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 6: Heterogeneous Effects of Different Start Times on Schedule Adherence (Gender)

	Absent (1)	Late > 10 Mins. (2)
Diff. Start Time	0.414***	0.215***
	(0.065)	(0.051)
Diff. Start Time × Female	0.016	-0.077
	(0.093)	(0.067)
Observations	28,187,210	25,483,590
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 7: Heterogeneous Effects of Different Days of the Week on Schedule Adherence (Gender)

	Absent (1)	Late > 10 Mins. (2)
Diff. Day-of-the-Week	0.342***	0.159***
	(0.034)	(0.027)
Diff. Day-of-the-Week × Female	-0.029	-0.042
	(0.038)	(0.028)
Observations	28,375,930	25,647,992
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our second stage estimates for different days of the week. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 8: Heterogeneous Effects of Different Start Times on Schedule Adherence (Part-Time Employees)

	Absent (1)	Late > 10 Mins. (2)
Diff. Start Time	0.824***	0.376***
	(0.086)	(0.062)
Diff. Start Time × Part-Time	-1.60***	-0.805***
	(0.127)	(0.092)
Observations	28,177,778	25,475,488
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 9: Heterogeneous Effects of Different Days of the Week on Schedule Adherence (Part-Time Employees)

	Absent (1)	Late > 10 Mins. (2)
Diff. Day-of-the-Week	0.401***	0.186***
	(0.034)	(0.028)
Diff. Day-of-the-Week × Part-Time	-0.730***	-0.388***
	(0.046)	(0.037)
Observations	28,177,778	25,475,488
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our second stage estimates for different days of the week. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 10: Heterogeneous Effects of Different Start Times on Schedule Adherence (Tenure)

	Absent (1)	Late > 10 Mins. (2)
Diff. Start Time	2.43***	1.37***
	(0.233)	(0.159)
Diff. Start Time × log(Tenure)	-0.327***	-0.193***
	(0.034)	(0.022)
Observations	28,177,778	25,475,488
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 11: Heterogeneous Effects of Different Days of the Week on Schedule Adherence (Tenure)

	Absent (1)	Late > 10 Mins. (2)
Diff. Day-of-the-Week	3.31***	1.98***
	(0.380)	(0.273)
Diff. Day-of-the-Week × log(Tenure)	-0.491***	-0.301***
	(0.058)	(0.042)
Observations	28,177,778	25,475,488
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our second stage estimates for different days of the week. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

A Supplementary Appendix

A.1 Scheduling Algorithm

As mentioned in the main text, all stores (across both retailers) in our sample use the same commercial algorithm to forecast demand and schedule labor. While the commercial product underlying the algorithm is identical, the parameters and variables underlying the algorithm may differ between and within companies. For example, how much labor at the cash register for one customer visit may differ between stores if there are variations in average customer basket sizes between stores (i.e., some customers may buy many small-priced items, while customers at other stores may one or two large-priced items). Furthermore, we know that corporate officers can make adjustments to these parameters, which can substantially affect the scheduling process across stores. These differences are fully accounted for in our identification strategy by including store $\times$ year-week fixed effects, which we elaborate on in Section 4.

In our context, each shift data entry includes the start and end times, the duration, the employee ID, the assigned task, and a timestamp that shows when the shift was generated or last edited. If a shift has been edited, the associated timestamp will also list the responsible manager's ID. Thanks to our workforce scheduling algorithm's tracking capabilities, we can follow each shift's entire lifecycle: its initial creation, its distribution to the workforce, and any subsequent edits that are made after distribution. For example, managers can manually delete shifts if an employee informs them of their unavailability for that shift. We use this information to compute the amount of advance notice that is provided for each shift, which is included as a control variable in our empirical specifications.

The algorithm generates schedules in increments of weeks for all shift-based workers. In general, this algorithm operates in three steps. In the first step, the algorithm forecasts demand in 15-minute time intervals. In the second step, the algorithm generates shifts to meet customer service and workload levels that are determined collaboratively between the creators of the commercial algorithm and corporate officers. In the final step, the algorithm assigns the employees to these shifts. These three steps occur 2-3 weeks in advance of each shift's work date. Crucially, the set of shifts that are outputted in this process satisfies all employee contracts, labor laws (e.g., Fair Workweek laws), and company policies.

Although the algorithm plays an important role in the initial creation of work schedules, it is essential to note that store managers still have the ability to manually adjust these schedules. Accordingly, the set of schedules that are ultimately distributed to employees may differ substantially from the set of shifts that are outputted by the algorithm. This manual intervention is necessary for various reasons, such as accommodating employee preferences, dealing with unexpected changes in demand, or managing sudden absences.

A key advantage of the workforce scheduling software that is used by both companies is that it meticulously tracks all scheduling actions and adjustments made by managers. Specifically, this system records in detail what was edited, when it was edited, and by whom it was edited. Finally, payroll timecards are merged based on shift level identifiers that are assigned to every shift. Consequently, the data we analyze (described below in Subsection 3.3 provides us with a full, unredacted view of labor scheduling processes in all stores ($n \geq$1,000) in our sample along with lateness and absenteeism rates in all employees ($n \geq 135,000$).

These high-resolution data provide several crucial benefits for our empirical strategy. First, the shift level identifiers allow us to measure lateness and absenteeism without measurement error. Because work schedules are sent to payroll and also monitored by corporate officers, an employee who privately communicated to his manager about his impending lateness or absenteeism would, by and large, be deleted by the manager. Accordingly, our data are highly precise: the deviations between the finalized work schedules and time-card/punch-card records from payroll accurately measure schedule inadherence. Second, by having full information about the timing and nature of adjustments, we can accurately measure the "inconsistency" of work schedules, which we define in Section 4. For instance, we are fully informed about the advance notice an employee received for their shift, and we are also aware of the degree to which an employee's shift in a given week varies from their work schedule in the prior week.

A.2 Additional Results

Table 12: First Stage Interaction Effects

	Diff. Start Time (1)	Diff. Day-of-the-Week (2)
Pct. PTO	0.239***	0.213***
	(0.036)	(0.041)
log(Tenure in Days)	-0.017***	-0.011***
	(0.0002)	(0.0003)
Part-Time	0.087***	0.045***
	(0.0009)	(0.0009)
Female	-0.015***	-0.004***
	(0.0007)	(0.0008)
log(1+ Days Notice)	-0.070***	-0.061***
	(0.0004)	(0.0005)
log(Store Operating Duration)	0.169***	-1.06***
	(0.007)	(0.015)
log(Algo Forecast)	-0.002	-0.214***
	(0.003)	(0.005)
Pct. PTO $\times$ log(Tenure in Days)	-0.041***	-0.036***
	(0.006)	(0.007)
Pct. PTO $\times$ Part-Time	0.424***	0.753***
	(0.021)	(0.021)
Pct. PTO $\times$ Female	-0.017	0.031**
	(0.013)	(0.015)
Observations	28,350,251	28,350,251
Adjusted R^2	0.045	0.031
Store-Year-Week FEs	✓	✓

Notes: The estimates above correspond to our first stage fixed effects regression where our schedule inconsistency variables are regressed on our instrument (interacted by employee characteristics), fixed effects, and other control variables. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 13: Sample Summary Statistics

Variable	N	Mean	SD	Median
Panel A: Shift-Level Outcomes				
No. Shifts	29,046,142	1.00	0.00	1.00
Scheduled Mins.	29,046,142	439.85	85.06	480.00
Male	29,015,564	0.36	0.48	0.00
Tenure (Days)	29,027,130	1186.37	1681.76	590.00
Wage	29,020,791	15.28	4.54	15.00
Diff. Day-of-the-Week	29,046,142	0.24	0.43	0.00
Diff. Start Time	29,046,142	0.13	0.34	0.00
Late by 10 Mins.	26,227,509	0.06	0.24	0.00
Absent	29,046,142	0.10	0.30	0.00
Advance Notice (Days)	29,046,142	20.53	6.47	22.00
Paid Time Off	29,046,142	0.27	0.44	0.00
Panel B: Store-Week Level Outcomes				
Scheduled Mins.	190,871	66934.45	24691.25	62670.00
No. Shifts	190,871	152.18	58.53	141.00
Pct. Diff. Day-of-the-Week	190,871	0.24	0.07	0.24
Pct. Diff Start Time	190,871	0.13	0.06	0.13
Pct. Late by 10 Mins.	190,871	0.06	0.04	0.04
Pct. Absent	190,871	0.10	0.07	0.09
Panel C: Store-Level Outcomes				
Scheduled Mins.		11731721.62	5799988.03	11447025.00
No. Shifts		26672.31	13604.75	25855.00
Pct. Diff. Day-of-the-Week		0.24	0.05	0.24
Pct. Diff Start Time		0.13	0.04	0.13
Pct. Late by 10 Mins.		0.06	0.04	0.05
Pct. Absent		0.10	0.04	0.10
Panel D: Worker-Week Level Outcomes				
Scheduled Mins.	7,382,960	1730.45	631.32	1920.00
No. Shifts	7,382,960	3.93	1.24	4.00
Pct. Diff. Day-of-the-Week	7,382,960	0.25	0.28	0.20
Pct. Diff Start Time	7,382,960	0.13	0.22	0.00
Pct. Late by 10 Mins.	7,382,960	0.06	0.15	0.00
Pct. Absent	7,382,960	0.10	0.23	0.00
Panel E: Worker-Level Outcomes				
Scheduled Mins.	135,136	94540.65	114791.62	44610.00
No. Shifts	135,136	214.94	250.53	108.00
Pct. Diff. Day-of-the-Week	135,136	0.25	0.14	0.25
Pct. Diff Start Time	135,136	0.14	0.12	0.12
Pct. Late by 10 Mins.	135,136	0.06	0.09	0.03
Pct. Absent	135,136	0.19	0.20	0.12

Notes: The statistics above present summary statistics for our entire sample. The estimates in Panels B, C, D, and E are constructed from our shift level dataset (Panel A). Note that we intentionally dropped the number of observations in Panel C (cross-sectional summary statistics at the store-level to mask the number of stores in our sample.

Table 14: Second Stage Estimates for Different Start Times

	Absent (1)	Late > 10 Mins. (2)	Absent (3)	Late > 10 Mins. (4)
Diff. Start Time	0.358***	0.218***	0.367***	0.232***
	(0.054)	(0.048)	(0.058)	(0.051)
Observations	28,401,422	25,670,643	28,401,422	25,670,643
Store-Worker-Year-Week FEs	✓	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. The first two columns use the raw count of employees on PTO as the instrument, while the latter two columns use the log of one plus the raw count of employees on PTO as the instrument. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 15: Second Stage Estimates for Different day-of-the-week

	Absent (1)	Late > 10 Mins. (2)	Absent (3)	Late > 10 Mins. (4)
Diff. Day-of-the-Week	0.140^{***}	0.082^{***}	0.141^{***}	0.085^{***}
	(0.019)	(0.017)	(0.020)	(0.018)
Observations	28,401,422	25,670,643	28,401,422	25,670,643
Store-Worker-Year-Week FEs	✓	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different week of the day. The first two columns use the raw count of employees on PTO as the instrument, while the latter two columns use the log of one plus the raw count of employees on PTO as the instrument. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 16: Heterogeneous Effects of Different Start Times on Schedule Adherence (Gender)

	Absent (1)	Late > 10 Mins. (2)	Absent (3)	Late > 10 Mins. (4)
Diff. Start Time	0.310^{***}	0.198^{**}	0.345^{***}	0.222^{***}
	(0.082)	(0.078)	(0.079)	(0.068)
Observations	10,306,305	9,314,797	18,067,027	16,330,879
Store-Year-Week-Worker FEs	✓	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The first two columns are estimates based on the sample of shifts assigned to male employees. The second two columns are estimated on the basis of the sample of shifts assigned to female employees. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 17: Heterogeneous Effects of Different Days of the Week on Schedule Adherence (Gender)

	Absent (1)	Late > 10 Mins. (2)	Absent (3)	Late > 10 Mins. (4)
Diff. Week-of-the-Day	0.102^{***}	0.072^{**}	0.091^{***}	0.070^{***}
	(0.033)	(0.030)	(0.025)	(0.022)
Observations	10,229,045	9,260,664	17,912,159	16,229,871
Store-Worker-Year-Week FEs	✓	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different days of the week. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The first two columns are estimates based on the sample of shifts assigned to male employees. The second two columns are estimated based on the sample of shifts assigned to female employees. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 18: Heterogeneous Effects of Different Start Times on Schedule Adherence (Part-Time Employees)

	Absent (1)	Late > 10 Mins. (2)	Absent (3)	Late > 10 Mins. (4)
Diff. Start Time	0.627***	0.315***	-0.385***	0.030
	(0.096)	(0.079)	(0.099)	(0.080)
Observations	20,167,829	18,100,149	7,973,375	7,390,386
Store-Worker-Year-Week FEs	✓	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different start times. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The first two columns are estimates based on the sample of shifts assigned to full-time employees. The second two columns are estimated on the basis of the sample of shifts assigned to part-time employees. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.

Table 19: Heterogeneous Effects of Different Days of the Week on Schedule Adherence (Part-Time Employees)

	Absent (1)	Late > 10 Mins. (2)	Absent (3)	Late > 10 Mins. (4)
Diff. Week-of-the-Day	0.235***	0.116***	-0.106***	0.010
	(0.030)	(0.027)	(0.025)	(0.021)
Observations	20,167,829	18,100,149	7,973,375	7,390,386
Store-Worker-Year-Week FEs	✓	✓	✓	✓

Notes: The estimates above correspond to our second stage estimates for different days of the week. All specifications include: (i) the (log) amount of advance notice for the shift, (ii) the (log) of store's operating duration, and (iii) the (log) of store's demand forecast. The first two columns are estimates based on the sample of shifts assigned to full-time employees. The second two columns are estimated on the basis of the sample of shifts assigned to part-time employees. The unit of observation is at the shift level. Standard errors that are double clustered at the employee and year-week levels are presented in parentheses. *, **, and *** imply that coefficients are significant at the 10, 5, and 1%, respectively.