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On-Demand Schedules, Worker Absenteeism and Patient Dissatisfaction in Home Care Services

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ABSTRACT

Service companies often adopt on-demand scheduling to balance labor costs and fluctuating market demand. However, research shows that such practices can reduce worker productivity and retention. In this study, we examine how on-demand scheduling affects two critical outcomes: worker absenteeism and patient dissatisfaction. We extend the conceptualization of undesirable scheduling by introducing *schedule discontinuity*—the presence of unpaid interruptions within a worker's daily schedule—alongside the more commonly studied *schedule inconsistency*, or variability in work hours across weeks. Using data on 1.2 million home care visits in a Canadian healthcare provider, we find that both schedule inconsistency and discontinuity significantly increase absenteeism and patient dissatisfaction. Specifically, moving from the 25th to 75th percentile in discontinuity (inconsistency) raises absenteeism by 20.00% (19.29%), and customer complaints by 27.33% (40.27%). To assess the practical implications for employers, we formulate and solve a schedule optimization problem that minimizes schedule discontinuity (or inconsistency), while satisfying demand and supply constraints. Applying a machine learning predictive model to these optimized schedules, we estimate reductions in the probability of absenteeism by 9.5% (8.2%) and in the probability of patient complaints by 7.7% (2.3%), demonstrating that modest scheduling adjustments can substantially improve worker and service outcomes.

1 | Introduction

A growing fraction of the workforce is shifting away from the traditional nine-to-five, five-day work week toward more flexible scheduling arrangements that present not only variation in the number of hours worked, but also in how these hours are distributed over time (Kalleberg 2001; Cappelli 2008; Spreitzer et al. 2017; Bavafa and Terwiesch 2019). This trend partly reflects efforts by employers to improve productivity by offering workers greater autonomy over their schedules (Kelliher and Anderson 2010). However, flexible schedules are often used not simply to benefit employees, but to give employers greater control over when workers are assigned, within their stated availability, to better respond to fluctuating demand and manage labor costs (Lambert 2008; Kamalahmadi et al. 2021)—a practice commonly known as 'workforce on demand' (Spreitzer et al. 2017; Gaskell 2021). These employer-driven on-demand schedules are not a fringe phenomenon affecting just a few worker collectives: close to 16.27% of the more than 9280 workers who responded to the US General Social Survey in six waves from 2002 to 2022

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reported that they experienced unstable schedules imposed by their employers, with the lowest-income workers facing the most irregular schedules. On-demand schedules are particularly common in the service sector. A study of over 30,000 workers employed by large retail and food-service firms in the United States found that 51% had schedules determined solely by their employer, while 37% experienced week-to-week variability (Schneider and Harknett 2019).

On-demand scheduling shifts the burden of accommodating erratic demand onto workers (Kalleberg and Vallas 2018), with potentially negative consequences for their well-being, quality of life, and job performance. Prior research associates on-demand schedules with poorer work-life balance (Henly and Lambert 2014; Golden 2015; Evans and Young 2017; Choper et al. 2022), physical and mental health (Bohle et al. 2004; Cho 2018; Schneider and Harknett 2021), parenting mood (Ananat and Gassman-Pines 2020), and overall worker well-being (e.g., Zhou et al. 2019). These adverse consequences have underscored the existence of limits to human flexibility and have triggered a public policy debate about the need to regulate and limit the use of irregular schedules for low-wage jobs (Wogan 2017; Piasna 2019).

Recent studies have begun to illuminate how worker performance is affected by on-demand schedules, focusing on two facets: unpredictability (i.e., impromptu schedule changes) and inconsistency (i.e., variation of the schedule within and across weeks). Schedule unpredictability has been found to decrease restaurant servers' sales efforts (Kamalahmadi et al. 2021) and schedule inconsistency has been found to decrease grocery store cashiers' work pace (Lu et al. 2022). Moreover, improving schedule consistency and predictability, together with other aspects of scheduling practices for retail store workers, has been found to improve retail store labor productivity (Kesavan et al. 2022). Schedule inconsistency of full-time salaried nurses working in home health care was also found to increase nurse voluntary turnover—a known hindrance to operational performance (Bergman et al. 2023).

In this paper, we make two key contributions to the burgeoning efforts to understand the impact of on-demand schedules on worker performance. First, we expand the conceptualization of the undesirable features of on-demand schedules to include discontinuity, which we define as the presence of unpaid interruptions within a worker's schedule during a workday. The undesirability of discontinuity for performance is predicated on the idea that transitions between work and non-work activities are costly for workers. Transitioning between the work and non-work spheres consumes workers' time and mental resources (Evans et al. 2015; Monsell et al. 2000; Kinnunen et al. 2017), diminishing the extent to which idle time between tasks can be effectively used for personal purposes.

Second, we extend existing research on the performance effects of on-demand schedules by examining outcomes beyond productivity (Kamalahmadi et al. 2021; Lu et al. 2022). Specifically, we explore how caregivers' on-demand schedules influence both their absenteeism and the patient complaints related to their service delivery. In caregiving services, reducing absenteeism is critical to maintaining the quality and continuity of care. Patient complaints, meanwhile, reflect potential risks to patient well-being that transcend efficiency considerations. In fact, both absenteeism and patient complaints pose serious risks to business continuity and reputation (Silverman and Boyette 2019; Carolino 2023; England and Wales High Court 2023; Pierson 2024), making it essential to understand whether on-demand schedules contribute to these issues. Additionally, continuity and quality of service in the caregiving sector carry significant societal implications, especially given the rising prominence of the homecare industry. In the United States alone, over 3.4 million caregivers were employed in 2020, and they are expected to exceed 4 million by 2026 (U.S. Bureau of Labor Statistics 2021). Globally, the home healthcare market is expected to increase by 3.1% from 2022 to 2030, reaching 4 billion U.S. dollars (Future Market Insights Report 2022).

Our study leverages granular data collected from a Canadian home healthcare service organization to examine the impact of on-demand scheduling practices. This context is particularly suitable for our analysis due to the pervasive use of on-demand schedules within the organization, aligning with broader trends observed in the homecare sector (Oh 2017; Campbell 2019). At the time of data collection, absenteeism and poor customer care were critical issues for the organization, representing significant concerns for its leadership.

We explore the relationship between on-demand scheduling features (i.e., inconsistency and discontinuity) and caregiver absenteeism and patient complaints by constructing a weekly panel dataset. For each working week, the dataset captures independent and dependent variables, along with a vector of covariates that capture detailed information on patient visits conducted between January 2012 and December 2016 (75,078 observations). We use Poisson worker fixed-effects models to estimate the effects of schedule discontinuity and across-week schedule inconsistency on worker absenteeism and patient complaints. Results are robust to the estimation using the control function approach to account for potential endogeneity of schedule inconsistency and discontinuity (Akturk et al. 2022). Effect size estimates indicate that schedule inconsistency and discontinuity cause nontrivial levels of absenteeism and patient complaints for the homecare organization that we study.

We also conduct a policy simulation study to investigate how much absenteeism and patient complaints can be reduced through feasible and cautious reductions of schedule inconsistency and discontinuity, given capacity and demand constraints for the studied organization. Specifically, we develop a scheduling policy that minimizes discontinuity (or, alternatively, inconsistency), allowing a shift of at most 30 min in the starting time of each appointment while maintaining the same sequence of daily assignments to each caregiver as initially set by the unit's planners. These minor timing shifts are inconsequential to customers, who typically express their preferences in terms of large time windows (e.g., 4 h) in which they desire to be attended. Finally, we apply a machine learning predictive algorithm to estimate the effects of these policies and find that they reduce the probability of caregiver absenteeism by 9.5% (8.2% when the policy mandates inconsistency minimization) and the probability of patient complaints by 7.7% (2.3% for inconsistency minimization) compared to those associated with the actual schedule.

Our findings provide novel and compelling evidence that inconsistent and discontinuous schedules can undermine worker outcomes, even when workers can restrict the timeframes in which their employer can schedule them, as is the case in our setting. We also find that substantial improvements in caregivers' attendance at work and patient satisfaction can be attained with minor scheduling changes that do not clash with patients' requirements. This finding challenges the oversimplified statement in the literature that on-demand schedules are a necessary reflection of employers' decisions to pass on to workers the burden of serving irregular demand patterns (e.g., Schneider and Harknett 2021). In fact, our policy simulation indicates that worker outcomes could be improved with reductions in schedule discontinuity and inconsistency that would still satisfy the changing needs of the patients. This suggests that schedule inconsistency and discontinuity can partially originate from a lack of awareness of the true impact of these schedules on worker outcomes and from the lack of planning tools that can assist planners in avoiding unnecessary schedule inconsistency and discontinuity. In the pursuit of adapting to uncertain customer demand, managers responsible for creating on-demand schedules should consider the consequences of undesirable characteristics of workers' schedules. Likewise, policymakers interested in patient care should promote legislation and instruments that incentivize caregiving organizations to update the digital infrastructure they use to plan caregivers' work.

2 | Background and Research Setting

2.1 | Background

Firms commonly rely on labor volume flexibility (for short, labor flexibility) to adapt to fluctuations in demand. Labor flexibility is especially critical within service industries, such as healthcare, retail, call centers, or hospitality. Traditionally, companies have pursued labor flexibility by paying overtime to full-time employees, hiring part-time workers to cover systematic demand peaks within some time interval (day, week, etc.), and relying on temporary workers to meet more irregular demand (Korunka 2021).

In recent years, companies have begun to adjust workers' schedules to demand, interrupting the schedule when there is no demand, or significantly modifying it across time while paying workers only for the hours worked (De Stefano 2015). This on-demand scheduling represents a sharp departure from consolidated labor relations, as it transfers to the workers the costs of adjusting to demand variability. Concomitantly, research in organizational behavior and sociology has investigated the consequences of on-demand schedules for workers, highlighting the negative effects on work-life balance (Golden 2015), health (Cho 2018; Ananat and Gassman-Pines 2020), and psychological distress (Schneider and Harknett 2019), independent of income considerations.

More recently, research in operations management has begun to explore the implications of on-demand scheduling for workers performance, particularly focusing on different facets of worker productivity. Kamalahmadi et al. (2021) investigate how schedule unpredictability affects the productivity of servers at 25 full-service casual dining restaurants, measured by the sales they generated from the customers they served. The authors operationalize unpredictability both as (1) schedules that are released 2 days before the day of service (short-notice schedules) and as (2) schedules that are released the same day of service (real-time schedules). They find that, compared to regular schedules, which are posted 1 week before the day of service, real-time schedules reduce server productivity by 4.4%, while short-notice schedules do not cause a significant change in server productivity. The analysis also suggests that the productivity loss is driven by reduced upselling and cross-selling efforts under real-time scheduling. Lu et al. (2022) investigate the effect of schedule consistency on the productivity of cashiers at a retailer. The authors propose two operationalizations of schedule consistency: (1) hour-of-the-day consistency (percentage of days the employee worked in the same hourly slot in the 4 weeks preceding the focal transaction) and (2) day-of-the-week consistency (percentage of work weeks the employee worked on the same day of the week in the 4 weeks preceding the focal transaction). They find that cashier productivity, measured as work pace, increases by 0.77% when hour-of-the-day consistency rises from the 10th to the 90th percentile, and by 1.22% for the same change in day-of-the-week. For new hires, these effects are even stronger, rising to 2.75% and 5.95%, respectively. Kesavan et al. (2022) study the implementation of sustainable scheduling practices in 28 retail stores across two U.S. metropolitan areas. Their multicomponent intervention, which simultaneously improves schedule consistency and predictability, increases average weekly hours and gives workers more control over their schedules, resulting in a 5% improvement in store productivity, driven by higher sales and decreased labor hours.

Other studies have focused on the effects of on-demand schedules on voluntary turnover—a phenomenon that can significantly undermine firm performance due to operational disruptions, replacement costs, employee morale, and poor service quality (e.g., Hausknecht et al. 2009; Hausknecht and Holwerda 2013; Reilly et al. 2014). Bergman et al. (2023) examine how the inconsistency of schedules assigned to nurses in a homecare setting impacts their likelihood of voluntarily quitting their job. Operationalizing inconsistency as the coefficient of variation across various aspects of the schedule—such as daily hours worked and the length of the workday—within a 28-day moving window—they find that high schedule inconsistency over the course of the year increases the average nurse's probability of quitting by 20%. Similarly, schedule unpredictability is found to drive employees' voluntary turnover in a longitudinal survey of 50,000 workers employed at 120 of the largest U.S. retail and food service firms between 2016 and 2018 (Choper et al. 2022). Workers subject to on-call schedules are 21% (6% points) more likely to leave their employer than those without on-call shifts. Additionally, those who receive their schedules just 1 to 2 weeks in advance are 35% (9% points) more likely to quit than workers who receive at least 2 weeks of advance notice.

Despite these significant advances, the literature leaves two important open questions that we aim to address with this study. First, while the existing research has established that workers subject to on-demand schedules reduce their effort to the detriment of productivity (Kamalahmadi et al. 2021; Kesavan et al. 2022; Lu et al. 2022), it is not clear whether, and to what extent, on-demand schedules also affect the continuity and quality of the service provided by workers, in particular, absenteeism and client satisfaction. Investigating this potential consequence of on-demand schedules is important because both absenteeism and poor-quality services are sources of operational, reputational, and possibly legal risk for the firm. Second, while past research has investigated the consequences of schedule inconsistency and unpredictability on worker productivity and turnover behavior, research on work-life conflict points to a third problematic feature of on-demand schedules: the cost of transitioning between the domains of work and non-work (Ashforth et al. 2000; Kreiner 2006). To the extent that worker schedules include unpaid daily discontinuities between successive task assignments, the cost associated with these boundary transitions may hinder worker performance, presenting a further challenge for the firm.

2.2 | Research Setting

This study originates from a collaboration with HealthCo (a pseudonym), a leading healthcare service provider in Canada. During the data collection period, HealthCo employed over 15,000 people across more than 250 clinics and 70 home healthcare offices, offering a broad variety of services including eldercare, nursing, physiotherapy, occupational therapy, exercise, behavioral therapy, and nutrition. Our research specifically draws on data from one of HealthCo's home healthcare branches, located in one of Canada's most populous provinces. Within this branch, we focus on healthcare aides (hereafter referred to as "caregivers"), who comprise the majority of the division's workforce, in contrast to specialized professionals like physiotherapists or nurse practitioners. The caregivers are tasked with providing care in patients' homes, not in clinics.

The studied caregivers provide general assistance with a wide variety of tasks, including basic wound care, medication reminders, personal-care tasks (bathing, toileting, oral care), meal preparation, companionship, and basic housekeeping duties. To be eligible to work as a caregiver in the focal province, applicants must be registered with the Care Aide and Community Health Worker Registry, which requires the completion of an approved Health Care Aide education program. The caregivers do not need to be nurse practitioners or to have received any medical training. Workers are paid a base rate per hour, which varies based on their level of seniority, and they are only paid for the hours they work. Workers do not receive an additional premium over their base rate for last-minute changes to their schedules.

The planning process is organized as follows. By the beginning of each month (time t_0) patients and caregivers must communicate their respective needs and availability to planners through a dedicated web-based interface. Patients specify their needs in content (what services they require) and timing (when they need them), with timing preferences expressed as four-hour intervals for the caregiver visit. Caregivers' preferences indicate the exact hours of the day when each caregiver is available for work for each day of the week. There is no guarantee that all available hours will be filled, as this depends on demand and the availability of other caregivers. Yet caregivers are committed to working the assigned hours within their stated availability. During the week (t_0; t_1) planners generate a preliminary schedule for the 2-week period (t_2; t_4), which is shared with caregivers at t_1, to ensure that no errors have been made and to allow for necessary adjustments due to changes in patient needs or, in exceptional cases, in caregiver availability. Planners make the required adjustments during the week (t_1; t_2) and release the finalized ("frozen") schedule at t_2. Schedule execution is controlled daily by planners to accommodate last-minute cancellations by patients or caregivers. The planning process is bi-weekly, such that the subsequent preliminary schedule is generated in the week (t_2; t_3), adjusted during week (t_3; t_4), released at t_4, and executed during (t_4; t_6). The process is organized by departments, each serving a specific section of the city and relying on a dedicated set of caregivers (Figure 1 illustrates the planning stages).

Month 1 week 1 (T0; T0+1)	Month 1 week 2 (T0+1; T0+2)	Month 1 week 3 (T0+2; T0+3)	Month 1 week 4 (T0+3; T0+4)	Month 2 week 1 (T0+4; T0+5)	Month 2 week 2 (T0+5; T0+6)
Communicate changes in caregiver availability Communicate patient needs in content and timing					
Preliminary schedule for M1W3 & W4 generated	Release of schedule Day 1 & 2: communicate changes Day 3 to 5: accommodate changes	Execute schedule Ongoing last minute changes in schedule	Execute schedule Ongoing last minute changes in schedule		
		Preliminary schedule for M2W1 & W2 generated	Release of schedule Day 1 & 2: communicate changes Day 3 to 5: accommodate changes	Execute schedule Ongoing last minute changes in schedule	Execute schedule Ongoing last minute changes in schedule

FIGURE 1 | Illustration of the scheduling process at Health Co.

It is important to underscore that caregivers in this setting can be assigned tasks within their available time during the planning period, but are not contractually bound to accept last-minute requests to serve patients, as in typical on-call settings. The majority of workers (67% of our worker-week observations) report an availability of 40 or more hours per week—a full work week. As the operations leader explains, this is done "to maximize their chances of receiving visits". Yet, their average weekly utilization rate (i.e., number of hours worked divided by number of hours available) is only 35%, meaning that many of their available working hours remain unfulfilled on average. Hours fulfillment is subject to multiple factors that vary from week to week, for example, changes in patients' physical condition or location, patient requests to reschedule visits, and patient turnover. During the study period, an average of 58.53% of patients required a change in the number of homecare visits each month, and an average of 28.12% of the patients either entered or exited the system monthly, reinforcing the notion of constantly changing demand. The combined effect of unfilled hours and demand variability leads planners to create on-demand schedules that, as shown later, incorporate substantial schedule variability for each caregiver across weeks.

3 | Hypotheses

The general framework for understanding the effect of on-demand schedules on worker performance is provided by the literature on work-life conflict (Kirby et al. 2013). Work-life conflict can be defined as a form of inter-role conflict that arises when pressures from the work and non-work domains (e.g., family, friends) are mutually incompatible in some way (Greenhaus and Beutell 1985, 77). Research suggests that one major facet of work-life conflict (refer to Michel et al. 2011 for a meta-analytic review) is *time-based conflict*, which occurs when work-time obligations interfere with an individual's ability to fulfill personal life needs and commitments (Greenhaus and Beutell 1985). Time-based conflict leads to critical negative consequences for workers, including stress, anxiety, and psychological burnout, among others (for a review, see Greenhaus et al. 2006). Workers who experience time-based conflict often respond by engaging in coping behaviors that help reduce its negative consequences; for instance, missing work to accommodate life demands and relieve the stress of being unable to care for children, behaviors which, however, have adverse effects for the organization (Krischer et al. 2010).

Because of the work-time demands they impose, on-demand schedules represent an important source of time-based conflict. Following the previous framework that links undesirable facets of work-life arrangements to workers' coping behaviors, we extend past research in two main directions. First, we examine how on-demand schedules affect two types of outcomes related to coping behaviors: absenteeism and customer complaints. These outcomes both reflect a worker's compliance with basic task requirements, such as being present at work and preventing service encounter failures that result in customer dissatisfaction. Second, in addition to extending the study of the consequences of schedule inconsistency (see Lu et al. 2022; Bergman et al. 2023) to outcomes related to service continuity and quality (i.e., worker absenteeism and patient dissatisfaction), we augment the existing conceptualization of the undesirable facets of on-demand schedules by formalizing the novel construct of schedule discontinuity, which captures the existence of unpaid interruptions within a worker's daily schedule.

Although workers in our setting can block time by specifying their availability, we argue that time-based conflicts between work and non-work time may still arise when this availability is not fully utilized by the employer—a common occurrence in our context. For example, consider a worker who indicates availability for 4 h per day, Monday through Friday (20 h total), but is only scheduled for 8 h of work. The way these eight work hours are distributed within the 20 available hours can significantly affect the worker's ability to make effective use of the remaining 12 non-work hours. A schedule in which the worker is assigned 4 h of work on 2 days may allow them to use their non-work time more effectively than a schedule in which they work 1 h, pause for 2 h, and then work another hour, repeated over 4 days. In other words, simply allowing workers to block time does not eliminate work-time conflic; when a worker's availability is underutilized and non-work time remains unpaid, the distribution of work hours becomes a critical factor.

3.1 | Schedule Inconsistency

Schedule inconsistency is a fundamental feature of on-demand schedules. It captures the extent to which the distribution of hours worked varies across time (e.g., from one day to another or from one week to another). Inconsistent schedules are an important driver of time-based conflict (Zeytinoglu et al. 2004; Henly and Lambert 2014), because they impede workers' ability to establish routines in their personal lives (Messersmith 2007). Personal routines—that is, automatic sets of consecutive actions in everyday life (Avni-Babad 2011)—are essential, as personal activities require planning, coordination, and time commitments with third parties such as family (e.g., time to dine together, to pick up kids), service providers (e.g., personal care, healthcare, courses), friends (periodic get-togethers), among others (Fenwick and Tausig 2001; Allen and Armstrong 2006). Without routinized work schedules, individuals constantly scramble to readjust their lives to meet work demands (Baba and Jamal 1991). Such continuous replanning entails an additional cognitive load, which can progressively deplete the worker's mental resources (Leso et al. 2021). Similarly, schedule inconsistency impairs a worker's ability to establish timings for family or social relationships, creating conflict and misunderstandings that can drive emotional exhaustion (Suleiman et al. 2021). In extreme cases, irregular work routines can alter workers' circadian rhythms and lead to adverse health conditions (Lu et al. 2022; Harknett et al. 2020).

We expect that the cognitive, emotional, and physiological depletion associated with schedule inconsistency prompts workers to miss work. Particularly troublesome is schedule inconsistency across weeks, which occurs when a worker's schedule for a given weekday is not stable (Lu et al. 2022). Many human activities, including family, social, religious, educational, economic, and leisure activities, are organized along weekly Monday-to-Sunday cycles (Gershuny 2011). For example, people often use weekends to plan personal time for the upcoming week and to recharge. Facing a situation where work patterns display significant inconsistency across weeks makes it particularly hard for workers to reserve regular slots for recurring activities, thereby creating ongoing time-based conflict. Across-week schedule inconsistency is especially prevalent for caregivers in our setting: on average, 30% of scheduled hours in a week do not overlap with the scheduled hours in the previous week. Since workers may respond to time-based conflict by adopting coping behaviors, such as absenteeism to gain additional personal time, we anticipate that significant schedule inconsistency will have an impact on worker absenteeism:

H1a. *The inconsistency of a caregiver's schedule across two consecutive weeks is positively associated with that caregiver's absenteeism.*

The perceived quality of the service encounter between patient and caregiver is potentially affected by schedule inconsistency, possibly triggering formal complaints from the patient. Despite the basic nature of the caregiver services considered here, several factors can make a successful service encounter at times challenging (National Health Service 2024). Patients may have cognitive limitations (e.g., dementia) or physical conditions (e.g., sleep deprivation, chronic pain) that limit their ability to behave appropriately and, in the worst-case scenario, may result in aggressive behavior toward the caregiver (Schnelli et al. 2020). Patients may also present certain disabilities, such as limited mobility, which make the caregivers' job physically demanding, or impaired hearing, which hinders proper communication (Höglander et al. 2020). Lastly, patients may have multiple chronic conditions, which require complex medication regimens and monitoring, thereby increasing the risk of errors and the need for meticulous care planning (Moorman and Macdonald 2013).

The combined effect of the unique work challenges faced by caregivers and the physical, cognitive, and emotional exhaustion caused by inconsistent schedules can undermine the success of the service encounters. Stressed-out caregivers may deliver inadequate care (e.g., improper administration of medications), attend unreliably to the patient visit (e.g., late arrivals, rushed interactions), fail to communicate effectively, or even behave in a disrespectful or unempathetic manner (Willows HealthCare 2024); thereby triggering patient complaints reported through formal channels. We therefore expect that:

H1b. *The inconsistency of a caregiver's schedule across two consecutive weeks is positively associated with patient dissatisfaction with that caregiver's service.*

3.2 | Schedule Discontinuity

Workers' ability to extract utility from their personal time is also impacted by the discontinuity of the work schedule, which we define as the extent to which work hours within a given day are subject to unpaid interruptions (hereafter, interruptions). Schedule discontinuity requires workers to extend their working day in order to earn the same amount of income. As shifts lengthen, less personal time remains once the workday ends—a situation that can result in greater psychological distress, poorer sleep quality, and lower overall happiness (Schneider and Harknett 2019).

While it may seem that workers could use the time during the interruptions for personal purposes, various factors limit this option. Practically, the length of an interruption may not provide sufficient time to travel and complete personal tasks (e.g., homecare, grocery shopping) while ensuring a timely return to work. From a cognitive and psychological standpoint, discontinuous schedules consume workers' time and mental resources, reducing the extent to which idle time between tasks can be effectively used for personal purposes. Three mechanisms highlight this adverse cognitive and psychological impact of schedule discontinuity. First, workers must exert mental effort to overcome residual activation from the previous task when transiting to a new one (Evans et al. 2015). Second, when preparing for an upcoming task, especially one that differs from the previous one, workers must retrieve and activate a distinct set of cognitive processes required to perform it (Monsell et al. 2000; Rogers and Monsell 1995). Third, such discontinuous setups hinder workers' ability to disconnect emotionally and cognitively from work, often leading to rumination on past and upcoming tasks, which impairs well-being (Kinnunen et al. 2017; Querstret and Cropley 2012).

In this case as well, absenteeism can be seen as a coping mechanism for workers facing discontinuous schedules. They may seek to recover part of the energy depleted by these interruptions by staying home instead of showing up for work. Likewise, they may purposefully skip work to attend to personal matters that cannot be accommodated within the constrained time slots between consecutive task assignments. These issues are especially relevant in our setting, where schedule interruptions occur multiple times a week: 70.02% of scheduled caregiver-weeks include at least one interruption, and 53.57% include more than one. When these discontinuities occur, it is typically infeasible for workers to reach their homes to attend to personal matters. In fact, in our dataset, the median duration of schedule gaps is 2 h and 15 min (excluding the transit time between patients), while the average round-trip travel time between the preceding patient, the caregiver's home, and the next patient is 2 h and 14 min. Even though caregivers could, in principle, use this time for personal matters not requiring them to be home, our interviews reveal that they struggle to mentally disconnect from work, knowing that they will soon need to show up at another patient's house and be responsible for the quality of care provided. Schedulers in the unit report that these 'time gap' are a primary source of caregiver complaints. Therefore, we hypothesize that absenteeism may serve as an effective coping mechanism for managing the burdens of discontinuous schedules:

H2a. *The discontinuity of a caregiver's schedule during a working week is positively associated with that caregiver's absenteeism.*

As caregivers are aware that the time contained within schedule discontinuities is unpaid, they often attempt to use it for personal reasons, despite the abovementioned difficulties. We expect that these difficulties can adversely affect the quality of care, potentially triggering customer complaints. To begin with, as caregivers attempt to squeeze personal activities into schedule interruptions, they increase the likelihood of arriving late to the patient's home—a frequent complaint among patients in our setting. For the same reason, they may lack sufficient time to properly "set up" for the upcoming visit, increasing the risk of errors in medication administration. More broadly, the stress associated with trying to fit personal activities into fragmented schedules may reduce the caregiver's ability to be empathetic toward the patient, further raising the likelihood of service encounter failures that could potentially trigger formal customer complaints. We therefore propose that:

H2b. *The discontinuity of a caregiver's schedule during a working week is positively associated with patient dissatisfaction with that caregiver's service.*

4 | Data and Variable Definitions

To empirically test our hypotheses, we extract archival data covering 1,252,746 home healthcare visits performed by 1026 caregivers between January 2012 and December 2016 from HealthCo's planning system. For each visit, we observe the date, start and end time, type of service provided, worker identifier, and patient identifier. We complement this data with information about caregivers' schedule preferences, which each caregiver updates monthly to indicate their daily availability. We also collect relevant human resource data, including workers' birth dates and gender, along with a range of other personnel details (e.g., start/termination date in the organization, job title, type of training received,[1] and hourly pay rate). Lastly, we have access to digitally recorded textual information in the form of notes taken daily by schedulers regarding caregiver absences (including the day of the absence and whether it was due to sickness or other non-sickness reasons), as well as patients' formal requests "not to send this caregiver ever again" (no other patient dissatisfaction measures are available). To align our empirical strategy with our theoretical argumentation, which posits that schedule inconsistency impacts caregiver performance by disrupting their ability to establish weekly routines, we conduct the analysis at the weekly level. This approach also enables us to observe the effects of undesirable schedules over an extended period, increasing the likelihood of capturing their impact. Thus, we aggregate the data at the weekly level, resulting in a dataset comprising 75,078 worker-week observations for 1026 caregivers.

4.1 | Dependent and Independent Variables

We measure *caregiver absenteeism* as the total number of days a worker is reported absent in each week due to non-sickness reasons. Consistent with our theoretical focus on the effect of scheduling on workers' coping behavior (rather than on their health), we exclude cases in which the worker is absent due to illness or the need to care for a sick family member. To this end, we use the notes recorded by planners in the system to track the reasons for caregiver absenteeism. The average number of days with absences due to non-sickness reasons in our dataset is 0.07 per worker per week.

We measure *patient dissatisfaction* as the total number of "do not send" requests issued by patients about a specific caregiver during a given week. A "do not send" request is a strong indicator of extremely poor service, as it signals that the patient no longer wants to be served by that caregiver. Common reasons for such requests include consistent tardiness, excessive personal phone use during visits, failure to complete required tasks, and other similar issues. The average number of patient complaints in our dataset is 0.03 per worker per week.

To measure *schedule inconsistency* across weeks, we compute the overlap of time worked and not worked in two consecutive weeks, following a similar method to Lu et al. (2022). To do so, we divide each weekday into 48 30-min slots (9:00–9:30, 9:30–10:00, etc.). For each caregiver, we code each time slot as 1 if they worked in that time and 0 if they were available but did not work. We then subtract the value of each time slot in week (t–1) from the corresponding slot in week (t). We sum the absolute values of the differences across all slots to calculate the inconsistency between 2 weeks. By considering only time slots when the worker was available, we ensure that *schedule inconsistency* captures employer-driven variation. Moreover, we set the value of differences to 0 for days on which the worker was absent in week (t) or in (t–1). We do so to ensure that the schedule inconsistency we observe is due to the scheduling and not due to the worker being absent. The average schedule inconsistency is 21.26 half-hour slots, or 10.63 h, of difference from one week to the next. Because this variable is highly skewed, we apply a logarithmic transformation (adding one to all values). A higher value indicates greater schedule inconsistency.

We measure *schedule discontinuity* as the total number of interruptions a worker experiences during a given week. This measure excludes interruptions that reflect the caregiver's own availability preferences-for example, if a caregiver has reported that they are not available from 12:00 to 13:00, we do not count the lack of visits in that slot as a discontinuity. We exclude interruptions shorter than 30 min, as they may provide rest without meaningfully interfering with private time. However, our post hoc analyses explore alternative cutoffs for interruption length and yield consistent results. To ensure that discontinuity is not driven by absenteeism, we exclude from the calculation any interruptions on days when the worker skipped one or more assigned visits. As with schedule inconsistency, we apply a logarithmic transformation to the discontinuity variable (adding one to all values), due to its skewed distribution. A higher value indicates greater schedule discontinuity.

Interruptions in the schedule are not intended to allow caregivers to travel from one patient to another. In fact, travel times between consecutive patients are automatically calculated by the scheduling system and incorporated into the visit time. The default duration of each visit is set to 1 h (or an integer multiple of 1 h for 74.48% of the visits), but the caregiver's service is contractually stipulated to last 45 min, allowing 15 min for travel to the next patient. However, the scheduling system protects the feasibility of the schedule by automatically computing the travel time, T_{k+1}, required to reach the $(k+1)$th patient (either from the caregiver's home or the previous patient's location). If T_{k+1} is less than 15 min, and the $(k+1)$th patient's care can be completed within 45 min, then the system considers the travel time to $(k+1)$th patient to be included in the patient's 1-h visit window. If either of these conditions does not hold, the system adds T_{k+1} to the duration of the $(k+1)$th visit. These algorithms ensure that caregivers' travel time is compensated, and this calculation of travel time is mandated by the collective agreement that governs the contractual relationship between caregivers and their employers in our empirical setting. Thus, travel between patients is a paid part of a caregiver's job and is distinct from schedule discontinuity, which refers to unpaid idle time.

4.2 | Control Variables

We control for multiple worker-level variables that can affect worker performance and schedule characteristics, potentially biasing the regression estimates. To begin with, we account for *caregiver experience*, as more experienced caregivers could be more compliant when interacting with patients. We do so by including a variable that captures the total number of visits a caregiver has performed since being hired by the company.[2] Second, we control for *caregiver availability*, measured as the number of hours each caregiver chooses to be available for work in a given week. We include this variable because caregivers who make themselves available for fewer hours may be less committed to the job (e.g., they may rely less on the job as their main income source), which could, in turn, be associated with lower compliance and performance. Next, because caregivers may adjust their effort based on the workload of the department, we control for *department workload* by calculating the total number of visits performed by all caregivers in the department during the focal week, divided by the total number of active caregivers in that department-week. We further control for *travel distance*, measured as the average daily distance a caregiver travels during each week. As mentioned earlier, the travel time between visits is included in the total visit duration and is therefore paid for by the company. However, caregivers who travel longer distances may experience greater stress, which could lead to poorer compliance. Because this variable is highly skewed, we apply a logarithmic transformation. Next, given that task variety can influence worker effort, we control for *caregiver task variety*, measured as the number of different activity types the caregiver performs in a given week (e.g., companionship, homemaking, nursing, occupational health, overnight, and personal care). We also control for *caregiver patient variety*, defined as the number of different patients the caregiver has visited over a given week. Finally, we control for *caregiver hours worked*, calculated as the total number of hours a caregiver works during the focal week, since workload, and in particular, fatigue, is a known driver of workers' performance.

We also include controls for patient-level variables that may directly influence our dependent variables. For instance, certain patients may be more prone to submit "do not send" requests. We hence control for *patient prior complaints*, measured as the average number of complaints submitted before the focal week by the patients the caregiver visits in that week. Although this measure is censored for patients present before our observation window, there is no reason to expect that their behavior differs systematically from what we observe during the period. Additionally, patients who have relied on HealthCo services for a longer period may generally be more satisfied and less likely to complain. Thus, we control for *patient seniority*, measured as the number of years between the contract start date and the focal week. We calculate the variable by taking the average seniority of all patients the caregiver visits in a given week.

Next, we control for two external factors. First, we include an indicator for the presence of a public holiday in the week, as this may alter visit demand (i.e., patients canceling more visits to spend time with their families) and may influence the performance of the workers (i.e., reduced motivation). Second, we include the monthly unemployment rate,[3] since poor labor market conditions can affect how workers respond to undesirable schedules (Cappelli and Chauvin 1991).

Furthermore, we include caregiver fixed effects to account for time-invariant individual characteristics, including unobserved worker quality. Because caregivers do not switch departments, these fixed effects also control for unobserved time-invariant department characteristics. We also include time fixed effects (week and year dummies) to account for seasonality and other environmental factors.

TABLE 1 | Summary statistics of main variables of interest.

	Variable	Mean	SD	Min.	Max.
1	*Caregiver absenteeism*	0.07	0.29	0	5
2	*Patient complaints*	0.03	0.18	0	6
3	*Schedule inconsistency*	2.58	1.22	0	5.61
4	*Schedule discontinuity*	1.03	0.84	0	3.26
5	*Caregiver experience*	6.74	1.73	0	10.31
6	*Caregiver availability*	15.31	7.75	1	24
7	*Department workload*	22.82	3.72	1	34.20
8	*Travel distance*	2.86	1.40	0	8.90
9	*Patient prior complaints*	0.59	0.77	0	14
10	*Patient seniority*	2.27	2.08	0	39.12
11	*Caregiver patient variety*	8.15	6.95	1	49
12	*Caregiver task variety*	1.96	1.04	0	6
13	*Caregiver hours worked*	22.82	15.20	0.25	168
14	*Unemployment*	6.14	0.60	4.90	7.50
15	*Public holiday*	0.19	0.39	0	1

Note: Descriptive statistics are presented per caregiver-week (sample size 75,078 observations). Log transformations are reported for Schedule inconsistency, Schedule discontinuity, Caregiver experience, and Travel distance.

TABLE 2 | Correlation table of the main variables of interest.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*Caregiver absenteeism*	1.00													
2	*Patient complaints*	0.03**	1.00												
3	*Schedule inconsistency*	0.03**	0.08**	1.00											
4	*Schedule discontinuity*	0.03**	0.09**	0.40**	1.00										
5	*Caregiver experience*	−0.01**	0.00	0.12**	0.24**	1.00									
6	*Caregiver availability*	−0.05**	−0.01**	0.12**	0.05**	−0.13**	1.00								
7	*Department workload*	0.06**	0.06**	0.16**	0.14**	0.14**	−0.23**	1.00							
8	*Travel distance*	0.06**	0.06**	0.24**	0.26**	0.07**	−0.01**	0.24**	1.00						
9	*Patient prior complaints*	0.10**	0.04**	0.04**	0.09**	0.08**	−0.19**	0.29**	0.18**	1.00					
10	*Patient seniority*	−0.05**	−0.05**	−0.17**	−0.16**	0.24**	−0.04**	−0.11**	−0.15**	−0.04**	1.00				
11	*Caregiver patient variety*	0.11**	0.13**	0.40**	0.54**	0.27**	−0.17**	0.44**	0.42**	0.30**	−0.24**	1.00			
12	*Caregiver task variety*	−0.02**	0.02**	0.23**	0.34**	0.14**	0.15**	−0.13**	−0.01*	−0.18**	0.01**	0.14	1.00		
13	*Caregiver hours worked*	0.04**	0.07**	0.37**	0.50**	0.28**	0.10**	0.24**	0.28**	0.15**	0.05**	0.53**	0.16**	1.00	
14	*Unemployment*	−0.07**	−0.01**	−0.02**	−0.01**	−0.04**	0.08**	−0.05**	−0.02**	−0.13**	−0.02**	−0.07**	0.05**	−0.01**	1.00
15	*Public holiday*	−0.00	−0.01	0.02**	−0.00	0.00	−0.01	−0.01*	0.00	0.01*	0.00	−0.00	−0.01**	−0.00**	−0-02**

Note: Descriptive statistics are presented per caregiver-week (sample size 75,078 observations). Log transformations are reported for Schedule inconsistency, Schedule discontinuity, Caregiver experience, and Travel distance.
**$p < 0.01$.
*$p < 0.05$.

Table 1 reports summary statistics, and Table 2 presents the correlations among the key variables of interest. Logarithmic transformations are reported for *schedule inconsistency*, *schedule discontinuity, caregiver experience*, and *travel distance*. To assess potential multicollinearity, we calculated variance inflation factors (VIFs). The average VIF for all variables (1.40) and the VIFs for our two main independent variables (1.37 for *schedule inconsistency* and 1.80 for *schedule discontinuity*) are well below the commonly accepted threshold level of 10.

5 | Hypotheses Testing

5.1 | Multivariate Regression Model

Given that our dependent variables, *caregiver absenteeism* and *patient complaints*, are non-negative count variables, we employ caregiver fixed-effects Poisson regression models. To account for the potential correlation of observations within the same caregiver over time, we compute robust standard errors clustered at the caregiver level. We use the following model to estimate the effects of *schedule inconsistency* and *discontinuity* on *caregiver absenteeism*:

$$\Pr\left(Z_{it}=z_{it} \mid \tau_{i(t-1)}, \boldsymbol{x}_{\mathbf{i(t-1)}}\right) = F\left(Z_{it}, \beta_0 \tau_{i(t-1)} + \boldsymbol{\beta_1 x}_{i(t-1)} + c_i + w_{(t-1)} + y_{(t-1)} + v_{it}\right) \quad (1)$$

where Z_{it} is the number of absences of caregiver i in week t, $\tau_{i(t-1)}$ represents *schedule inconsistency* and *schedule discontinuity* of caregiver i in week t–1, c_i represents caregiver fixed-effects, $w_{(t-1)}$ represents week of the year fixed-effects, $y_{(t-1)}$ year fixed-effect, v_{it} represents independent random noise and $\boldsymbol{x}_{\mathbf{i(t-1)}}$ represents the following vector of control variables:

$$\begin{aligned}\boldsymbol{x}_{\mathbf{i(t-1)}} = (&\textit{Caregiver experience}_{i(t-1)}, \textit{Caregiver availability}_{i(t-1)},\\ &\textit{Department workload}_{i(t-1)}, \textit{Travel distance}_{i(t-1)},\\ &\textit{Patient prior complaints}_{i(t-1)}, \textit{Patient seniority}_{i(t-1)},\\ &\textit{Caregiver patient variety}_{i(t-1)}, \textit{Caregiver task variety}_{i(t-1)},\\ &\textit{Caregiver hours worked}_{i(t-1)}, \textit{Public holiday}_{i(t-1)},\\ &\textit{Unemployment}_{i(t-1)})\end{aligned} \quad (2)$$

F is a standard Poisson function. Moreover, we lag the independent and control variables t–1 to prevent reverse causality issues (Wooldridge 2010). Since we have information on realized schedules rather than initially planned ones, absenteeism on any day of week t affects the realized schedule for that week and could potentially drive τ_{it}. To address this potential threat of reverse causality, we lag the explanatory variables and exclude from the calculation of the independent variables any days when absenteeism occurred. This formulation assumes that the effects of inconsistent or discontinuous schedules carry over into the following week, consistently with prior empirical studies (Lu et al. 2022; Bergman et al. 2023).

Similarly, we use the following caregiver fixed-effects Poisson model to estimate the effects of *schedule inconsistency* and *discontinuity* on *patient complaints*:

$$\Pr\left(Y_{it}=y_{it} \mid \tau_{i(t-1)}, \boldsymbol{x}_{\mathbf{i(t-1)}}\right) = F\left(Y_{it}, \boldsymbol{\beta}_0 \cdot \tau_{i(t-1)} + \boldsymbol{\beta_1} \cdot \boldsymbol{x}_{i(t-1)} + c_i + w_{(t-1)} + y_{(t-1)} + \varepsilon_{it}\right) \quad (3)$$

where Y_{it} is the number of patient complaints caregiver i received in week t, being all the other variables and fixed-effects the same as in the absenteeism model, and $\boldsymbol{\varepsilon_{it}}$ independent random noise.

5.2 | Main Results

In Table 3, we present the main results for the estimation of the caregiver absenteeism and patient dissatisfaction models. Positive coefficients indicate increases in the number of caregiver absences or patient complaints.

Model 1 of Table 3 presents estimates for the caregiver absenteeism model. The coefficient of *schedule inconsistency* is positive and significant ($\beta=0.13$ $p<0.01$), providing support for Hypothesis 1a. Regarding the economic significance of the coefficient, we find a 19.29% increase in *caregiver absenteeism* when *schedule inconsistency* increases from 2.07 (25th percentile, i.e., a 3.5-h difference in adjacent schedules across 2 weeks) to 3.46 (75th percentile, i.e., a 15.5-h difference in adjacent schedules across 2 weeks). The positive and significant coefficient ($\beta=0.10$, $p<0.05$) of *schedule discontinuity* provides support for Hypothesis 2a. Regarding the economic significance of the coefficient, we find a 20.00% increase in *caregiver absenteeism* when *schedule discontinuity* increases from 0 (25th percentile, i.e., a schedule with no interruptions in the week) to 1.79 (75th percentile, i.e., a schedule with 5 interruptions in the week).

Model 2 presents the results for the patient dissatisfaction model. The coefficient of *schedule inconsistency* is positive and significant ($\beta=0.24$, $p<0.01$), providing support for Hypothesis 1b. Regarding the economic significance of the coefficient, we find a 40.27% increase in *patient complaints* when *schedule inconsistency* increases from the 25th to the 75th percentile. The positive and significant coefficient ($\beta=0.13$, $p<0.05$) of *schedule discontinuity* provides support for Hypothesis 2b, corresponding to an increase of 27.33% in *patient complaints* when schedule discontinuity increases from the 25th to 75th percentile.

5.3 | Potential Endogeneity Concerns

Schedules are not randomly assigned to workers, and some of the factors that affect schedule characteristics may also be associated with worker absenteeism or patient complaints. The controls and fixed effects included in our models help mitigate these concerns by capturing individual and environmental factors that can bias the estimates of the parameter β_0. The use of lagged predictors further reduces the risk of reverse causality, particularly when considering that while the dependent variables refer to week (t), the predictor variables are measured in weeks (t–2) and (t–1), whereas the schedules for these weeks are constructed in weeks (t–4) and (t–3). Nevertheless, unobserved time-varying factors, such as planners' behavior, could still influence both schedule characteristics and the outcomes

TABLE 3 | Poisson models of caregiver absenteeism and patient complaints.

Variables	Dependent variable: Caregiver absenteeism (1)	Dependent variable: Patient complaints (2)
Schedule inconsistency	0.129**	0.241**
	(0.020)	(0.035)
Schedule discontinuity	0.099*	0.134*
	(0.039)	(0.055)
Caregiver experience	−0.073**	−0.167**
	(0.024)	(0.031)
Caregiver availability	−0.010*	0.001
	(0.005)	(0.006)
Department workload	0.001	0.036*
	(0.010)	(0.014)
Travel distance	−0.015	0.022
	(0.020)	(0.033)
Patient prior complaints	0.014	0.066
	(0.031)	(0.053)
Patient seniority	−0.029	−0.102**
	(0.020)	(0.037)
Caregiver patient variety	0.008	0.040**
	(0.005)	(0.007)
Caregiver task variety	0.069*	0.130**
	(0.028)	(0.036)
Caregiver hours worked	0.004*	−0.006+
	(0.002)	(0.004)
Public holiday	−0.077+	0.027
	(0.042)	(0.062)
Unemployment	−0.148**	−0.128**
	(0.038)	(0.046)
Caregiver fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	65,271	50,884
Number of caregivers	724	503
Wald χ^2	362.09**	366.09**

Note: In the Poisson regression models, Stata excludes 8631 (23,299) caregiver-week observations in the absenteeism (patient complaints) model corresponding to caregivers who had (a) just a single week or (b) multiple weeks all citing zero absenteeism (patient complaints) as they do not contribute to the likelihood function. Moreover, 1175 (895) observations are lost due to the lagging of the independent and control variables in the absenteeism (patient complaints) models. Standard errors clustered by caregivers in parentheses.
$^{**}p < 0.01$.
$^{*}p < 0.05$.
$^{+}p < 0.10$.

studied. Planners have some discretion in shaping the schedules, and their discretionary behavior may be associated with worker performance. For example, planners may design more or less favorable schedules based on a caregiver's past behavior or personal rapport. A planner might sanction caregivers who previously behaved poorly (e.g., last-minute absences or no-shows) or, conversely, reward caregivers they favor with more stable schedules, effectively creating incentives for non-compliant caregiver behaviors. As a result, planner discretion could lead to schedule inconsistency and schedule discontinuity being correlated with the error terms $\boldsymbol{\nu_i}$ and $\boldsymbol{\varepsilon_i}$ in Equations (1) and (3) respectively.

Given that the models in Equations (1) and (3) are non-linear, we address this potential endogeneity concern using a control functional approach (Akturk et al. 2022). The control function approach is a two-stage procedure. In the first stage, each potentially endogenous variable is predicted as a function of all control variables, as well as exogenous instrumental variables. In the second stage, the main dependent variable is modeled as a function of the first-stage residuals, the endogenous variables, and all control variables (Papke and Wooldridge 2008; Lin and Wooldridge 2019). By including the first-stage residuals in the second-stage equation, this approach controls for the portion of variation in the endogenous variable that is correlated with the unobserved variable, that is, planner's behavior, so that the remaining variation in the endogenous variable is independent of the error term (Petrin and Train 2010; Sharma et al. 2020). Since the residuals are estimates obtained from the first stage, which add extra variation in the second stage, we use a nonparametric bootstrap to obtain valid standard errors (Wooldridge 2010, 2015).

We use two exogenous variables as instrumental variables: *flu outbreaks* and *extreme precipitation*. In particular, we create the variable *flu outbreaks* as a dichotomous variable that equals 1 if an extreme number of flu cases is reported in the province during a given week, and 0 otherwise. To identify weeks with flu outbreaks, we collect weekly influenza case data for the province over the study period from the Government of Canada Flu Watch. A week is classified as experiencing a flu outbreak if reported cases exceed the 90th percentile of the distribution (i.e., more than 170 cases). Flu outbreaks are likely to disrupt caregiver schedules in several ways: (1) patients may cancel non-critical services, such as homemaking or companionship visits, to reduce contact and avoid flu exposure; (2) patients may request additional visits for tasks they or their family members typically handle but cannot perform due to illness, such as meal preparation or cleaning. While flu outbreaks could also lead to caregivers or their dependent family members (i.e., a child or an elder parent) to fall ill, potentially causing absenteeism, our dependent variable excludes absences related to sickness or caring for a sick family member (only 0.59% of sickness-related absences are due to caring for a sick family member). Therefore, we do not expect flu outbreaks to directly influence caregiver behavior. However, since we cannot fully rule out the possibility that caregivers may be absent due to other flu-related concerns (i.e., avoiding exposure), we constructed an alternative instrument, which we describe in Section 6.4.

The second instrument we use is *extreme precipitation*. We create the variable *extreme precipitation* as a dichotomous indicator, taking the value of 1 if an extreme amount of precipitation occurred in the focal week and area, and 0 otherwise. To identify weeks with extreme precipitation, we collected daily precipitation data across the province during the study period from the Government of Canada Historical Climate Data. A week is classified as having extreme precipitation if its average daily precipitation exceeds the 90th percentile of the weekly average distribution (10.68 mL). Extreme precipitation events are likely to disrupt caregivers' schedules, as patients may reschedule visits to avoid potential weather-related delays. Additionally, such events can generate new demands for caregiver visits, as family members who typically support patients may be unable to do so due to the weather. Since our predictive variables are lagged, it is unlikely that caregiver behavior in the focal week is directly affected by extreme precipitation in the prior week. The exclusion restriction of the instrument could be violated if the extreme precipitation continues from week (*t*–1) into week (*t*), potentially causing the worker to be absent in week (*t*) due to weather conditions. To mitigate this concern, we set the instrument to zero if extreme precipitation occurs in both week (*t*–1) and week (*t*). We assess the relevance of the instruments through the following regression for each of the two schedule characteristics, s_{it}, namely schedule inconsistency and schedule discontinuity:

$$s_{it} = \gamma_0 + \gamma_1 flu\ outbreak_t + \gamma_2 extreme\ precicipation_t + \boldsymbol{\gamma_3 x_{it}} + e_{it} \tag{4}$$

where γ_1 and γ_2 capture the effect of the two instrumental variables on the schedule of worker *i* in week t. Table A4 in the appendix reports the estimates of Equations (8). We find that *schedule inconsistency* increases significantly when there is a flu outbreak ($p < 0.01$) and extreme precipitation ($p < 0.01$). This is consistent with our expectations, as both flu outbreaks and extreme precipitation alter the distribution of the visits assigned to the focal worker. We also find that *schedule discontinuity* decreases when there is a flu outbreak ($p < 0.01$) and extreme precipitation ($p < 0.05$); suggesting the addition or rescheduling of visits during these events may help fill schedule gaps.

We show the results of the control function approach in Table 4, which yield equivalent conclusions to those of our main analysis. Even after accounting for the potential endogeneity of planner behaviors, we continue to find that schedule discontinuity and schedule inconsistency are positively associated with worker absenteeism and patient complaints.

6 | Robustness Checks

6.1 | Alternative Model Specifications

Since our dependent variables represent rare events, Poisson regression may overestimate *p*-values, leading to false positives. To investigate whether this is the case, we use a negative binomial specification (Cameron and Trivedi 2010) as well as a rare events logistic regression, using a binary transformation of the dependent variables. We continue to find positive

TABLE 4 | Control Function Approach of Caregiver Absenteeism and Patient Complaints.

Variables	Dependent variable: Caregiver absenteeism (1)	Dependent variable: Patient complaints (2)
Schedule inconsistency	0.180**	0.256**
	(0.027)	(0.044)
Schedule discontinuity	0.157**	0.161*
	(0.042)	(0.071)
Caregiver experience	−0.078**	−0.161**
	(0.028)	(0.035)
Caregiver availability	−0.011**	0.005
	(0.004)	(0.007)
Department workload	0.002	0.042**
	(0.009)	(0.014)
Travel distance	−0.021	0.019
	(0.018)	(0.030)
Patient prior complaints	0.015	0.099+
	(0.027)	(0.053)
Patient seniority	−0.025	−0.105**
	(0.018)	(0.036)
Caregiver patient variety	0.003	0.038**
	(0.005)	(0.007)
Caregiver task variety	0.054*	0.109**
	(0.025)	(0.035)
Caregiver hours worked	0.002	−0.006+
	(0.002)	(0.003)
Public holiday	−0.081+	0.007
	(0.045)	(0.074)
Unemployment	−0.143**	−0.171**
	(0.034)	(0.047)
Residuals schedule inconsistency	−0.004**	−0.001
	(0.001)	(0.002)
Residuals schedule discontinuity	−0.016+	−0.005
	(0.010)	(0.013)
Caregiver fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	65,271	50,721
Number of caregivers	724	498
Wald χ^2	703.51**	437.47**

Note: Nonparametric bootstrapped errors in parentheses.
**$p < 0.01$.
*$p < 0.05$.
+$p < 0.10$.

and significant results for our main variables of interest (see Table A5). We also note that when the dependent variable is highly unbalanced due to zero inflation, the regression can become more sensitive to outlying independent observations (Hall and Shen 2010). We hence perform additional checks for outliers. Specifically, we first run our main models and compute DFBETAS for both independent variables. We then calculate the cutoff point of $2\sqrt{n}$, where n is the number of observations, and identify potential outliers as those with DFBETAS greater than the cutoff. The resulting final sample for the absenteeism model includes 61,168 observations (4103 observations dropped from the main analysis), and for the patient complaints model includes 39,485 observations (11,399 observations dropped from the main analysis). Results from these restricted samples confirm the robustness of our findings (see Table A6).

Next, we perform a further check to investigate whether our results could be driven by the co-occurrence of patient complaints and absenteeism. To this end, we compute a dichotomous variable equal to 1 if the caregiver is absent and receives a complaint in the focal week, and 0 otherwise. This dichotomous variable is equal to 1 for 0.27% of the observations, indicating that such co-occurrence is rare. Nevertheless, we re-estimate the patient complaints model restricting the sample to observations in which the caregiver is not absent, and find that our results remain unchanged in this subsample analysis (see Table A7).

Lastly, we assessed the robustness of our findings to alternative lag structures for the predictive variables, which help reduce potential feedback effects (i.e., the concern that *prior* absenteeism may influence future scheduling). Specifically, we test models using lags of (t–2), (t–3), (t–4), and (t–5). The results are consistent across lags (t–2) to (t–4), supporting the robustness of the observed effects. At lag (t–5), schedule inconsistency remains a significant predictor, while schedule discontinuity loses significance, suggesting that the influence of scheduling characteristics is relatively stable, which further mitigates concerns related to reverse causality but, as it can be expected, weakens over longer time horizons (see Table A8).

6.2 | Alternative Operationalizations of Independent Variables

To assess the sensitivity of our results to the chosen operationalizations of our main independent variables, we re-estimate our models using alternative operationalizations. First, we operationalize schedule inconsistency by grouping time into six 4-h clusters (8 am–12 pm, 12 pm–4 pm, 4 pm–8 pm, etc.) instead of using 30-min slots. Specifically, we code each cluster as 1 if the caregiver worked at least 30 min during the 4-h period and 0 otherwise. We then calculate week-to-week differences based on this coding. The rationale behind this approach is that workers might be particularly sensitive to inconsistencies in the general time of the day they work (e.g., mornings or early afternoons) rather than the specific hour. The results hold with this operationalization (see models 1 and 4 of Table 5). Second, while our main analysis defines schedule discontinuity as the number of gaps longer than 30 min, we test alternative cutoffs of 20 min and 40 min. We find that our results are qualitatively similar when using the alternative cut-off points (see models 2, 3, 5 and 6 of Table 5).

6.3 | Data Aggregation

In our main analysis, we aggregate the data at the weekly level, as this aligns best with the theoretical framework we propose. However, the granularity of our dataset allows for a more detailed analysis, including the use of daily data instead of weekly aggregates. To assess the sensitivity of our model to data aggregation, we conduct an additional analysis in which we calculate the dependent variables at the daily level and determine schedule characteristics based on the 7 days preceding each focal day. Specifically, we define the dependent variables—caregiver absenteeism and patient complaints—at the daily level by coding them as 1 if the caregiver was absent (or received a complaint) on the focal day, and 0 otherwise. We compute the independent variables—schedule inconsistency and discontinuity—using the same methodology as in our main analysis, but apply it using a rolling window with one-day increments. We exclude from the analysis any records where the dependent variables fall on days when the focal worker is not available. The results from this model reveal that even when using this alternative level of aggregation, we continue to find support for our main predictions (see Table A9).

6.4 | Alternative Control Function Approach

The exclusion restriction of the *flu outbreak* instrument would be violated if it directly impacted the caregivers' decision to be absent, rather than doing so through its effect on scheduling. We mitigate this risk by excluding from the caregiver absenteeism variable any cases in which the caregiver is sick or needs to care for a sick family member. However, there may still be residual cases in which flu-related concerns directly lead to absenteeism; for instance, if the caregiver opts to miss work to avoid the risk of contracting the flu from the patients. We hence compute an alternative instrument: *patient dispersion* of the department, measured as the average distance between all possible pairs of patients in a department in a given week.

The relevance condition is satisfied, as in departments and weeks where patients are more geographically dispersed, it is more difficult for schedulers to create compact schedules. The results from the first-stage regressions confirm that this instrument is a significant predictor of the schedule variables. The exclusion restriction is also satisfied. Although the distance between patients in the department could affect the outcomes via increased caregiver travel, we control for the focal caregiver's travel distance in our models. The results from the second stage of the model are robust to the use of patient dispersion as an alternative instrument to flu outbreaks (see Table A10).

6.5 | Bi-Weekly Scheduling

Given schedules are planned on a bi-weekly basis, it is plausible that the effects of schedule inconsistency or discontinuity on

TABLE 5 | Caregiver schedule's influence on caregiver absenteeism and patient dissatisfaction (alternative operationalizations of schedule inconsistency and discontinuity).

	Caregiver absenteeism			Patient dissatisfaction		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Schedule inconsistency_cluster	0.130**			0.192**		
	(0.025)			(0.038)		
Schedule inconsistency		0.128**	0.129**		0.243**	0.241**
		(0.020)	(0.020)		(0.035)	(0.035)
Schedule discontinuity	0.112**			0.166**		
	(0.039)			(0.054)		
Schedule discontinuity_20 min		0.127**			0.144**	
		(0.040)			(0.056)	
Schedule discontinuity_40 min			0.099*			0.135*
			(0.039)			(0.055)
Caregiver experience	−0.063**	−0.075**	−0.073**	−0.142**	−0.169**	−0.167**
	(0.023)	(0.024)	(0.024)	(0.029)	(0.031)	(0.031)
Caregiver availability	−0.010*	−0.010+	−0.010*	0.001	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Department workload	0.002	0.002	0.001	0.036*	0.036*	0.036*
	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)
Travel distance	−0.013	−0.017	−0.015	0.026	0.021	0.022
	(0.020)	(0.020)	(0.020)	(0.034)	(0.033)	(0.033)
Patient prior complaints	0.015	0.013	0.014	0.062	0.064	0.066
	(0.031)	(0.031)	(0.031)	(0.053)	(0.053)	(0.053)
Patient seniority	−0.033	−0.028	−0.029	−0.110**	−0.100**	−0.102**
	(0.020)	(0.020)	(0.020)	(0.037)	(0.037)	(0.037)
Caregiver patient variety	0.010+	0.005	0.008	0.043**	0.038**	0.040**
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Caregiver task variety	0.075**	0.066*	0.069*	0.137**	0.128**	0.130**
	(0.028)	(0.028)	(0.028)	(0.036)	(0.037)	(0.036)
Caregiver hours worked	0.005*	0.004+	0.004*	−0.004	−0.007+	−0.006+
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Public holiday	−0.076+	−0.077+	−0.077+	0.027	0.026	0.027
	(0.042)	(0.042)	(0.042)	(0.063)	(0.062)	(0.062)
Unemployment	−0.147**	−0.150**	−0.148**	−0.128**	−0.131**	−0.128**
	(0.038)	(0.038)	(0.038)	(0.046)	(0.046)	(0.046)
Caregiver fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald χ^2	345.86**	364.21**	362.15**	345.86**	367.30**	366.08**
Number of observations	65,271	65,271	65,271	50,884	50,884	50,884
Number of caregivers	724	724	724	503	503	503

Note: Standard errors clustered by caregiver in parentheses.
**$p < 0.01$.
*$p < 0.05$.
+$p < 0.10$.

worker outcomes may vary depending on whether these features are experienced in the first or second week of the scheduling cycle. Specifically, workers may have more time to prepare for the schedules in the second week, potentially mitigating the negative effects. To empirically examine this possibility, we construct a binary variable indicating whether the observation falls in the first or second week of the bi-weekly schedule cycle. This variable equals 1 if the calendar week number is odd (e.g., 1st, 3rd, 5th week of the year) or 0 if it is even (e.g., 2nd, 4th, 6th week of the year). We then interact the *odd week* with both *schedule inconsistency* and *discontinuity*. The interaction terms in both the absenteeism and patient complaints models are statistically insignificant (see Table A11). These findings suggest that, in our setting, the impact of schedule variability and discontinuity does not differ meaningfully between the first and second week of the planning cycle.

7 | Alternative Explanations

7.1 | Income Volatility and Lost Income

The adverse effects of on-demand schedules may be explained by job dissatisfaction induced by income volatility associated with schedule volatility (Haley-Lock 2011; Luce et al. 2014; Ben-Ishai 2015; Golden 2015; Schneider and Harknett 2019), which in our study is captured by schedule inconsistency. However, income volatility and schedule volatility are conceptually distinct. A worker may face *no income volatility*—working the same number of hours each week—while still facing substantial *schedule volatility* (e.g., inconsistency) if the timing of those hours varies substantially from week to week. Nevertheless, to ensure that our results are not driven by income volatility, we include it as a control in our models. Following Schneider and Harknett (2021), we define *income volatility* as the difference between the maximum and minimum weekly pay within a rolling four-week window (the focal week and three preceding weeks). The results, reported in Table 6 (models 1 and 5), show that even after controlling for income volatility, both *schedule inconsistency* and *schedule discontinuity* remain significant and positively associated with caregiver absenteeism and patient dissatisfaction. In addition, we consider whether our findings may be driven by potential income lost due to unfilled hours. To test this, we create a proxy for the potential income in the focal week (i.e., if the worker worked during the idle time) by estimating the number of additional visits the caregiver could have completed during the idle time and multiplying that number by the caregiver's hourly wage. Specifically, given that the average visit duration is 1.5 h, we calculate how many such visits could have been scheduled during each idle gap and then estimate the corresponding income. Upon entering this control in the regression models, we continue to find support for the postulated effects (see Table A12).

7.2 | Overnight Gaps

On-demand schedules, particularly those with schedule discontinuity, are likely associated with shorter overnight breaks, which can erode workers' physical and cognitive resources (Danziger et al. 2011; Ibañez and Toffel 2020; Schneider and Harknett 2019), and hence may lead to higher absenteeism and poorer patient service. To account for this potential mechanism, we include a control variable in our models: the variable capturing *overnight gaps length*, defined as the average duration of all the overnight gaps within the focal week.[4] We find that the regression coefficients of *schedule inconsistency* and *schedule discontinuity* are robust to the inclusion of this control (see Table 6, models 2 and 6), suggesting that their effects go beyond sleep deprivation.

7.3 | Short Gaps

Our primary focus in this study is on within-day gaps that interrupt a worker's schedule beyond what could reasonably be considered a short rest period—operationalized as idle time between visits of less than 30 min. To explore whether shorter gaps also play a role, we construct the variable *short within-day gaps*, which counts the number of gaps shorter than 30 min experienced by the worker during the focal week. The regression coefficients of *schedule inconsistency* and *schedule discontinuity* are robust to the inclusion of this control (see Table 6, models 3 and 7); while the negative effect on absenteeism is present also for discontinuity driven by short breaks.

7.4 | Short-Notice Changes

Part of a caregiver's schedule inconsistency and discontinuity may be caused by short-notice schedule changes, which have also been shown to reduce caregivers' well-being (French et al. 2001; Bamberg et al. 2012) and performance (Kamalahmadi et al. 2021). Although we do not directly observe short-notice changes, we explore their potential effects indirectly by measuring the number of atypical (i.e., non-regularly visited) patients visited by each caregiver during the focal week. If a caregiver visits an atypical patient—defined as one whom the caregiver did not visit in the 7 days preceding or following the focal visit—it is likely that the caregiver is filling in for the regular caregiver, indicating a last-minute adjustment to the schedule. The regression coefficients of *schedule inconsistency* and *schedule discontinuity* are robust to the inclusion of this control (see Table 6, models 4 and 8), suggesting that their effects are not affected by the presence of short-notice changes in the schedule.

7.5 | Patient Severity

The severity of the conditions of the patients served by a caregiver in a given week may influence both caregivers behavior and patient reaction to the service. This did not seem to be a concern for HealthCo, which did not track patient severity levels, likely because the company offers only basic care services. Nevertheless, we try to account for the severity of the patient conditions by controlling for the average duration of the visits throughout the week. The rationale is that more demanding or complex patients may require longer visits, which could be more physically and emotionally draining for workers. To calculate this variable, we measure the duration of each visit as the difference between the start and end time and take

TABLE 6 | Caregiver schedule's influence on caregiver absenteeism and patient dissatisfaction (alternative explanations).

	Caregiver Absenteeism				Patient Dissatisfaction			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Schedule inconsistency	0.092**	0.106**	0.129**	0.121**	0.199**	0.219**	0.242**	0.227**
	(0.023)	(0.021)	(0.020)	(0.020)	(0.043)	(0.037)	(0.035)	(0.036)
Schedule discontinuity	0.116**	0.070+	0.096*	0.099*	0.197**	0.113+	0.131*	0.134*
	(0.039)	(0.039)	(0.039)	(0.039)	(0.062)	(0.060)	(0.055)	(0.055)
Caregiver experience	−0.076**	−0.054*	−0.076**	−0.068**	−0.182**	−0.150**	−0.170**	−0.160**
	(0.027)	(0.024)	(0.024)	(0.024)	(0.035)	(0.034)	(0.031)	(0.030)
Caregiver availability	−0.009+	−0.011*	−0.010*	−0.010*	−0.000	0.002	0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)
Department workload	−0.010	0.002	0.002	0.001	0.031+	0.036*	0.036*	0.035*
	(0.011)	(0.010)	(0.010)	(0.010)	(0.016)	(0.015)	(0.014)	(0.014)
Travel distance	−0.018	−0.012	−0.017	−0.017	0.023	0.010	0.021	0.021
	(0.023)	(0.021)	(0.020)	(0.020)	(0.038)	(0.034)	(0.034)	(0.033)
Patient prior complaints	0.017	0.035	0.015	0.016	0.079	0.051	0.066	0.069
	(0.034)	(0.037)	(0.031)	(0.031)	(0.059)	(0.059)	(0.053)	(0.053)
Patient seniority	−0.028	−0.040+	−0.030	−0.029	−0.108**	−0.122**	−0.102**	−0.102**
	(0.021)	(0.023)	(0.020)	(0.020)	(0.040)	(0.040)	(0.037)	(0.037)
Caregiver patient variety	0.010+	0.006	0.005	0.002	0.041**	0.036**	0.038**	0.033**
	(0.006)	(0.005)	(0.005)	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)
Caregiver task variety	0.067*	0.056+	0.066*	0.066*	0.123**	0.132**	0.128**	0.125**
	(0.030)	(0.029)	(0.028)	(0.028)	(0.040)	(0.037)	(0.036)	(0.036)
Caregiver hours worked	0.002	0.002	0.003+	0.004*	−0.008*	−0.008+	−0.007+	−0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Public holiday	−0.070	−0.066	−0.077+	−0.077+	0.033	0.037	0.027	0.026
	(0.044)	(0.042)	(0.042)	(0.042)	(0.070)	(0.063)	(0.062)	(0.062)
Unemployment	−0.163**	−0.144**	−0.149**	−0.150**	−0.113*	−0.132**	−0.130**	−0.129**
	(0.041)	(0.039)	(0.038)	(0.038)	(0.049)	(0.048)	(0.046)	(0.047)
Income volatility	0.035				0.080*			
	(0.022)				(0.037)			
Overnight gaps length		−0.102+				−0.086		
		(0.058)				(0.100)		
Short breaks			0.076*				0.056	
			(0.033)				(0.049)	
Short-notice change				0.065+				0.087
				(0.037)				(0.059)
Caregiver fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 6 | (Continued)

	Caregiver Absenteeism				Patient Dissatisfaction			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Wald χ^2	359.44**	328.45**	365.90**	365.47**	322.74**	287.27**	363.90**	362.90**
Number of observations	56,477	61,106	65,271	65,271	44,766	48,149	50,884	50,884
Number of caregivers	561	705	724	724	401	497	503	503

Note: Standard errors clustered by caregiver in parentheses.
**$p < 0.01$.
*$p < 0.05$.
$^{+}p < 0.10$.

the average duration across all visits performed by the caregiver during the week. The results for our main independent variables remain robust to the inclusion of this control (see Table A13).

7.6 | Blocked Availability

Given that workers can block available time (e.g., to accommodate personal responsibilities), one might argue that the negative impact of undesirable schedules could be mitigated, as workers may reduce time-based conflict when setting their schedule preferences. However, as discussed in the hypothesis development section, time-based conflict may still persist because workers are not always assigned visits during all of their available hours. These unfilled hours are likely to be used more effectively when schedules are consistent and continuous rather than inconsistent and discontinuous, even within the constraints of workers' stated availability. As previously noted, in this setting, most workers provide full-time availability to maximize their chances of being assigned visits.

That said, caregivers who provide high availability may be placing fewer timing constraints on their schedules, potentially exposing themselves to greater time-based conflict due to undesirable schedules. To explore this issue, we re-run our main regression models on the sub-group of workers who provide full-time availability (i.e., 40 h or more) (see Table A14). We find that both schedule inconsistency ($\beta = 0.10$, $p < 0.01$) and discontinuity ($\beta = 0.10$, $p < 0.05$) are positive predictors of caregiver absenteeism. Moreover, both schedule inconsistency ($\beta = 0.22$, $p < 0.01$) and discontinuity ($\beta = 0.12$, $p < 0.10$) are positive predictors of patient complaints. We also re-estimate the models for the subgroup of caregivers who are available to work less than 40 h a week. In this case, schedule inconsistency is a positive and significant predictor of caregiver absenteeism ($\beta = 0.11$, $p < 0.01$), but schedule discontinuity is not significant ($\beta = 0.20$, $p > 0.10$). Moreover, schedule inconsistency is a positive and significant predictor of patient complaints ($\beta = 0.25$, $p < 0.01$), but schedule discontinuity is not significant ($\beta = 0.12$, $p > 0.10$).

In sum, the direction and magnitude of the effects are roughly comparable across the two groups. A possible explanation, based on our field interviews, is that workers with limited availability often do so because they hold another part-time job. As such, they may experience time-based conflict at levels similar to workers with full-time availability. Nevertheless, the lack of significant effects for schedule discontinuity among the restricted-availability subgroup may be attributed to the lower average discontinuity experienced by this group (1.17) compared to those with full-time availability (3.90).

8 | Policy Simulation

Regression results suggest that HealthCo could benefit from reducing discontinuity and inconsistency of the caregivers' schedules. Yet it is unfeasible for HealthCo to apply tout-court the policies implied by the regression results and implement perfectly stable and uninterrupted schedules due to capacity and demand constraints. For example, if a patient requires care on Monday morning and the caregiver has other patients scheduled in the afternoon, it is not feasible to move the patient's appointment to the afternoon to prevent a gap in the caregiver's schedule. Similarly, if a patient needs to be seen on Monday instead of Tuesday in a particular week, the visit cannot simply be shifted to Tuesday to maintain the caregiver's schedule consistency. These examples illustrate that while the regression analysis indicates the desirability of consistent and continuous schedules, practical constraints limit the full implementation of such policies. Hence, the question is whether it is possible to increase in a feasible way schedule consistency and continuity and how much this would reduce absenteeism and patient complaints.

To estimate such potential benefits realistically, we follow a two-step optimization-simulation approach. In the optimization step, we develop a planning policy that applies parsimonious changes to the original schedules to create new schedules with lower discontinuity and inconsistency. In the simulation step, we apply a machine learning algorithm to assess the effect of the improved schedule on the probability of absenteeism and customer complaints. Figure 2 provides an overview of the policy simulation procedure.

8.1 | Planning Policy Development

We propose a mathematical formulation that minimizes the number of gaps between visits for each caregiver in each day. Since the gaps often do not have the same timing across consecutive weeks, we expect this algorithm to also reduce schedule inconsistency. To yield credible results, we specify a set of constraints that allows very limited changes to the observed

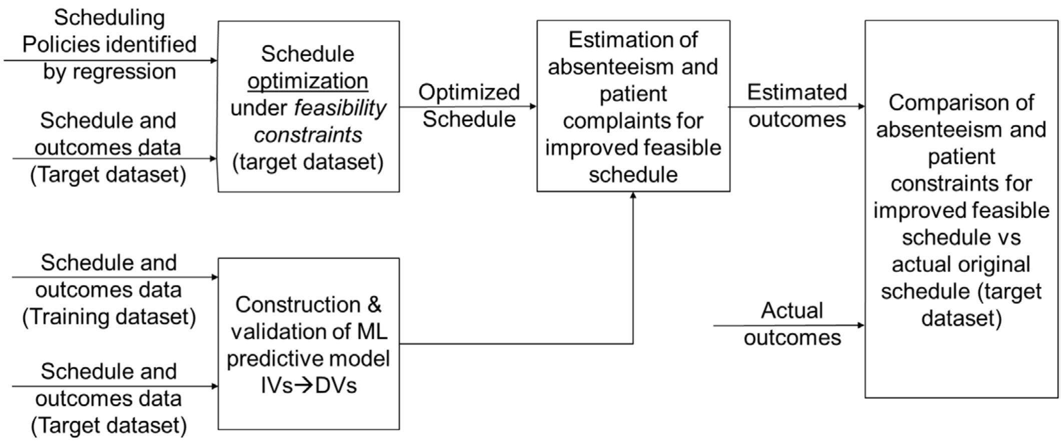

FIGURE 2 | Policy simulation procedure.

schedules. Specifically, we define an integer linear formulation for each caregiver and each day as follows:

$$(\text{SP}): \quad \min \quad z = \sum_{i \in A} y_i \tag{5}$$

$$\sum_{h = s_i - \delta}^{s_i + \delta} x_{ih} = 1, \quad i \in A \tag{6}$$

$$y_i \geq x_{ih} = x_{i+1h+l_i}, \quad i \in A \tag{7}$$

$$x_{ih}, y_i \in \{0, 1\} \tag{8}$$

where the set $\mathcal{A}$ indicates all the activities assigned to a caregiver in a given day, s_i is the current starting time of activity i, l_i is the length, in hours, of the same activity, and δ is the maximum anticipation or postponement allowed in the scheduling of activity i. The set $\mathcal{A}$ is identical to the set of activities actually executed by each caregiver; the model is thus not allowed to change the caregiver's set of daily assignments, including their sequencing. The decision variable x_{ih} takes value 1 if activity i starts at hour h, while the decision variable y_i takes value 1 if there is a gap after activity i is completed. The objective function (5) ensures that we minimize the total number of gaps. Constraints (6) guarantee that all the activities are assigned within the time window defined by the parameter δ. That is, if the current starting time of activity i is at time s_i, then such activity can be scheduled only within the time window $\left[s_i - \delta, s_i + \delta\right]$. For example, if the flexibility parameter δ is set at 1 h, and a certain visit in the original schedule begins at 10 a.m., we allow scheduling that visit only in the interval 9 a.m.–11 a.m. In this way, we can check the implications of the policy for modest values of δ, ensuring that we can make conservative estimates of the possible benefits of the new scheduling policy. Constraints (7) define the logical relation between the scheduling variables x and the gap variables y—that is, they ensure that if an empty slot between two consecutive activities exists, the corresponding binary variable is set to 1, thus ensuring a correct counting of the number of gaps in a day in the objective function. Finally, constraints (8) define the domain of the decision variables.

We solved problem (SP) using an off-the-shelf Mixed Integer Programming solver. The result is a daily schedule for each caregiver in each day that minimizes the number of gaps while

TABLE 7 | Reduction in schedule inconsistency and discontinuity.

Delta	0.5	1	2	3	4
Discontinuity	22%	29%	35%	39%	41%
Inconsistency	5%	9%	11%	13%	14%

respecting the time window imposed by the parameter δ. As we expected, for increasing values of δ we observe a decreasing number of gaps, and also less schedule inconsistency (see Table 7). In particular, we note that for a conservative value of $\delta = 0.5$ hours, we obtain a 24% reduction in discontinuity and a 6% reduction in inconsistency.

8.2 | Simulated Policy Approach Description

The second step in our procedure is to estimate the effect of this scheduling policy on absenteeism and customer complaints. In this way, we can estimate how much the firm could have reduced absenteeism and customer complaints just by applying modest scheduling changes, without changing the number of workers' daily visits. In principle, such calculation could be done using the estimation from the Poisson model. However, Machine Learning (ML) is preferred for prediction purposes because it is based on algorithms that do not assume a log-linear relationship—as Poisson regression does—and can thus uncover complex nonlinear patterns in the data (Shmueli 2010; Chou et al. 2023). Additionally, ML models outperform traditional regression approaches in terms of predictive accuracy when the dependent variable is imbalanced (Dube and Verster 2023)—as occurs with absenteeism and patient complaints in our models. We thus develop a predictive model using machine learning techniques to forecast caregiver absenteeism and patient complaints using the same predictors as in the main regression model. Given that observations with two or more absences per week and two or more patient complaints per week are quite rare (fewer than 1% of the cases) we transform the multi-class forecasting problems into binary classification problems. We create two new dependent variables: *caregiver_absenteeism_binary* (equal to zero if the worker was not absent in the focal week and equal to one otherwise) and *patient_complaints_binary* (equal to if zero if

TABLE 8 | Change in probability of caregiver absenteeism and patient complaints.

Flexibility value	Caregiver absenteeism		Patient complaints	
	Probability	Change	Probability	Change
0.0	0.073	0.000	0.026	0.000
0.5	0.066	0.096	0.024	0.077
1.0	0.064	0.123	0.022	0.154
2.0	0.061	0.164	0.022	0.154
3.0	0.060	0.178	0.021	0.192
4.0	0.057	0.219	0.021	0.192

the worker did not receive any complaint in the focal week and equal to one otherwise). The problem is therefore framed as a classification task in which we forecast the probability of having at least one absence (patient complaint) in a given week.

Following standard machine learning (ML) modeling development practices, we first divide the dataset into training and testing sets, assigning 80% of the data to training and 20% of the data to testing. We ensure that caregivers present in the training set do not appear in the testing set, and vice versa. That is, we train the model on a set of 767 caregivers and test it on a non-overlapping set of 238 caregivers. To deal with the fact that the dataset is imbalanced, we apply a resampling technique exclusively to the training set. To tackle the classification problems, we use the AutoGluon multilayer strategy (Erickson et al. 2020). We create two classification models, the first using (binary) absenteeism as the dependent variable and the second using (binary) complaints.

Both models perform well on the testing dataset. The absenteeism model has a balanced accuracy of 90.4%, a precision of 95.3%, a recall of 88.7%, and an F1 score of 92.1%. The complaints model performs similarly (89.6% balanced accuracy, 92.2% precision, 88.5% recall, and 90.6% F1 score), although not quite as well because it is less balanced (only 2.6% of caregiver-weeks present customer complaints, while 7.3% present absenteeism). Therefore, these models achieve enough accuracy to be used in the inference step. The online appendix gives a detailed description of the multilayer strategy and the oversampling-undersampling technique used to deal with the imbalanced dataset.

We apply the two ML predictive models to the different schedules obtained through the optimization model for various values of the parameter δ, obtaining the expected probabilities of caregiver absenteeism and patient complaints for each caregiver in the training set in each week. We then compare these results with those in the actual schedule. Table 8 shows how the probabilities of caregiver absenteeism and patient complaints change for each value of the flexibility parameter δ. The first row of Table 8 obtained using a flexibility value of 0, corresponds to the probability of caregiver absenteeism and patient complaints under the actual schedule, which are equal to 7.3% and 2.6%, respectively. For $\delta = 0.5$ h, we observe a 9.5% reduction in absenteeism and a 7.7% reduction in patient complaints compared to the actual schedule.

Lastly, we convert the risk of absenteeism and patient complaints into number of absences and number of patient complaints. The original testing schedule had a total of 1336 weeks with at least one absence and 333 weeks with at least one patient complaint. If we assume that these absences and complaints follow the same distribution as in the main dataset, this gives a total of 1520 absences and 359 patient complaints in the testing set. Under the conservative assumption that the proportions of absences and patient complaints do not change under the new schedules, we compute the number of absences and patient complaints for each new schedule. Figures 3 and 4 show the reduction in the number of absences and patient complaints induced by the optimal schedules of the policy simulation. The figures show that the benefits of reducing gaps in workers' schedules decrease marginally with δ. Interestingly, the biggest reductions of absenteeism and customer complaints are achieved by allowing 30-min changes in the schedule; larger changes (up to 4 h) yield marginally decreasing benefits. If the decrease in absenteeism and patient complaints can be considered a reflection of lower work-life balance problems for workers, this means that slight modifications in the schedule policy (i.e., 30 to 60 min) can be a pareto-efficient way to reduce time conflict. It is important to note that this policy is not only effective, but also feasible. In our setting, patients usually specify a window of time in which they want their visit, but not an exact time. For example, they may say that they prefer the caregiver to come early in the morning, during lunch, or in the evening from 7 p.m. to 9 p.m. Thus, the minor adjustments we explore in the scheduling policy present a realistic way to reduce noncompliance. Even capping adjustments at 30 min, the firm is expected to have had 146 fewer absences and 28 fewer patient complaints over the period observed in a 5-year period.

We repeat the procedure described in 8.1 and 8.2 to investigate the consequence of reducing schedule inconsistency. To this end, we develop an alternative mathematical formulation that minimizes inconsistency over two consecutive weeks, assuming the previous week's schedule as given. To test the effect of such a policy, we modify the proposed formulation by changing the objective function to the minimization of the schedule inconsistency over two consecutive weeks and keep the same values of the parameter δ, to ensure consistency with the discontinuity minimization approach. We then use these schedules to estimate the expected percentage and number of absences and complaints. The results we obtain are in line with those presented

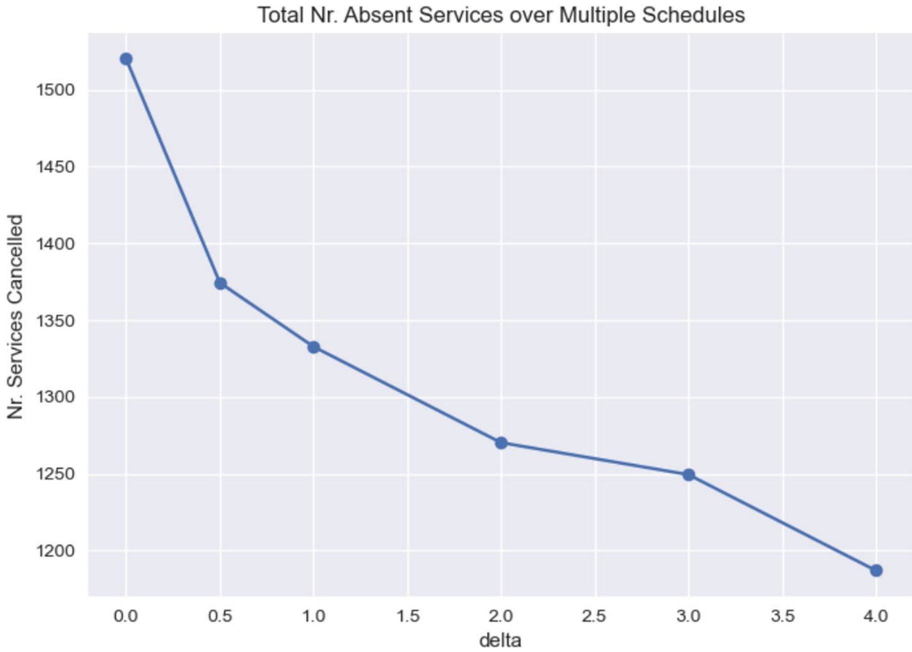

FIGURE 3 | Reduction in number of absences following policy simulation.

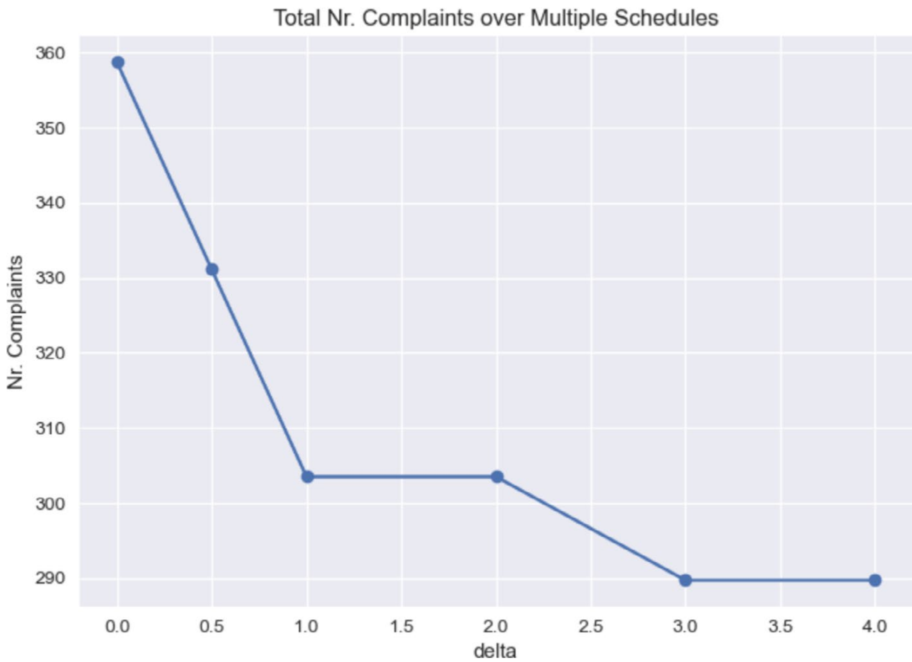

FIGURE 4 | Reduction in number of patient complaints following policy simulation.

for the approach that minimizes discontinuity. That is, we observe a monotonic reduction of both absences and complaints with respect to the value of δ, ranging from 10.9% to 8.2% in the case of absences and from 3.8% to 2.3% in the case of patient complaints.

9 | Discussion and Conclusions

A burgeoning stream of research suggests that shifting the burden of adapting to demand variability on workers is problematic. It is therefore critical for research to identify the specific features of on-demand schedules that impair worker outcomes, quantify their impact, and explore potential policy interventions to alleviate these effects.

Our study is the first one to provide empirical evidence on how on-demand schedules affect worker behaviors that impair service continuity and quality. Prior research on worker responses to scheduling practices has largely focused on voluntary turnover (Choper et al. 2022; Bergman et al. 2023) or revenue generation (Kamalahmadi et al. 2021; Lu et al. 2022). In contrast, our findings demonstrate that on-demand schedules contribute to absenteeism and service delivery failures severe enough to prompt patients to formally reject the caregiver. These outcomes carry substantial implications for the employer: absenteeism disrupts service continuity and incurs costly rescheduling efforts, while patient complaints tarnish the organization's reputation and institutional legitimacy—especially relevant in the healthcare context, where such complaints are closely monitored by health insurance companies and regulatory bodies. Beyond organizational consequences, these issues raise broader societal concerns, given the essential nature of healthcare services. Ultimately, our findings point to a flexibility paradox: the very scheduling flexibility intended to enhance customer service can hinder the quality of care, potentially resulting in severe consequences for both organizations and their stakeholders (Evans et al. 2015; Monsell et al. 2000; Kinnunen et al. 2017).

We also provide novel empirical evidence on the effects of daily gaps in workers' schedules on workers' outcomes. Although schedule discontinuity has been identified as an undesirable feature of on-demand schedules (Kossek et al. 2020), to the best of our knowledge, this is the first study to empirically examine its impact. Leveraging data that capture within-day gaps in schedules, we find that indeed such discontinuities lead to higher absenteeism and patient complaints. Thus, our findings highlight the need to account for work continuity when designing employee schedules.

Our results further emphasize that undesirable scheduling characteristics can adversely affect workers, even when they are allowed to specify the timeframes during which they are available to work, as is the case in our setting. In particular, our results show minimal differences in the effect of on-demand schedules between workers that provide full availability vs. workers who set restrictions on their availability. This finding suggests that permitting workers to limit their availability does not, by itself, mitigate the negative consequences of volatile or fragmented schedules.

From a more micro-level perspective, our findings provide evidence that workers may engage in strategic coping behaviors, such as absenteeism and the delivery of suboptimal service. Qualitative records from HealthCo suggest that patients' complaints align with this interpretation: when faced with time conflicts, caregivers are reported to leave tasks unfinished, rush through assignments, or handle personal matters, like phone calls, during work hours. These behaviors appear to be adaptive responses to the challenges and conflicts generated by on-demand schedules. By shedding light on these behaviors, our findings contribute to the growing body of research that provides micro-level insight into how workers respond to on-demand scheduling practices (e.g., Kamalahmadi et al. 2021).

Our study also offers significant practical implications. An optimization-simulation analysis reveals that schedule inconsistency and discontinuity at HealthCo partly result from planners' efforts to accommodate patients' timing preferences. These efforts, while well-intentioned, lead to unnecessarily irregular schedules that paradoxically undermine customer service. In fact, allowing the optimization algorithm to adjust the original schedules' visit start times by up to 30 min—within the bounds of customers' service expectations—could reduce schedule discontinuity by 24% and inconsistency by 6%. Based on the machine learning estimates, these improvements correspond to a decrease in absenteeism from the current level of 9.5% and a reduction in patient complaints from 7.7%.

Our simulation demonstrates a pragmatic response to the flexibility paradox: improved schedules can be generated using inexpensive, off-the-shelf mixed-integer programming solvers that can be easily integrated into the organization's scheduling system. Notably, the scheduling software used by this company was not a subpar in-house solution but a reputable industry-standard package. Yet, because software vendors and users often lack awareness of the detrimental effects of schedule inconsistency and discontinuity, current tools rarely include optimization features to mitigate these risks.

In sum, the flexibility paradox is not an inescapable dilemma. Firms can better balance customer requirements with worker needs by leveraging digital technologies that minimize unnecessary reactions to demand variability—much like retailers have done to counter the bullwhip effect in supply chains. From a policy perspective, our simulation suggests that legislators could consider incentivizing digital innovation in business planning systems for on-demand scheduling. Such interventions would not only benefit workers but also the broader public that depends on their service.

Our study also contributes to the ongoing societal debate about whether workers should be financially compensated for their availability, even when it is unfilled (Wogan 2017; Piasna 2019). Assuming that paid but unassigned hours would eliminate the adverse effects of schedule inconsistency and discontinuity on absenteeism and patient complaints, the cost of this approach may be substantial. Paying caregivers for their full availability would be problematic in our research setting, where capacity utilization is at a level of 45%. Shifting to compensation for each caregiver's full availability (capped at 40 h), considering the distribution of hourly rates of the workers, would increase labor costs by 48% Given that this is a labor-intensive setting where the ratio of EBITDA to revenues hovers around 10%–15%, this would not be feasible.

Like all studies, ours has limitations. First, since we observe realized, rather than planned schedules, we cannot directly measure short-notice changes. We address this limitation by including a proxy for such changes, and the results remain robust. Second, similarly to other studies in this literature (e.g., Kamalahmadi et al. 2021), we cannot directly observe the psychological mechanism underlying the observed effects of on-demand schedules on caregivers' performance. Yet a solid body of research associates on-demand schedules with worker stress, and our findings remain robust after ruling out alternative explanations. Third, as our data is not experimental, causality claims must be taken with due caution. Still, the inclusion of numerous control variables together with the control function approach helps mitigate endogeneity concerns. Finally, we do not have access to information that would enable us to quantify the cost impact of schedule inconsistency and discontinuity. Rigorous estimation of these effects goes beyond our research questions and requires different data and analysis that link to both operating costs (e.g., costs of replanning absences) and opportunity costs (e.g., revenue losses due to patient churn and loss of public or insurance contracts).

Our case study has boundaries of validity that potentially limit its generalizability. In particular, we study relatively low-skilled caregivers providing basic services, precisely the population most often subject to on-demand schedules. It remains an open question how higher-educated workers performing more complex tasks would react to such schedules. For instance, software developers who have chosen to work on crowdsourcing platforms (e.g., TopCoder or UpWork) may retain autonomy over their schedules, but in periods of low demand or intense competition, they too may be subject to schedule inconsistency and discontinuity as they may be forced to accommodate market demands. Future research may aptly explore the extent to which on-demand schedules pose a threat to worker performance in work environments characterized by highly educated workers executing complex tasks.

Endnotes

[1] Training includes annual orientation programs covering topics such as personal care training, infection control, care for children, ceiling track lift, and universal precautions.

[2] For the caregivers who were hired during our study period, caregiver experience is the number of visits the caregiver has performed up to the current week. If the caregiver was hired prior to the beginning of the studied period, we follow Lu et al. (2022) and measure caregivers experience as the sum of two components. The first component is the total number of visits the caregiver had performed from the beginning of the studied period until the focal week. The second component is the estimated visits prior to the studied period, which is measured as the product of (1) the average number of visits per week of the studied period, and (2) the number of calendar weeks since the hiring date until the beginning of the studied period.

[3] We obtained the monthly unemployment levels for the province for 2012–2016 from Statistics of Canada.

[4] Note that overnight gaps of more than 7 days were set as missing values.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1:** Supporting Information.