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The Impact of Schedule Consistency on Shift Worker Productivity: An Empirical Investigation

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Abstract. ***Problem definition*:** Lawmakers have begun to introduce "fair schedule" legislations that require employers to provide shift workers with more predictable and consistent work schedules. Business owners are concerned that the resultant loss of scheduling flexibility could reduce overall operational efficiency. We argue this is not necessarily the case. ***Academic/practical relevance:*** Although recent studies suggest that increasing schedule predictability by reducing "just-in-time" scheduling can increase productivity, few have examined the effects of schedule consistency on worker productivity. Our study fills this void by investigating the impact of schedule consistency on cashier productivity in grocery retailing. ***Methodology*:** We estimate econometric models using transaction level scanner data including more than 1.2 million shopping baskets processed by 126 cashiers working for a local grocer. Work schedule consistency is operationalized via two metrics: (1) hour-of-the-day consistency measuring whether a cashier is consistently scheduled to work in the same hours of the day, and (2) day-of-the-week consistency measuring whether a cashier is consistently scheduled to work on the same days of the week. ***Results:*** We find that, on average, hour-of-the-day consistency and day-of-the-week consistency increase cashier productivity by 0.95% and 1.63%, respectively. These effects are much stronger for inexperienced cashiers (e.g., an average productivity boost of 3.39% and 7.93%, respectively, for the new hires). ***Managerial implications*:** Our findings suggest that (a) business owners can increase shift workers' productivity by providing them with more consistent work schedules, and (b) the productivity of less-experienced shift workers, especially new hires, is more vulnerable to inconsistent work schedules, highlighting the potential for operational efficiency gains from greater schedule consistency, especially for businesses employing a high portion of inexperienced shift workers.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/msom.2022.1132.

Keywords: fair schedule • schedule consistency • shift worker • worker productivity • staffing • responsible operations management • retail operations • people-centric operations management • work experience

1. Introduction

In 2018, about 26 million employees in the United States were shift workers, defined as those who worked for fewer than 35 hours per week (U.S. Bureau of Labor Statistics 2019). Hiring shift workers is common in retail and food-service sectors, where businesses often rely on so-called "just-in-time" work scheduling to cope with volatile demand (Kamalahmadi et al. 2021). Although such practices afford businesses with operational flexibility, they can result in highly unpredictable and inconsistent work schedules for shift workers. Shifts may be assigned with short notice and subject to frequent changes (i.e., unpredictable schedules), or employees may be assigned varying work hours between days or varying work days between weeks (i.e., inconsistent schedules).

Unfortunately, unpredictable and inconsistent work schedules can have many drawbacks for shift workers, making it difficult for them to carry out various non-work activities or to work another part-time job and negatively affecting their well-being. The SHIFT project out of Harvard University reveals that unpredictable and inconsistent work schedules are a much more significant contributor to poor health outcomes than low wages (Schneider and Harknett 2019).

The "fair scheduling" movement aimed at giving more predictable and consistent schedules to shift workers has increasingly gained regulators' attention at the state and the city level. For example, the state of Oregon and cities such as New York and Seattle have enacted legislations on fair scheduling (Williams et al. 2018). Lawmakers have attempted to bring such reforms to the federal level as well. In December 2019, a bill to improve work schedules for part-time seasonal employees was introduced, requiring businesses to notify workers their shift schedules with more advance time, offer extra pay for last-minute schedule changes initiated by the employer, and provide adequate rest time between consecutive shifts.

In response to such legislative initiatives, businesses have argued that providing predictable and consistent schedules to shift workers can be detrimental to operational efficiency, because doing so limits their ability to adjust work shifts in real time to meet volatile demand. As such, many business executives, especially those from sectors such as retail and food services, strongly oppose fair schedule legislations. The contrasting views about providing predictable and consistent work schedules between lawmakers and businesses imply a tradeoff between shift workers' well-being and businesses' operational efficiency. Is such a tradeoff inevitable? Is it possible that predictable and consistent work schedules can benefit not only shift workers but also business owners? Although concrete evidence on the impacts of predictable and consistent work schedules is of great interest to various stakeholders including lawmakers, employers, and employees, there is very limited research on this topic (Schneider and Harknett 2019). A recent study based on aggregate store level data from Gap Inc. finds that responsible scheduling practices intended to improve schedule predictability and consistency increase both labor productivity and sales (Kesavan et al. 2021). Another study using General Social Survey data reports that regular work schedules reduce work-family conflicts (Economic Policy Institute 2015). These findings suggest that predictable or consistent schedules can potentially benefit not only workers but also employers, despite that scheduling workers without regard to the predictability or consistency of their work shifts may afford employers more flexibility to respond to demand changes. Although a few recent studies have investigated the impact of schedule predictability at the worker level (Lambert et al. 2019, Kamalahmadi et al. 2021), to our knowledge, no study has examined the impact of schedule consistency, another important aspect of fair work scheduling, at this granular level.

We suggest that schedule consistency is conceptually different from schedule predictability. Schedule consistency refers to the extent to which workers' shifts fall within the same hours of the day or days of the week over an extended period of time and captures the actual regularity of the realized schedule, whereas schedule predictability depends on "how far in advance schedules are posted" (Lambert et al. 2019, p. 0.176). An inconsistent schedule can be made predictable by announcing it well in advance. However, even with advance notice, workers can still have an inconsistent schedule if their work hours vary considerably between days and/or their work days vary considerably between weeks. Despite the conceptual difference, schedule consistency and schedule predictability tend to be positively correlated empirically: a work schedule that is more predictable also tends to be more consistent.

The mechanisms through which schedule predictability and schedule consistency affect workers' productivity are also different. Schedule predictability (via advance notice) affects productivity by allowing shift workers to plan ahead and thus achieve higher performance (Kamalahmadi et al. 2021). Schedule consistency improves worker productivity mainly through developing better rhythmicity (Grote et al. 1994) and work-life balance (Olsen and Dahl 2010). People who are forced to frequently break their biological rhythms can experience symptoms of fatigue, disorientation, and insomnia (Zhu and Zee 2012). Inconsistent work schedules also make it difficult for workers to attend to nonwork activities or family commitments that often have a regular daily or weekly schedule (e.g., children's afterschool activities).

Building on the emerging literature on fair work scheduling (related terms include responsible scheduling and employee-friendly scheduling), our study intends to shed additional light on the impact of work scheduling by (a) developing empirical measures of individual shift workers' schedule consistency, (b) quantifying how these schedule consistency measures relate to worker productivity, and (c) uncovering how the relationships may be moderated by work experience in the context of grocery retailing. A key distinction between our study and prior work scheduling research is that our study examines the impact of work schedule consistency on individual productivity, whereas the existing literature has mostly focused on the impacts of store-level staff planning on store performance. For example, in the field of operations management (OM), prior studies have attempted to quantify the impacts of store-level labor planning on retail store performance (Chuang et al. 2016). Perdikaki et al. (2012) find that matching labor with customer traffic is a key driver of retail store performance. We note that store-level staff planning and employee-level scheduling are not the same. In retailing, store-level staff planning is a capacity decision that focuses on the optimal number of employees at different time points. In contrast, employee-level scheduling is about allocating specific work hours and work days to individual employees given the store-level staff capacity plan. It is conceivable that even with a highly flexible store-level staffing schedule, an employer can still attempt to provide relatively consistent employee-level schedules to its shift workers.

The few recent studies on scheduling at the worker level focus on schedule predictability (Kamalahmadi et al. 2021) as opposed to schedule consistency. Although inconsistent work schedules can undermine both employee well-being and performance (Sharma 2003, Henly and Lambert 2014), there is little empirical evidence based on real world transaction data at the individual worker level to shed light on potential productivity gains from improving schedule consistency for shift workers. Therefore, it is important to measure employee-level work schedule consistency and quantify its impact on shift worker productivity, the main goal of our study. In real world operations, managers are likely to give more consistent work schedules to experienced shift workers for reasons such as rewarding workers' loyalty (Deeprose 1994). However, experienced shift workers may develop coping strategies over time to better deal with inconsistent work schedules and therefore might be less affected by schedule inconsistency than inexperienced shift workers. Thus, we also investigate how work experience may moderate the effect of work schedule consistency on shift worker productivity.

To address these research questions, we distinguish between two aspects of work schedule consistency based on the notions of daily (circadian) and weekly (circaseptan) rhythmicity (Sharma 2003). Specifically, hour-of-the-day consistency captures the extent to which an employee's current work hour is scheduled in the same hour of the day (e.g., 7–8 a.m.) as the employee's previous shifts. Day-of-the-week consistency reflects the extent to which an employee's current work shift is scheduled on the same day of the week (e.g., Monday) as the employee's past shifts. Our empirical analysis uses transaction level scanner data from a local grocery chain, which records, for each of the more than 1.2 million shopping baskets, the number of items scanned and the amount of time it took a cashier to complete the transaction. We find that, on average, hour-of-the-day consistency and day-of-the-week consistency can improve cashier productivity, operationalized as the number of items processed per second, by about 0.95% and 1.63%, respectively, after controlling for an extensive set of potential confounding factors (e.g., fixed cashier effects, fixed day and operating hour-of-the-day effects, fixed store-terminal effects, perceived store-hour workload, and individual cashier productivity change). The positive impact of day-of-the-week consistency on productivity is stronger for cashiers with less experience. The positive effects of both types of work schedule consistency become considerably stronger when only the subsample of cashiers hired during our study period were considered. For this "new hire" subsample, on average, hour-of-the-day consistency and day-of-the-week consistency can improve a new cashier's productivity by about 3.39% and 7.93%, respectively.

Our study makes several contributions. First, with a different empirical context and identification approach, our study corroborates and extends the recent literature (Kamalahmadi et al. 2021, Kesavan et al. 2021) on the effects of work scheduling on shift worker productivity. Our study is the first to provide fine-grained empirical evidence with respect to work schedule consistency. This can have both public policy and managerial implications because our findings suggest that improving employee-level work schedule consistency can benefit not only employees, as the literature reports, but also employers through improved worker productivity (Fisher et al. 2020). Our findings should help lessen businesses' concerns about regulations promoting schedule consistency for shift workers leading to a loss of operational efficiency.

Furthermore, our quantitative findings can provide some guidance on how businesses may improve employee-level work schedule consistency. For example, businesses should distinguish between hour-of-the-day and day-of-the-week consistency, and improving either metric can lead to improved productivity. Schedule consistency, specifically day-of-the-week consistency, has greater effects on productivity for cashiers with less experience. The effect of schedule consistency is especially strong for new cashiers: both hour-of-the-day and day-of-the-week consistency have considerably larger positive effects, suggesting that improving either metric can greatly help new hires to improve their productivity. This finding contrasts the common practice of awarding "better" schedules to experienced workers and suggests that businesses should balance the need to reward worker tenure and loyalty (which is often associated with retention) and the need to protect less-experienced shift workers (new hires in particular) with more consistent schedules.

2. Literature Review and Hypotheses

We review two relevant streams of research: (1) staff planning and work scheduling and (2) people-centric operations management.

2.1. Staff Planning and Work Scheduling

Staff planning and work scheduling are important research themes in OM. Strictly speaking, staff planning and work scheduling are two related but distinct concepts. The former often leans toward a capacity optimization problem (e.g., optimizing the number of workers for a shift), whereas the latter focuses on the actual allocation of work among individual employees (Perdikaki et al. 2012, Tan and Netessine 2019). Our study is more closely related to work scheduling, thereby our review only briefly covers the staff planning literature while focusing on prior work scheduling research.

A large body of literature utilizes mathematical modeling in staff planning decisions. Many analytical routing, queueing, and demand forecasting models have been developed to optimize staff planning to reduce costs or improve system performance (Gans et al. 2003, Bhandari et al. 2008, Gurvich et al. 2008). These studies typically assume that inconsistent schedules for individual workers are an inevitable consequence of adjusting staff capacity to meet volatile demand (Van den Bergh et al. 2013, Defraeye and Van Nieuwenhuyse 2016). As a result, the goal of many of these studies is to determine labor capacity in different time slots or locations to meet customer demand, typically assuming that (1) employee productivity is constant, irrespective of the work schedule; and (2) employees are available at any time when needed, largely because of modeling tractability issues (Tan and Netessine 2014). This stream of research almost exclusively looks at system performance (e.g., a store or a firm).

Questioning the assumptions of constant employee productivity and unrestricted availability of workers, behavioral operations management researchers estimate the effects of external factors such as work environments or peers on employee productivity (see Bendoly et al. 2006 for a comprehensive review of the behavioral operations management literature). For example, using laboratory experiments, Schultz et al. (1998) demonstrate that workers' production rate is affected by the work environment, contrasting many prior studies' assumption of a constant production rate. Because real-world systems are more complex than laboratory settings, Boudreau et al. (2003) call for observational studies in real-world environments to validate the results of laboratory experiments. Answering this call, Tan and Netessine (2014) use check-level data from a restaurant chain to study staff planning problems.

Turning to work scheduling studies, a long line of analytical research on scheduling looks into resource (e.g., workers or machines) allocation problems (Pinedo 2012). Researchers have studied appointment scheduling (Truong, 2015), transportation scheduling (Zhu et al. 2014), and workforce scheduling (Berman et al. 1997). The optimization models in this stream of research typically assume a central planner whose objective function varies across studies. Despite the large amount of analytical research on work scheduling, empirical research is scant, likely because of the limited access to real-world data to construct scheduling related variables (Schneider and Harknett 2019). Table 1 summarizes key empirical work scheduling studies related to our research.

The few empirical studies typically use perceptual measures to examine the effects of work scheduling on employee well-being but not on employee performance. Several studies investigate the effects of work schedule flexibility (Zeytinoglu et al. 2004, Lambert 2008, MacEachen et al. 2008, Jang et al. 2012). Schedule flexibility in these studies is not the same as schedule consistency in our research. In practice, a firm provides schedule flexibility by allowing a worker to choose between a standard 40-hour weekly schedule (9 a.m.–5 p.m., Monday–Friday) or a schedule with extended hours for extra pay or reduced hours for additional personal time. Under such a policy, an employee first chooses the preferred total number of work hours, and the employer then schedules the employee's work shifts such that they add up to the chosen number of work hours. This policy typically does not prioritize individual workers' schedule consistency; rather, it is mostly driven by firm-level staff capacity needs.

Several other studies investigate schedule (in)stability (Dickson et al. 2018, Schneider and Harknett 2019). These studies generally find that unstable work schedules cause stress and income volatility. Schedule stability in these studies is measured by the degree of advance notice and frequency of schedule changes, and therefore is conceptually similar to schedule predictability in Kamalahmadi et al. (2021). However, findings from these studies are based on employee self-reported data and the dependent variables pertain mainly to the well-being of workers.

Only a handful of studies uses secondary data from real world operations to investigate the impacts of work scheduling. Kesavan et al. (2021) examine whether five store interventions (e.g., tech-enabled schedule changes) affect four dimensions of responsible scheduling practices (e.g., predictability and consistency), and in turn, increase store performance. Although an advantage of the study is the breadth of interventions and scheduling practices investigated, such a study design makes it challenging to tease out the distinct effect of any specific intervention or practice on store performance. To our knowledge, Kamalahmadi et al. (2021) is the only study that uses transactional data to investigate the effects of schedule predictability on the productivity of individual workers (measured by dollar amount per dinning ticket) in a restaurant setting, and how this effect differs between workers with varying intrinsic sales ability. Our study differentiates from but complements Kamalahmadi et al. (2021) by estimating the effects of schedule consistency on shift worker productivity. The online appendix highlights the similarities and differences among Kesavan et al. (2021), Kamalahmadi et al. (2021), and our study in terms of constructs, conceptualization/causal mechanisms, empirical contexts, methodologies, findings, and implications.

2.2. People-Centric Operations

Also relevant to our study is the emerging literature on people-centric operations. This literature incorporates human behavior factors to investigate the conditions under which people can perform at their best

Table 1. Prior Empirical Studies on the Impacts of Work Scheduling

Study	Data source	Level of analysis	Work schedule measures	Findings related to our study
Dickson et al. 2018	Self-reported (survey of 1,717 workers in the state of Illinois)	Mixed (perceived store schedule and individual schedule)	Perceptual measures based on two questions • "How often does your schedule change after it has been posted?" • "Typically, how far in advance do you find out your upcoming work schedule?"	An unstable work schedule is the most common cause of workers' stress and income volatility.
Jang et al. 2012	Self-reported (data from the 2008 National Study of the Changing Workforce)	Mixed	Perceptual measures based on four questions (e.g., "are employees allowed to change their work hours within certain constraints?")	Work schedule flexibility is associated with reduced stress.
Kamalahmadi et al. 2021	Archival data from a large restaurant chain	Individual level	A set of dummies indicating if (1) a work schedule change is announced on the day of service, (2) a work schedule change is announced within two days before the day of service, and (3) no change is made.	Short-notice schedules do not harm server productivity overall, but real-time schedules do by 4.4%. Short-notice schedules improve high-ability servers' productivity by 4.3% but hurt low-ability servers' productivity by 1.9%.
Kesavan et al. 2021	Field experiments (at 28 Gap stores)	Store level	Four dimensions of responsible scheduling practices: consistency, predictability, adequacy, and control	Implementing the responsible scheduling practices altogether increases store productivity (sales per labor hour) by 5.1%, increases weekly sales by 3.3%, and decreases weekly labor hours by 1.8%.
Lambert 2008	Qualitative study (22 work sites in Chicago)	Firm level	Perceptual measures based on questions on the extent to which front-line managers can change: • the number of hours employees work • the distribution of employees' hours across a week • the number of employees scheduled for any hour week-to-week.	Scheduling flexibility protects some workers from instability at the expense of other workers.
Lambert et al. 2019	Field experiment	Mixed level	The degree to which schedules are posted in advance.	The intervention of posting schedules further in advance in the treatment stores did not improve schedule predictability.
MacEachen et al. 2008	Qualitative study (30 Canadian service firms)	Firm level	Perceptual measures of flexible work schedules through open-ended interviews.	Flexibility blurs the boundary between home and work, possibly creating "unlimited" work hours.

Table 1. (Continued)

Study	Data source	Level of analysis	Work schedule measures	Findings related to our study
Schneider and Harknett 2019	Self-reported (survey of Facebook users)	Mixed	Perceptual measures that gauge the amount of advance notice of schedules respondents received at work and the week-to-week variability in respondents' work hours.	Unstable work schedule results in distress, poor rest quality and unhappiness.
Tausig and Fenwick 2001	Self-reported (data from the 1992 National Study of the Changing Workforce)	Mixed	Perceptual measures of four alternate work schedules compared with the standard full time work schedule	Alternate work schedules do not "unbind" time. However, the perceived control of work schedules improves work-life balance.
Zeytinoglu et al. 2004	Self-reported (Survey data in Canada)	Individual level	Perceptual measures of five flexibility indicators capturing whether an employee has long workweek, flextime, compressed workweek, variable workweek length and/or variable workweek schedule.	Flexible work schedules are created for business reasons rather than for individual workers' interests.

(Roels and Staats 2020). For example, using archival data from a hospital emergency department, KC et al. (2020) show that the tendency of hospital workers to choose easy tasks over difficult tasks can undermine their work performance in the long run. Altman et al. (2020) demonstrate that negative customer emotion erodes agent productivity in online customer contact centers. Pendem et al. (2016) find that unexpected work breaks result in increased performance when the breaks allow workers to keep their attention on the focal task. These studies collectively suggest that humans should not be treated like machines and individual discretion is important to performance improvement.

Although workers directly control their effort level at work, employers can indirectly influence workers' effort level by triggering a response from workers to an external or peer stimulus. Prior studies have identified triggers such as workload imposed on servers (Tan and Netessine 2014) or perceived peer productivity (Tan and Netessine 2019). These triggers can be fine-tuned by employers by creating or changing policies or routines that may be friendly to workers and at the same time can influence worker behaviors to improve performance. Our study adds to the people-centric operations literature by looking into the productivity implications of work schedule consistency. By designing more consistent schedules for workers, an employer can not only promote workers' well-being but also increase their productivity.

To summarize, although firms have started offering employees more work hour flexibility and advance notice of work schedule, few have explicitly prioritized individual workers' schedule consistency. Empirical research on work scheduling focuses mostly on the effects of work schedule on workers' well-being, and only a few have examined the effects on individual workers' performance. With few exceptions, prior empirical studies rely on self-reported perceptual measures of work schedules. Although it is important to understand employees' perception of their work schedules, these measures can be quite noisy and unreliable. Unfortunately, few data sets are available that allow researchers to construct objective measures of schedule consistency (Schneider and Harknett 2019). Our study attempts to fill some of these gaps by using transaction level retail store scanner data to measure schedule consistency and estimate its impact on cashier productivity.

2.3. Measures of Schedule Consistency

In line with the notions of daily (circadian) and weekly (circaseptan) rhythmicity (Sharma 2003), we develop two measures of schedule consistency: hour-of-the-day (HOTD) and day-of-the-week (DOTW) consistency. We measure HOTD consistency for each hourly slot an employee worked during the two-year study period. For any given hourly slot an employee worked on any given shift, HOTD consistency for the focal hourly slot is operationalized as, among all the days the employee worked during the past four *calendar* weeks, the percentage of days the employee worked in the same hourly slot. For example, if an employee worked seven days in the past four calendar weeks and on five of the seven days the employee worked in the 9 a.m.–10 a.m. slot, the HOTD consistency for the 9 a.m.–10 a.m. slot during the current work shift would be 71.4% (=5/7). All the transactions this employee processed during the 9 a.m.–10 a.m. slot of the focal work shift would be associated with the same HOTD consistency. Our expectation is that, all else being equal, the employee is likely to be more productive in the hourly slots that have higher HOTD consistency.

Similarly, we measure DOTW consistency for each day an employee worked during the two-year study period. For any given day an employee worked, DOTW consistency is operationalized as, among all the weeks the employee worked during the previous four *calendar* weeks, the percentage of work weeks the employee worked on the same day of the week. For example, if an employee worked in three of the past four calendar weeks and in two of the three work weeks the employee worked on Monday (the focal day), the DOTW consistency for the shift on the focal Monday would be 66.7% (=2/3). All the transactions this employee processed on the focal shift would have the same DOTW consistency.

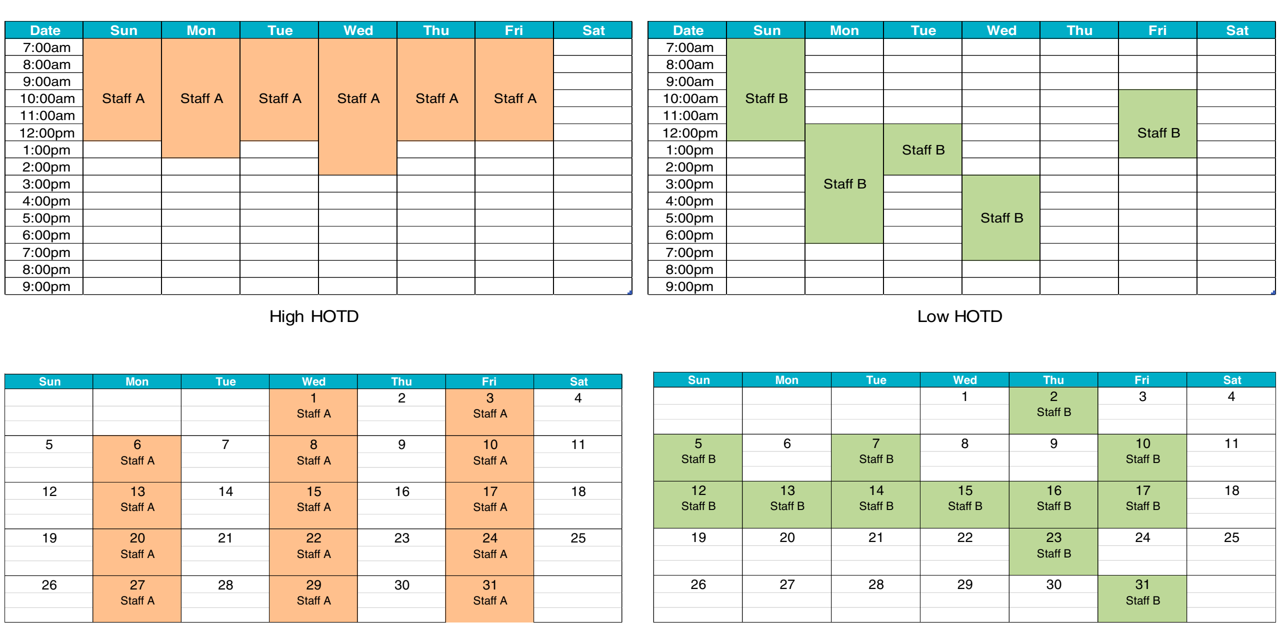
In constructing the two measures, as the denominator, we use prior days or weeks each employee actually worked during the previous 28 calendar days or four calendar weeks because the number of work days or work weeks varies substantially between shift workers and even for the same worker over time. For robustness checks, we test different time windows used for calculating these two measures (i.e., past three, five, and six calendar weeks). Figure 1 shows two examples comparing high HOTD and DOTW consistency with low HOTD and DOTW consistency, respectively. The top panels are weekly work schedules, whereas the bottom panels are monthly work schedules.

In summary, according to our operationalization, a schedule with high consistency is one where work shifts are scheduled in the same hours of the day and on the same days of the week. Alternatively, Kesavan et al. (2021) deem a schedule as consistent when the same number of work hours is scheduled for each week. We note that, based on our conceptualization, even when a shift worker works the same number of hours each week, the employee can still have an inconsistent work schedule if those hours vary from week to week in terms of hours of the day and/or days of the week.

2.4. Hypotheses

Inconsistent work schedules can be detrimental to employee productivity (Golden 2015). First, inconsistent work schedules can disrupt workers' rhythms. Biological

Figure 1. (Color online) Illustration of High vs. Low HOTD and DOTW Consistencies



rhythms allow human bodies to know what to expect and adjust accordingly. Consistent work schedules can help regulate workers' biological rhythms, improve workers' mental and physical health and in turn productivity (Murphy and Cooper 2000). Workers can form habits by following a consistent schedule and get accustomed to performing certain activities at specific times. This helps workers establish routines that can be beneficial to productivity. Research suggests that employees with consistent work schedules can better take advantage of "muscle memory" to achieve higher performance in routine jobs (Refinetti et al. 2015). In contrast, disruption to the biological rhythms can have a negative effect on both the brain and the body (Zhu and Zee 2012), and therefore worsen productivity.

Second, an inconsistent work schedule also makes it more challenging for workers to arrange their nonwork activities, many of which follow a regular daily or weekly schedule (e.g., children's afterschool activities). No matter how advanced the work schedule is posted, inconsistent work schedules can still complicate family or personal responsibilities such as parenting, other forms of caregiving, and schooling (Cauthen 2011). This can take a toll on family relationships and create psychological distress and unhappiness (Schneider and Harknett 2019), which in turn hurts worker productivity.

Finally, work schedule inconsistency also can negatively affect employee commitment and job satisfaction (Scandura and Lankau 1997), leading to reduced productivity. Taken together, a shift worker likely will have higher (lower) productivity if she has a more (less) consistent work schedule.

Hypothesis 1. *Hour-of-the-day work schedule consistency has a positive effect on shift worker productivity.*

In addition to daily (circadian) rhythms, weekly (circaseptan) rhythms can also affect worker productivity (Ayers et al. 2014, Refinetti et al. 2015). A circaseptan rhythm refers to an approximately seven-day cycle within which many biological processes resolve. Disruption to biological rhythms in a weekly cycle can have significant adverse health consequences and hurt work-life balance (Ortiz-Tudela et al. 2014). Following the same logic, we propose the following.

Hypothesis 2. *Day-of-the-week work schedule consistency has a positive effect on shift worker productivity.*

We also hypothesize that work experience can moderate the effects of schedule consistency on productivity because the more experienced a worker is, the more likely she has developed coping strategies to mitigate (but not eliminate) some of the negative impacts of schedule inconsistency. Research suggests that workers can broaden their knowledge and skills through increased experience, which allows them to improve their productivity over time (Narayanan et al. 2009). Exposure to a problem allows a worker to become aware of the problem, develop a response, test the response, evaluate the consequence, and finally confirm or modify the response to the problem (Kolb 1984). Thus, workers' capability to cope with schedule inconsistency should grow with their work experience.

In our research context, over time, a cashier may experiment with different coping mechanisms (e.g., finding a flexible babysitter) and retain the effective ones to lessen the undesirable effects of an inconsistent work schedule. In contrast, inexperienced cashiers likely have been exposed to fewer types of inconsistent work schedules and the associated challenging situations, and thus have not developed effective coping tactics to mitigate the potential negative impacts of inconsistent work schedules. Therefore, inconsistent work schedules should be more detrimental to the productivity of the less experienced workers.

Hypothesis 3. *Work experience moderates the effects of (a) hour-of-the-day consistency and (b) day-of-the-week consistency on shift worker productivity such that their positive effects on productivity are stronger for less-experienced shift workers.*

3. Data and Empirical Strategy

3.1. Research Setting

Our research setting is a local grocer located in the Pacific Northwest of the United States. We worked closely with the company to understand its operations and interacted regularly with its senior management team and store managers. According to the focal grocer, throughout the period under study, each store posted the work schedules for all the cashiers with about the same lead time, and therefore, there was little variation in the amount of advance notice of work schedules across cashiers and over time. The management team expressed a desire to better understand cashier productivity because they believed that improving cashier productivity is important to enhancing customer shopping experience and effective staff planning.

The transaction level scanner data used in our study contains the records of more than 1.2 million shopping baskets checked out by 126 cashiers at two stores in 2016 and 2017. For each transaction, we know (1) the number of items scanned; (2) transaction start and end time; (3) unique employee ID; (4) the payment method; (5) store and terminal ID; and (6) other miscellaneous information such as whether a coupon is used for the purchase or a cash back is requested. We provide below a detailed description of how we create the main variables of interest and the controls.

3.2. Variables

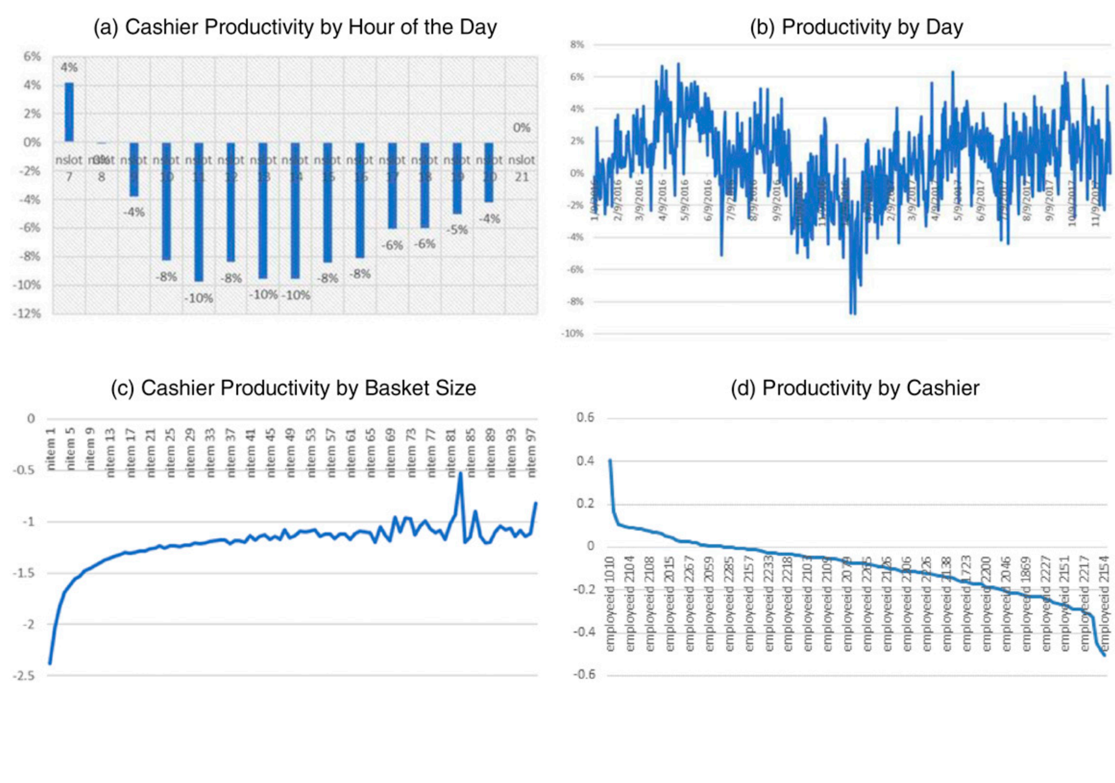
3.2.1. Dependent Variable. We measure cashier productivity for each transaction by dividing the number of items scanned by the transaction time (in seconds). We then transform the variable into its natural logarithm (*Ln_ItemPerSec*) because it is right-skewed (mean = 0.122 > median = 0.097; Albright and Winston 2014). The transformation also facilitates the interpretation of the main effects in terms of percentage changes. Figure 2 suggests that cashier productivity varies across (a) hours of the day, (b) days during our research period, (c) basket sizes (number of items), and (d) cashiers.

3.2.2. Key Variables of Interest. As we elaborated in Section 2.3, we calculate *HOTD* and *DOTW* to measure work schedule consistency pertinent to the transaction in question. The same *HOTD* consistency value applies to all the transactions completed in the same hourly slot by the same cashier. Likewise, the same *DOTW* consistency value applies to all the transactions completed in the same day by the same cashier. In other words, *HOTD* varies by hour and cashier, and *DOTW* varies by day and cashier. In our main analyses, we compute *HOTD* and *DOTW* based on work shift patterns in the last 28 calendar days/four calendar weeks. We change the length of this window in robustness checks.

To measure cashier work experience, we create a variable *Nshifts*, which measures the total number of shifts a cashier has worked since the cashier was hired by the retailer. We consider two scenarios. First, if a cashier was hired during our study period, *Nshifts* for this cashier is simply the number of shifts the cashier has worked since hired up to the current shift. Our data set allows us to compute the precise number of shifts in this situation. Second, if a cashier was hired prior to the beginning of our study period, we need to estimate the number of shifts worked before our study period. In this case, *Nshifts* is the sum of two components. The first component is the total number of shifts a cashier had worked from the beginning of our study period until the current shift. The second component is the estimated work shifts prior to our study period, which is computed as the product of (a) the average number of work shifts per calendar week during our study period (i.e., the total number of shifts worked in our study period divided by the total number of calendar weeks observed in our study period) and (b) the number of calendar weeks since the hiring date until the beginning of our study period. In summary, the *Nshifts* measure varies by shift and cashier, and reflects the experience a cashier had accumulated since hired by the retailer up to the focal shift.

3.2.3. Controls. We use a number of control variables to ensure the validity of our inferences. First, research suggests that shift workers adjust their efforts based on perceived workload (Allon and Kremer 2019, Delasay et al. 2019), which can be correlated with work schedules. Thus, we create a proxy for perceived workload by counting the total number of baskets processed in an hour at each store and dividing it by the number of active checkout terminals at the focal store-hour. Second, a cashier may develop routines over time that

Figure 2. (Color online) Variation in Cashier Productivity



make the cashier more efficient in scanning items, and it is conceivable that a worker with improving productivity may be rewarded with a more consistent work schedule, which would imply reverse causality (i.e., past productivity influences current work schedule and is correlated with current productivity). This threat cannot be accounted for by including time invariant cashier fixed effects, which only provide control for baseline differences in cashier productivity. To alleviate this concern, we include productivity change as a control, which is operationalized as the change in productivity from the month before last to the previous month. A cashier's productivity in a particular month is operationalized as the total number of items scanned by the cashier during the month divided by the total number of seconds spent checking out those items. By including the productivity change variable, we directly control for within-worker, cross-time productivity variation. We log-transform the measures of perceived workload and lagged productivity (before computing productivity change) to account for skewness. In addition to productivity change, we separately use productivity in the previous month as an alternate (and stronger/more conservative) control for within-worker, cross-time variation in productivity and find consistent results.

Third, we measure *clopening*, which indicates whether an employee closes the store at night and then opens the store the next morning, a controversial but not-so-rare practice. We create a dummy variable that has a value of one (and zero otherwise) if the focal cashier worked in both the 7 a.m.–8 a.m. slot of a day and the 9 p.m.–10 p.m. slot (the last operating hour of the grocer) in the previous evening. Fourth, we include a fixed effect for each operating hour of the day (i.e., 7 a.m. through 10 p.m., or 14 dummies for 15 hourly slots) to account for differences in cashier productivity throughout the day.

Fifth, we include a fixed effect for each unique shopping basket size to account for the fact that the amount of time it takes to check out a shopping basket does not increase linearly with the number of items in the basket. Instead of imposing a particular functional form on the relationship between the number of items scanned per second and the shopping basket size, we estimate a fixed effect for each unique shopping basket size (from 1 through 98), thus capturing the baseline cashier productivity for each shopping basket of a given size. Sixth, we include a fixed effect for each store operating day during our study period. These daily dummies can control for any factors that vary by day but affect all cashiers in a similar fashion (e.g., holidays, special events, and inclement weather).

Seventh, we include a fixed effect for each cashier in our data. These cashier dummies can control for any factors that vary by cashier but stay the same throughout the study period (e.g., intrinsic ability and work ethics). Eighth, we include a fixed effect for each terminal in each store, which should control for any store-terminal idiosyncrasies that may affect checkout speed.

Ninth, we include a fixed effect for each type of payment method (e.g., cash, credit card, check, debit card, and gift card), which should control for the effects of payment methods on checkout speed. Finally, we include a set of fixed effects to control for whether a transaction involves (1) coupon redemption, (2) employee discounts, (3) request for cashback, or (4) vouchers of returned bottles. These activities can affect the amount of time it takes to complete a transaction.

Table 2 presents descriptive statistics and correlations of the key variables of interest in our analysis. The data used to estimate our empirical model contains a total of 1,238,418 transactions completed by 126 cashiers over two years. We note that the two schedule consistency variables are not highly correlated. We also checked the variance inflation factor (VIF; Aiken and West 1991) in all models to ensure it is below 10 (Hair et al. 1995).

3.3. Model Specification

We use the following regression model to estimate the effects of work schedule consistency on cashier productivity:

$$\begin{aligned} Ln\_ItemPerSec_{ij} = {} & \beta_1 HOTD_{ih(j)} + \beta_2 DOTW_{id(j)} \\ & + \beta_3 Nshifts_{in(j)} + \beta_4 HOTD_{ih(j)} \\ & \times DOTW_{id(j)} + \beta_5 HOTD_{ih(j)} \\ & \times Nshifts_{in(j)} + \beta_6 DOTW_{id(j)} \\ & \times Nshifts_{in(j)} + \gamma Controls_{ij} + \epsilon_{ij}, \end{aligned}$$

where subscript i denotes cashier, j transaction, h the hour of the transaction, d the day of the transaction, and n the shift of the transaction. The term ϵ_{ij} represents independent and identically distributed Gaussian random noises.

3.4. Potential Endogeneity Concerns

Endogeneity concerns in our empirical analyses because of reverse causality and omitted variable bias need to be addressed. We first elaborate that reverse causality is highly unlikely based on contextual arguments. Then, we address omitted variable bias through an extensive list of fixed effects and controls.

Reverse causality arises when the dependent variable (i.e., cashier productivity) affects the key independent variables (i.e., *HOTD* and *DOTW*). There are two types of reverse causality (Bellemare et al. 2017) depending on the time sequence: codetermination (also known as simultaneity, Wooldridge 2008) and sequential determination. Codetermination or simultaneity should not be a concern because our dependent variable is calculated at the current transaction level, whereas

Table 2. Descriptive Statistics of the Key Variables of Interest and Pearson Correlation Coefficients

Variable	Mean	Standard deviation	Median	Minimum	Maximum	(1)	(2)	(3)	(4)
(1) *Ln_ItemPerSec*	−2.37	0.67	−2.33	−6.93	3.58	1.00			
(2) *HOTD*	0.71	0.28	0.79	0.00	1.00	**0.013**	1.00		
(3) *DOTW*	0.79	0.29	1.00	0.00	1.00	**0.022**	**0.255**	1.00	
(4) *Nshifts*	544.79	660.56	317.03	2.00	3,356.26	−0.001	**0.116**	**0.135**	1.00

Notes. The number of observations is 1,238,418. Bold denotes statistical significance at the 0.001 level. We report *Ln_ItemPerSec* because it is the variable used in our regression model. When raw data are considered, mean = 0.093, standard deviation = 1.95, median = 0.097, minimum = 0.001, and maximum = 35.87.

our key independent variables are calculated based on how shifts were scheduled in the past. As for sequential determination, in theory, the focal grocer could have scheduled an individual cashier's shifts considering her past productivity, which can be correlated with her current productivity. We checked with the focal grocer and learned that (a) they did not measure cashier productivity based on items scanned per second, and (b) their scheduling decisions were based on store-level staff capacity needs and did not factor in the productivity of individual cashiers. The above contextual arguments aside, to further alleviate the concern that more productive cashiers could be assigned more consistent work schedules, we include a fixed effect for each cashier, which controls for the unique baseline productivity of each cashier. Moreover, we include a within-worker time-variant measure of productivity change for each cashier to control for the possibility that as a cashier becomes more/less productive over time, the focal grocer may assign her work schedules that are more/less consistent.

Omitted variable bias arises when factors not included in the regression can affect both productivity and schedule consistency of shift workers. We mitigate this concern by using the control variable approach (Olivares et al. 2012, Batt and Terwiesch 2015, Shang et al. 2017) with an extensive set of fixed effects and controls.

In our context, omitted variables could affect our estimation in several ways. First, both schedule consistency and productivity can be affected by store- and terminal-specific factors. For example, store location or terminal layout can affect customer traffic, which in turn can affect how store managers develop work schedules, assign cashiers to terminals, and how cashiers adjust their checkout speed. We thus include store-terminal fixed effects to control for idiosyncrasies that are unique to each terminal within each store.

Second and in a similar vein, store operating hour factors can affect both shift schedules and cashier productivity. Therefore, we include a fixed effect for each operating hour of the day in our regression.

Third, besides store operating hours, other unobserved time-varying factors can affect both cashier productivity and scheduling. For example, store managers may adjust shift schedules in order to accommodate a special local event or holiday. Cashier productivity is also likely to be influenced by these temporal factors. We thus include a fixed effect for each store operating day to control for these unobserved time-varying factors.

Finally, we include a cashier fixed effect to control for cashier-specific, time-invariant factors that can affect both productivity and work schedule consistency. Furthermore, we include perceived workload (specific to a store-hour) and productivity change (specific to a cashier-shift) to control for store-and-time-variant or cashier-and-time-variant factors that can affect both productivity and work scheduling for each individual cashier.

In summary, although endogeneity threats cannot be completely addressed in nonexperimental studies, with the rich transaction level data for more than 1.2 million shopping baskets checked out by 126 cashiers over a two-year period, we are able to include an extensive list of strong controls, which should mitigate concerns of reverse causality and omitted variable bias because of factors that vary by store terminals, operating hours, days of the study period, cashiers, store hours, and cashier shifts. Our regression models have R^2 of approximately 95%, indicating that omitted variables should not be a major concern.

4. Results

4.1. Main Results

Table 3 reports the results from our regression analyses. We run four models, all with the same controls. In model 1, reported in column 1, we focus on the main effects of the key variables of interest, that is, *HOTD*, *DOTW*, and *Nshifts*. The coefficient estimate of *HOTD* (0.00950) is positive and significant ($p < 0.001$), suggesting that, when a cashier works in an hour-of-the-day slot that she has always been scheduled to work over the past four calendar weeks, she is on average about 0.95% (i.e., $e^{0.00950} - 1$) more productive than when she works in an hour-of-the-day slot during which she has not worked in the past four calendar weeks. In our data set, measures of schedule consistency range from zero to one (Table 2), suggesting the above improvements are possible. Even if a smaller

Table 3. Impacts of Schedule Consistency on Cashier Productivity

	Log of number of items scanned per second			
Dependent variable	(1) Main effects	(2) Main effects + interaction	(3) Moderation effects	(4) Moderation effects (new hires)
HOTD	0.00950***	0.02274***	0.02279***	0.03389***
	(0.00233)	(0.00473)	(0.00498)	(0.00895)
DOTW	0.01631***	0.02279***	0.03926***	0.07932***
	(0.00207)	(0.00413)	(0.00445)	(0.00868)
Clopening	−0.04061†	−0.04024†	−0.03994†	−0.06645†
	(0.02162)	(0.02162)	(0.02162)	(0.03628)
Nshifts	0.00023***	0.00023***	0.00027***	0.00058***
	(0.00002)	(0.00002)	(0.00002)	(0.00011)
Perceived Workload	0.01731***	0.01727***	0.01717***	0.01968***
	(0.00221)	(0.00221)	(0.00221)	(0.00427)
Productivity Change	0.00469	0.00481	0.00379	0.03197***
	(0.00703)	(0.00703)	(0.00704)	(0.01202)
HOTD × DOTW		−0.01856***	−0.01734***	−0.01821*
		(0.00577)	(0.00582)	(0.01095)
HOTD × Nshifts			−0.000003	−0.00027***
			(0.000004)	(0.00006)
DOTW × Nshifts			−0.000032***	−0.00433***
			(0.000004)	(0.00005)
Controls	Included	Included	Included	Included
N	1,238,418	1,238,418	1,238,418	348,200
Adjusted R^2	0.94890	0.94890	0.94890	0.94936

Notes. In addition to perceived workload and productivity change, the following control variables are included in all models as fixed effects (960 in total): 14 hour of the day dummies, 98 number of items scanned dummies, 699 day of the study period dummies, 1 coupon use dummy, 1 exchange of cash dummy, 1 employee discount dummy, 1 cashback dummy, 1 return voucher dummy, 8 payment method dummies, 11 store-terminal dummies, and 125 cashier dummies. Standard errors are shown in parentheses.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.1$.

improvement is considered, for example, when *HOTD* improves from the 10th percentile (0.19) to the 90th percentile (1.00), cashier productivity still increases on average by 0.77% ($e^{0.00950\times(1.00-0.19)}-1$). This result supports Hypothesis 1.

Similarly, the coefficient estimate of *DOTW* (0.01631) is positive and significant ($p < 0.001$). This implies that when a cashier works on a day-of-the-week that she has always been scheduled to work over the past four calendar weeks, she is on average about 1.63% (i.e., $e^{0.01631}-1$) more productive than when she works on a day-of-the-week that she has not worked in the past four calendar weeks. When *DOTW* improves from the 10th percentile (0.25) to the 90th percentile (1.00), cashier productivity is expected to increase on average by 1.22% ($e^{0.01631\times(1.00-0.25)}-1$). This result supports Hypothesis 2.

The coefficient estimate of *Nshifts* is positive (0.00023) and significant ($p < 0.001$), suggesting that as a cashier works more shifts, she becomes more productive; on average, for every additional 50 shifts, her productivity increases by 1.2% (i.e., $e^{0.00023\times 50}-1$). This result lends face validity to our empirical analysis and highlights the power of transaction level scanner data in quantifying the effect of work experience on productivity.

The coefficient estimate of *Clopening* is negative (−0.04061) and marginally significant ($p < 0.1$), which is intuitive and highlights the detrimental impact of clopening on employee productivity.

Finally, although not central to our study, the coefficient estimate of *Perceived Workload* is, as one would have expected, positive and significant ($p < 0.001$), which we see as another sign of face validity. The coefficient estimate of *Productivity Change* is positive but insignificant ($p > 0.10$).

In model 2, we add the interaction between *HOTD* and *DOTW* (column 2). The coefficient estimate of the interaction is negative (−0.01856) and significant ($p < 0.001$), suggesting that the benefit of increasing one type of schedule consistency is higher when the other type of schedule consistency is lacking. For example, when $DOTW = 0$, increasing *HOTD* from zero to one increases productivity on average by about 2.3% (i.e., $e^{0.02274}-1$). However, when $DOTW = 1$, increasing *HOTD* from zero to one increases productivity by only about 0.42% on average ($e^{0.02274-0.01856}-1$).

In model 3, to investigate how work experience may moderate the impact of schedule consistency on productivity, we include the interactions between *HOTD* and *DOTW* and the variable *Nshifts*. The results are reported in column 3. The interaction between *DOTW* and *Nshifts* is negative and significant ($p < 0.001$), partially supporting Hypothesis 3. Although the interaction between *HOTD* and *Nshifts* is negative, the estimate is statistically insignificant. Taken together, these results suggest that the positive effect of day-of-the-week consistency on productivity

Table 4. Robustness Checks using Different Time Windows

	Log of number of items scanned per second		
Dependent variable	(1) Three weeks	(2) Five weeks	(3) Six weeks
HOTD	0.02250***	0.02427***	0.02445***
	(0.00479)	(0.00510)	(0.00517)
DOTW	0.03659***	0.04241***	0.04511***
	(0.00423)	(0.00460)	(0.00473)
Clopening	−0.04158†	−0.03964†	−0.03994†
	(0.02162)	(0.02162)	(0.02162)
Nshifts	0.00027***	0.00027***	0.00027***
	(0.00002)	(0.00002)	(0.00002)
Perceived Workload	0.01704***	0.01724***	0.01718***
	(0.00221)	(0.00221)	(0.00221)
Productivity Change	0.00180	0.00450	0.00474
	(0.00716)	(0.00703)	(0.00703)
HOTD × *DOTW*	−0.01901***	−0.01903***	−0.02040***
	(0.00551)	(0.00604)	(0.00620)
HOTD × *Nshifts*	−0.000003	−0.000004	−0.000003
	(0.000004)	(0.000004)	(0.000004)
DOTW × *Nshifts*	−0.000026***	−0.000036***	−0.000040***
	(0.000004)	(0.000004)	(0.000004)
Controls	Included	Included	Included
N	1,237,562	1,238,646	1,238,926
Adjusted R^2	0.94886	0.94887	0.94887

Note. Like the main analyses, the same set of fixed effects (960 in total) are included in all the robustness check models. Standard errors are shown in parentheses.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.1$.

is greater for less-experienced cashiers, whereas the positive effect of hour-of-the-day consistency does not appear to vary significantly across cashiers with different experience levels.

Because model 3 results suggest that the effects of schedule consistency can be stronger for less-experienced cashiers, in model 4, we separately analyze data from the 48 cashiers who were hired during our study period. This subsample analysis on the new hires shows much stronger effects of schedule consistency on productivity. Specifically, for the new hires, when *HOTD* and *DOTW* increase from zero to one, productivity increases on average by 3.39% and 7.93%, respectively. When *HOTD* and *DOTW* increase from the 10^{th} percentile to the 90^{th} percentile, the productivity improvements for the new hires are on average 2.75% and 5.95%, respectively. Furthermore, for the new hires, the interactions between *HOTD* and *Nshifts* and between *DOTW* and *Nshifts* are both negative and significant ($p < 0.001$), with a magnitude that is greater than their full sample counterparts. Taken together, results from the subsample analysis suggest that the productivity boost from work schedule consistency is the greatest for a newly hired cashier and the boost weakens as the employee accumulates work experience, lending support to Hypothesis 3 and highlighting the particular relevance of schedule consistency to the least experienced shift workers and to businesses that employ a large portion of inexperienced shift workers.

4.2. Robustness Checks

To ensure the robustness of our findings, we conduct several checks. First, we operationalize *HOTD* and *DOTW* using time windows different from the four-week window used in the main analyses. As alternatives, we use three-, five-, and six-week windows. The results are all qualitatively consistent, with the same coefficient estimate signs and significance levels (Table 4). We focus on four weeks in our main analyses because the focal grocer's cashier shift schedules are typically planned on a monthly basis.

Second, in the main analyses, we assign the same weight to each of the past four calendar weeks when calculating *HOTD* and *DOTW*. As a robustness check, we assign higher weights to more recent weeks in the four-week window used to calculate *HOTD* and *DOTW*. We test three alternative sets of weights, {0.4, 0.3, 0.2, 01}, {0.4, 0.4, 0.1, 0.1}, and {0.3, 0.3, 0.2, 0.2}, based on the notion that schedule consistency could be driven more by shift patterns from the more recent past than the more distant past. Again, the results (Table 5, columns 1–3) are qualitatively consistent with those of the main analyses, with the same coefficient estimate signs and significance levels.

Third, our *clopening* measure in the main analyses considers only the store opening hour (7 a.m.–8 a.m.). We create a new *clopening* dummy and set its value to one if an employee worked during any of the first three morning hours (7 a.m.–10 a.m.) after having worked the closing hour (9 p.m.–10 p.m.) in the

Table 5. Robustness Checks Using Different Weights/Clopening/Work Experience Variable

	Log of number of items scanned per second				
Dependent variable	(1) Different weights {0.4, 0.3, 0.2, 0.1}	(2) Different weights {0.4, 0.4, 0.1, 0.1}	(3) Different weights {0.3, 0.3, 0.2, 0.2}	(4) Different clopening	(5) Different work experience
HOTD	0.02285***	0.02402***	0.02732***	0.02296***	0.02552***
	(0.00485)	(0.00482)	(0.00499)	(0.00485)	(0.00510)
DOTW	0.03606***	0.03678***	0.03968***	0.03611***	0.04162***
	(0.00429)	(0.00425)	(0.00445)	(0.00429)	(0.00456)
Clopening	−0.03985†	−0.04061†	−0.04003†	−0.02266†	−0.03964†
	(0.02162)	(0.02162)	(0.02162)	(0.01289)	(0.02162)
Nshifts (Nweeks in (5))	0.00026***	0.00026***	0.00027***	0.00027***	0.00191***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00019)
Perceived Workload	0.01719***	0.01720***	0.01717***	0.01713***	0.01683***
	(0.00221)	(0.00221)	(0.00221)	(0.00221)	(0.00221)
Productivity Change	0.00424	0.00434	0.00393	0.00427	0.00436
	(0.00704)	(0.00704)	(0.00704)	(0.00704)	(0.00705)
HOTD × *DOTW*	−0.01692**	−0.02133***	−0.01944***	−0.01700***	−0.02023***
	(0.00555)	(0.00554)	(0.00582)	(0.00555)	(0.00579)
HOTD × *Nshifts*	−0.000002	−0.000002	−0.000002	−0.000002	−0.000018
	(0.000004)	(0.000004)	(0.000004)	(0.000004)	(0.000018)
DOTW × *Nshifts*	−0.000026***	−0.000023***	−0.000030***	−0.000027***	−0.000120***
	(0.000004)	(0.000004)	(0.000004)	(0.000004)	(0.000015)
Controls	Included	Included	Included	Included	Included
N	1,238,418	1,238,418	1,238,418	1,238,418	1,238,418
Adjusted R^2	0.94886	0.94886	0.94886	0.94886	0.94886

Note. Like the main analyses, the same set of fixed effects (960 in total) are included in all the robustness check models. Standard errors are shown in parentheses.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$.

previous evening. The average effect of *clopening* on cashier productivity is still negative and marginally significant but becomes smaller (Table 5, column 4). This result is expected because the employee would have had more rest before coming back to work in the alternative measure of *clopening*.

Fourth, we create an alternative measure of work experience—*Nweeks*, which is operationalized as the actual number of weeks worked during the study period plus the estimated number of weeks worked prior to the study period (the latter only applies to cashiers hired before our study period, assuming a cashier had the same percentage of work weeks prior to and during our study period). The results (Table 5, column 5) are again qualitatively consistent with the main analysis results, with the same coefficient estimate signs and significance levels.

4.3. Post Hoc Descriptive Analyses

In the post hoc analyses, we attempt to look into (1) whether workers' average productivity change is correlated with their average schedule consistency and (2) whether workers' average schedule consistency is correlated with retention. These are purely descriptive analyses and in no way suggest causality. Although the focal grocer did not explicitly consider cashier productivity when assigning work schedules, store managers might still give preferential treatment (e.g., a consistent work schedule) to those they perceived to be effective workers. Table 6 reports the descriptive statistics of five variables: *HOTD*, *DOTW*, *fixed employee effect*, *employee productivity change,* and *retention* (i.e., whether an employee stayed with the focal grocer through the end of our study period). Except for the 126 *fixed employee effects* and *retention* dummy, the other variables are averaged over the study period by cashier. The correlation coefficients suggest that cashiers with high baseline productivity (as manifested in a large and positive fixed employee effect estimate) tend to get more consistent work schedules, suggesting that it is possible store managers could have given more consistent schedules to those who are perceived as more effective. However, productivity change does not appear to correlate with schedule consistency or retention. Future research needs to look into causal evidence in addition to this preliminary correlational evidence.

Next, we examine the correlations between *HOTD*, *DOTW*, and the *retention* dummy, which is assigned a value of one if the cashier stayed with the grocer at the end of the study period and zero otherwise. As shown in Table 6, although *HOTD* consistency has negligible correlation with *retention*, *DOTW* consistency has positive and significant correlation with

Table 6. Descriptive Statistics and Pearson Correlation Coefficients

Variable	Mean	Standard deviation	Median	Minimum	Maximum	(1)	(2)	(3)	(4)	(5)
(1) *HOTD*	0.47	0.25	0.47	0.02	0.99	1.00				
(2) *DOTW*	0.58	0.25	0.64	0.00	1.00	**0.707**	1.00			
(3) *Fixed employee effect*	−0.15	0.15	−0.12	−0.83	0.10	**0.309**	0.260*	1.00		
(4) *Productivity change*	0.01	0.05	0.01	−0.21	0.37	0.030	0.029	0.157	1.00	
(5) *Retention*	0.48	0.50	0.00	0.00	1.00	0.065	0.269*	0.042	−0.098	1.00

Notes. The number of observations is 126. Bold (*) denotes statistical significance at the 0.001 (0.01) level.

retention, suggesting that giving consistent day-of-the-week schedules to workers perhaps can improve employee retention, although the simple correlation needs to be further investigated using research designs that would allow causal inference.

5. Discussion

Inconsistent day-to-day and week-to-week work schedules can interfere with nonwork activities and create mental and physical strains on shift workers by disrupting the rhythm of effort-recovery process—time needed for rest between shifts (Golden et al. 2013, Wood et al. 2013). Our analyses of a large amount of transaction level scanner data in the context of a local grocer show that work schedule inconsistency can significantly lower shift worker productivity, and this effect is stronger for less-experienced workers, especially for the newly hired workers.

Our study extends the staff planning and work scheduling literature by investigating the effect of work schedule consistency on individual shift workers' productivity. Our study contrasts with the relevant literature that focuses on system level performances and adds to the scant literature that looks into the effects of individual workers' schedules on their performances. This is an important extension to the OM literature, which has seen a growing emphasis on people-centric operations that emphasize individual discretion, looking into environmental and managerial variables that affect individual workers' performance while considering employee well-being. Our research provides concrete evidence that shift workers' productivity can be affected by environmental factors and should not be assumed to be constant. Our study adds schedule consistency to the list of relevant factors shown to affect workers' performance, such as perceived workload (Tan and Netessine 2014), coworkers' ability (Tan and Netessine 2019), and more closely related to our work, predictability of work schedules (Kamalahmadi et al. 2021).

From an OM perspective, staff planning can take a step further from considering the optimal staff capacity to meet the demand. Employers should be mindful about scheduling individual workers' work days and hours, as opposed to treating them as indifferent capacity units that can be plugged into any time slots as needed. Providing consistent work schedules apparently is beneficial to workers' well-being, as the literature has demonstrated. Our study further suggests that doing so can actually be beneficial to the employer because workers can become more productive under a more consistent work schedule, not to mention increased employee morale, job satisfaction, and retention, as well as increased customer satisfaction because of enhanced employee performance. Our findings should prove useful to multiple stakeholders, from employers to shift workers and lawmakers who push for fair schedules for shift workers.

Practically, our study shows that work schedule consistency should and can be measured at different levels. Our finding shows that, on average, hour-of-the-day consistency and day-of-the-week consistency can improve productivity by about 1% and 1.6%, respectively, suggesting that managers should evaluate individual workers' schedule consistency at both hourly and daily levels and try to increase at least one type of consistency depending on which one is easier to implement, especially for workers whose schedules have neither type of consistency. If an employer can choose to improve either one, then priority should be given to day-of-the-week consistency, which has a greater positive effect on productivity.

Our study also shows that less experienced workers benefit more from schedule consistency, especially day-of-the-week consistency, as indicated by the negative and significant moderation effect of cashier experience. Schedule consistency is particularly helpful in increasing new hires' productivity. These findings collectively suggest that there can be unintended consequences when managers reward experienced employees with more consistent schedules and leave the inexperienced and new hires with less consistent schedules. To maximize the overall benefit of schedule consistency, managers perhaps should prioritize work schedule consistency for less experienced employees, especially for new hires whose work hours and work days tend to be the least stable (Zeytinoglu et al. 2004, Henly et al. 2006), yet who have not developed routines that can help them cope with schedule inconsistency. If dynamic (inconsistent) work schedules are unavoidable, retailers may assign them to experienced cashiers. While it is reasonable to reward employee loyalty and tenure with schedule consistency (the post hoc analysis suggests *DOTW* consistency is positively correlated with *retention*), perhaps employers can find other ways to do so, balancing between the operational benefits gained by offering more consistent schedules to new hires and the need to recognize loyal employees and retain them. Our findings could have significant economic implications for businesses whose labor force comprises a large share of less-experienced shift workers.

To our best knowledge, our study is the first to quantify the detrimental effect of the controversial practice of clopening on shift worker productivity. Although clopening is not a general schedule consistency measure, we include the variable in our regression models and find negative effects on cashier productivity. Our robustness check suggests that the negative effect weakens when cashiers have a couple more hours of rest between closing and opening shifts. Because clopening not only worsens shift workers' well-being, but also reduces their productivity, unless there are compelling reasons, managers should minimize clopening when developing individual work schedules. In case clopening cannot be avoided, managers should set a minimum amount of rest time for the employees assigned to clopening shifts.

Finally, our study can potentially lend support to the push for fair scheduling legislations. Although few would question the benefits of consistent work schedules to shift workers, employers may be concerned about reduced operational efficiency as a result of schedule consistency constraints. The empirical evidence presented in our study highlights the economic benefits of consistent work schedules, which can alleviate, at least partially, employers' concerns that providing consistent work schedules could hurt efficiency.

We see a few promising avenues for further research. First, our data are drawn from one grocery chain. Although this research design is adopted in many empirical OM studies (Fisher and Ittner 1999), it can limit the generalizability of our findings. Also, our productivity measures are specific to cashiers. The findings do not necessarily generalize to other types of jobs (e.g., sales associates or call center staff). Future studies should validate our findings by estimating the effects of schedule consistency on workers' productivity for different job types across a variety of industries. Second, our data span only two years, and we focus on the short-term effects of work schedule consistency. With longer time-series data, future research can investigate the long-term effects of schedule consistency and determine how long these effects persist. Third, future research can explore a broader set of antecedents and consequences of schedule consistency. Our posthoc analyses provide some preliminary and correlational results in this regard but more rigorous investigations are needed. Finally, future research can attempt to develop a schedule optimizer that considers not only demand and aggregate staff capacity but also the productivity and schedule consistency of individual shift workers.

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