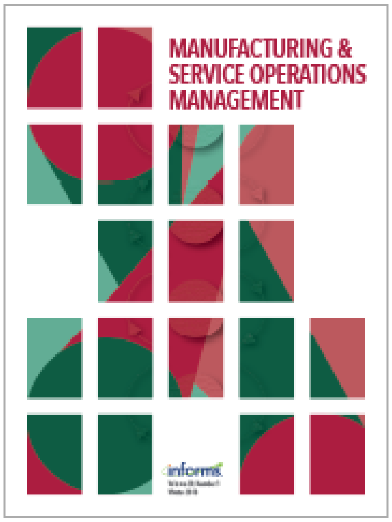

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Frontiers in Operations: Does Physician's Choice of When to Perform EHR Tasks Influence Total EHR Workload?

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Abstract. ***Problem definition*:** Physicians spend more than five hours a day working on Electronic Health Record (EHR) systems and more than an hour doing EHR tasks after the end of the workday. Numerous studies have identified the detrimental effects of excessive EHR use and after-hours work, including physician burnout, physician attrition, and appointment delays. However, EHR time is not purely an exogenous factor because it depends on physician usage behavior that could have important operational consequences. Interestingly, prior literature has not considered this topic rigorously. In this paper, we investigate how physicians' workflow decisions on when to perform EHR tasks affect: (1) total time on EHR and (2) time spent after work. ***Methodology/results*:** Our data comprise around 150,000 appointments from 74 physicians from a large Academic Medical Center Family Medicine unit. Our data set contains detailed, process-level time stamps of appointment progression and EHR use. We find that the effect of working on EHR systems depends on whether the work is done before or after an appointment. Pre-appointment EHR work reduces total EHR workload and after-work hours spent on EHR. Post-appointment EHR work reduces after-work hours on EHR but increases total EHR time. We find that increasing idle time between appointments can encourage both pre- and post-appointment EHR work. ***Managerial implications*:** Our results not only help us understand the timing and structure of work on secondary tasks more generally but also will help healthcare administrators create EHR workflows and appointment schedules to reduce physician burnout associated with excessive EHR use.

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1. Introduction

An Electronic Health Record (EHR) System is the digitized version of a patient's medical chart record containing medical history, diagnoses, treatment plans, immunization records, and test results.[1] EHRs reduce diagnostic errors and patient safety concerns (Hydari et al. 2019). EHRs also improve coordination and integration of care by providing real-time data at the point of care, efficient transfer of information across settings, and physician decision support (Rathert et al. 2019). As of 2021, 89% of office-based physicians in the United States had adopted an EHR system (Office of the National Coordinator for Health Information Technology 2021). In a 2018 survey of 500 primary care physicians in the United States, 63% of physicians agreed that EHRs had led to improved care. However, 71% of physicians also said EHRs significantly contribute to physician burnout (Stanford Medicine 2018).

Sinsky et al. (2016) found that outpatient clinicians spend two hours on EHR and desk work for every hour spent on direct clinical face time. Several recent studies have associated physician time spent on EHR systems with lower patient satisfaction (Marmor et al. 2018) and, for physicians, more work after-work hours (Attipoe 2021), attrition (Melnick et al. 2021), and burnout (Arndt et al. 2017). In an article in *The New Yorker* on physician EHR workload, Dr. Atul Gawande stated, "*Something's gone terribly wrong. Doctors are among the most technology-avid people in society; computerization has simplified tasks in many industries. Yet somehow, we've reached a point where people in the medical profession actively, viscerally, volubly hate their computers*" (Gawande 2018). In a 2019 statement, the

American Medical Association called an overhaul of the design and use of EHR systems a "national imperative" because of the high correlation between EHR use and physician burnout (American Medical Association 2019).

Although numerous studies have identified the detrimental impact of physician EHR workload, a key question remains. Is it possible to reduce EHR workload through better operational practices, such as structuring the EHR work differently? Interviews conducted by Zhang et al. (2016) and Attipoe (2021) show that physicians take varying approaches to manage their EHR work before or after appointments while in the examination room with the patient (multitasking) and, finally, after the end of the workday. In this paper, we seek to exploit the heterogeneity in physician actions across appointments to study how these differences impact total time spent using EHR and time spent after work hours on EHR.

In particular, we investigate the trade-offs of working on EHR tasks in different idle times between appointments (i.e., before and after appointments). The time between appointments represents the idle time from the primary task (seeing a patient) but is a time when secondary tasks may be completed. Doing EHR work before an appointment may help physicians initiate early tasks (Batt and Terwiesch 2017), prepare for tasks during the appointment (Altmann 2004), and efficiently capture key EHR details because of this effort. Alternatively, by doing work beforehand, it may take longer as task switching occurs (Staats and Gino 2012, KC 2014, Gurvich et al. 2020), and the work may fill to expand the time available (Parkinson 1955, Hasija et al. 2010). When work is completed after an appointment, it may be more efficient because all (or most) information is available, and there is better recall after an appointment (KC 2014). However, it is also possible that time increases because of lower productivity from longer work hours (Caruso 2014) and task interruptions (Froehle and White 2014).

We focus on EHR tasks performed during idle time because the idle time between appointments is a decision variable for hospital management during appointment scheduling. So, idle time can potentially influence physicians' practices around EHR usage. Additionally, the trade-offs associated with doing EHR tasks in idle time between appointments have been discussed qualitatively in prior studies (Zhang et al. 2016, Attipoe 2021). In these surveys, physicians have expressed various opinions and intuitive reasons for performing EHR in different time intervals, and we want to study idle time quantitatively.

This topic is critical to improving healthcare operations and is also part of a more general discussion on how to complete work (Narayanan et al. 2009, KC et al. 2020, Pendem et al. 2022). Although much emphasis is placed on the primary tasks to be completed, such as patient treatment or surgery (Bartel et al. 2020), assembling a car in a factory (Bernstein and Kök 2009), or answering a call in a call center (Aksin et al. 2007), operations also include secondary tasks that support the primary work (Legros et al. 2020). These might consist of EHR use, hand hygiene (Dai et al. 2015) diagnostic health tests (Batt and Terwiesch 2017), tool preparation in manufacturing, or data entry in call centers. Secondary work is necessary to complete primary work, and an open question is when (or possibly whether) it should be completed.

It is necessary to study secondary tasks separately because service operators typically have greater discretion on when to perform them. Secondly, during scheduling, workload due to secondary tasks is typically ignored, even though these tasks are often a significant burden on the operator. Lastly, these secondary tasks are usually performed outside of customer encounter time but may influence the workload and outcome of the service experience. Consequently, it may be possible to affect performance by identifying and implementing improved practices for managing secondary tasks.

This paper uses the critical context of EHR usage to shed light on this more general question. In particular, we focus on the following research questions:

1. How does the total time spent on EHR depend on when the EHR tasks are performed?
2. How does an increase in idle time between appointments affect the timing of EHR work?

The first research question permits us to examine the operational impact of secondary task structure. At least part of the answer addresses a classic question. Is it better to prepare before or wait until after the primary task is completed to work on secondary tasks? The answer to the second research question provides insights into managing appointment schedules to influence secondary task completion. For balancing workload, prior studies have discussed trade-offs associated with early task initiation (Batt and Terwiesch 2017), multitasking (KC 2014), and task switching (Staats and Gino 2012, Gurvich et al. 2020). However, the impact of structuring secondary tasks with scheduled appointments has not been studied.

We examine when EHR work should be completed using data from more than 150,000 appointments across 74 physicians in the family medicine unit of a large academic medical center in the United States. Our data set includes detailed information on appointments and physicians' EHR system use, including activity on individual patient records. This allows us to obtain time spent on EHR by a physician related to a particular patient. We perform our analysis at the appointment level because there is considerable heterogeneity in the timing of EHR tasks, even for the same physician. We focus our attention on two key outcome measures: total time spent on EHR systems and physicians' EHR time after regular work hours. We focus on these two measures because total EHR workload and EHR time spent during after-work hours significantly contribute to physician burnout (Tran et al. 2019), and studies (Sinsky et al. 2020) have identified these two measures as important aspects of hospital operational performance.

There are four times during a day when physicians might complete EHR work for an appointment: before the appointment ("prework"), during the appointment ("multitasking"), after the appointment but before the end of the day ("postwork"), or after the workday ("after-hours work"). Different trade-offs are associated with doing EHR tasks in each time period.

Our paper demonstrates that work structure is important for EHR tasks, because when it is performed significantly impacts total and after-work EHR time. Specifically, we find that prework can reduce the total time spent on EHR and after-hours EHR work, whereas postwork can reduce after-hours EHR work but increases the total time spent on EHR.

We estimate that performing an additional two minutes of prework reduces the sum of multitasking, postwork, and after-hours EHR work by 4.8 minutes. In other words, a two-minute increase in prework in an appointment leads to a net reduction in total EHR time of 2.8 minutes for that appointment, a decrease of 15.5%. Approximately 0.29 minutes of this reduction is from the decrease in after-hours EHR work, a decrease of 12%. In our setting, with 74 physicians, who average 13 appointments per day, this translates into a daily reduction of 44 fewer hours of total EHR work and 3.6 fewer hours of after-hour EHR work in the family medicine unit. Recent studies (Eschenroeder et al. 2021) have found that 43% of physicians report symptoms of burnout, and after-hours EHR work is associated with higher burnout. Our findings show that reordering EHR tasks by increasing prework can significantly reduce after-hours work and thus can be a strategy for reducing physician burnout.

If a physician spends two additional minutes on postwork, then after-hours work for that appointment decreases by 0.4 minutes, a reduction of 22%. This translates to a total reduction of 6.4 hours in after-hour EHR work per day across the family medicine unit. However, the total EHR workload goes up by 1.6 minutes per appointment, or 25 hours per day, across all physicians in our setting. To summarize, our results indicate that increasing prework helps reduce both total and after-hours EHR work. Alternatively, increasing postwork reduces after-hours EHR hours, but at the cost of increasing total EHR time.

Hospitals can encourage physicians to do more prework and postwork by increasing the idle time between appointments. We find that increases in idle time lead to significant increases in prework and postwork in our sample. The magnitude of the increase is significantly more for postwork than for prework. This suggests that during increases in idle times, physicians increase both but focus more on postwork.

Our solution approach and results contribute in the following principal ways.

First, we contribute to appointment scheduling literature to show that, typically, increasing idle time increases makespan for physicians (Robinson and Chen 2003); however, in the presence of secondary tasks, physicians can utilize idle time during the day to complete secondary tasks, leading to less after-hours work and a lower makespan. Therefore, in the presence of secondary tasks, increasing idle time may not always increase makespan.

Second, we contribute to the literature on task selection and sequencing. We find that performing some secondary tasks before the primary task can be a beneficial strategy, leading to less time spent on secondary work and less time spent on secondary work after the end of the workday. We also find that performing secondary tasks after the primary task helps reduce work at the end of the workday but would increase the total time spent on secondary tasks because of increased interruptions. Prior findings in the literature related to task sequencing have not focused on the relative value of doing pre-appointment and post-appointment secondary tasks.

Finally, our managerial insights help schedulers create appointment schedules that reduce burnout due to EHR workload. These varying effects of prework and postwork suggest that when clinicians create protected time for EHR tasks, the recommended use of that time would depend on the clinic's objective. If the objective is to reduce the total EHR workload, then greater emphasis can be placed on doing prework. If the objective is to reduce after-work EHR time, then increasing postwork would give a greater marginal benefit, albeit at the cost of increasing total EHR time.

2. Literature Review

Our paper is related to four streams of literature. The first stream of literature is research on the impact of technology on healthcare professionals' workload and productivity. Introducing technology in healthcare delivery has many advantages, such as improving patient access through additional delivery channels and improved physician decision support. However, recent studies have found that these technologies' operational impact may sometimes be harmful.

Technology-enabled channels of healthcare delivery, such as e-visits and telemedicine, increase physician workload (Bavafa and Terwiesch 2019), increase costs (Çakıcı and Mills 2021), and may worsen patient health disparities (Sunar and Staats 2022). Recent studies on EHR usage in the clinical services literature have found an association between increasing EHR usage with increasing burnout and turnover (Sinsky et al. 2016, Melnick et al. 2021) and lower patient satisfaction (Marmor et al. 2018). Lee et al. (2021) considered EHR documentation work from a queuing modeling perspective. We contribute to this literature by investigating the effect of structuring EHR work in the idle time between appointments on the total and after-hours EHR workload.

The second research stream related to our work is multitasking. Empirical studies on multitasking analyze servers simultaneously handling multiple customers or various task types (Narayanan et al. 2009, Staats and Gino 2012, KC 2014, Freeman et al. 2017, Gurvich et al. 2020). Gurvich et al. (2020) is a closely related paper to our context. They quantified the changeover time when the physicians switched between documentation and collaboration with other physicians. Patient interactions are not scheduled and are at the physician's discretion in their setting. A key distinguishing feature in our paper is that physicians alternate between scheduled face-to-face time with patients and documentation tasks. The progression of scheduled appointments creates idle time during the day, and we focus on physicians' use of this idle time for EHR tasks. A related set of papers on multitasking are queuing models with one server or group of servers balancing two work queues. Legros et al. (2020) discussed service operators' switching between customer interaction and back-office tasks. Unlike in Legros et al. (2020), doctors handle documentation during appointments and between patient visits in our setting.

The third stream of literature is related to the operational impact of task selection and sequencing by service workers. The sequencing of tasks can be driven by a motivation to shift work upstream, as in Batt and Terwiesch (2017). They found that early initiation of laboratory tests during the triage process in emergency departments (EDs) reduces treatment time but may increase the total number of tests performed. Another motivation for task selection could be a preference to complete tasks. KC et al. (2020) found that a preference to complete easy tasks is related to lower throughput and learning in an ED. Ibanez et al. (2018) found that in addition to preferring to do easier tasks first, physicians also prefer to batch similar tasks together, which negatively impacts productivity. In a related study, Feizi et al. (2023) found that ED physicians' preference for batching admissions leads to longer patient wait times. The preference for easier tasks may be driven by task familiarity, as Niewoehner et al. (2023) found with physicians' selection of patients in an ED. We contribute to this stream of work by studying how physicians use the interludes between appointments to complete secondary tasks such as EHR-related tasks.

The fourth stream of literature related to our work is appointment scheduling. Healthcare appointment scheduling has a long line of research (Gupta and Denton 2008). The principal problem in scheduling is allocating time for each appointment of the day to optimize performance measures such as idle time, physician overtime, and patient wait times. Recent literature in this field has incorporated factors such as no-shows, cancellations (Liu et al. 2010, Kong et al. 2020), walk-in customers (Chen and Robinson 2014), patient preferences (Feldman et al. 2014), and multi-priority patients (Sauré et al. 2020). To the best of our knowledge, recent literature has not incorporated the impact of doing secondary tasks such as documentation work between appointments. In scheduling literature, idle time between appointments has a detrimental effect on physician makespan. However, when EHR workload is considered, increased idle time can reduce physician makespan by reducing after-work hours doing documentation tasks. Our empirical investigation on the impact of physicians utilizing the idle time between appointments for documentation work will help guide future research on appointment scheduling.

3. Process Description and Hypothesis Development

3.1. Process Description

Detailed descriptions of physician actions related to a visit are available in Dobson et al. (2009) and Holman et al. (2016). We summarize the salient points below.

Upon a patient's arrival, the front desk gathers basic info. Patients who miss an appointment without notice are labeled as no-shows. When an exam room frees up, a nurse guides the patient and conducts initial checks, and then the physician enters the room. During the appointment, the physician performs various tasks: discussing patient info, reviewing electronic records, documenting details, conducting a physical exam, looking up treatments, discussing options, ordering tests/medications, providing prescriptions/instructions, and closing the appointment. Some EHR tasks, such as reviewing patient information, interpreting laboratory reports, finding missing or pending information, arranging tests or consultations, and completing forms, may be done before the appointment, whereas tasks such as finishing their notes, closing outpatient charts, and following up on laboratory results and patients' responses or comments may be done after the appointment or after the end of the workday.

3.2. Hypothesis Development

We develop hypotheses on the impact of performing EHR activity in idle time between appointments. The choice of performing EHR work in idle time between appointments leads to changes in the distribution of prework, multitasking, postwork, and after-hours work. We wish to analyze the impact of changes in prework, multitasking, postwork, and after-hours work on total and after-hours EHR work. There are trade-offs associated with performing EHR work in idle time before and after appointments. Prework and postwork done between appointments would help reduce multitasking in EHR activity. Thus, EHR activity can be performed without switching between physician-patient interaction and the computer, potentially reducing the time to perform these EHR tasks.

On the other hand, multitasking can potentially be more effective in saving time because the physician can update the EHR record while talking to the patient, reducing recall or fatigue-related issues later in the day. Similar trade-offs exist between postwork and after-hours work. Next, we present our hypotheses and discuss these trade-offs in detail. We describe the theoretical background of the mechanisms discussed in this section in the Electronic Companion (EC. 1).

There are four potential reasons why prework may increase total EHR time. First, prework will lead to physicians switching from face-to-face tasks with the previous appointment to interacting with the EHR to perform prework and then again switching from EHR work to face-to-face work with the following appointment. Therefore, adding prework in the idle time between appointments increases task switching between face-to-face work and EHR work. Task switching refers to shifting one's focus and attention from one task or activity to another. Although it can offer flexibility and variety, excessive switching can undermine focus, quality, and efficiency. Switching time may increase physicians' EHR system time. Literature in operations management and psychology has identified the detrimental effects of task switching because of increased changeover time (Staats and Gino 2012, KC 2014, Gurvich et al. 2020).

Second, idle time before an appointment may lead physicians to do more prework than usual. This demonstrates Parkinson's law, the adage that "work expands to fill the time available for its completion" (Parkinson 1955). Parkinson's law has been studied in contexts such as project management (Gutierrez and Kouvelis 1991) and call centers (Hasija et al. 2010). Third, if the physicians stop doing the prework of the focal appointment when the next patient is ready, then it will lead to an interruption in the EHR activity of the focal appointment. Froehle and White (2014) showed that interruptions can induce forgetting in a worker, leading to increased rework to complete the task.

Lastly, some prework tasks may be unnecessary, and the physician may need to rework in the patient's presence (Holman et al. 2016). Management literature has previously discussed the benefits of reduced rework with increasing customer engagement and service coproduction (Lengnick-Hall 1996, Roels 2014).

Despite these disadvantages, surveys of physicians indicate that they prefer to perform some prework on EHR before an appointment. In particular:

- *I find it useful to know the purpose of the visit and the scope of the patient's concerns and to review the data before the appointment. This allows me to formulate a tentative plan before I enter the exam room and makes it less likely that some aspect of care will fall through the cracks. Spending a few minutes reviewing the chart and patient questionnaire and discussing the patient with the nurse pays off with a more efficient, focused visit* (Sinsky et al. 2016).

Although some EHR work will always be done with the patient in the room, prework may help reduce the total EHR workload. First, doing some prework would be an example of early initiation of tasks. Early task initiation shifts the workload from more congested parts of the workday to an earlier non-value-added idle time and may reduce total processing time (Batt and Terwiesch 2017). Time with the patient in the examination room is busy for the physician. The physician must listen to the patient, review and type patient-supplied information into EHR, and recommend treatment options. Doing some EHR work, such as reviewing patient history and preparing notes before entering the room, may help reduce the time physicians spend alternating between talking to the patient and interacting with the EHR system. This would help the physician perform the remaining EHR work with the patient in the room more efficiently. This improvement in efficiency by moving tasks from busy server time is also related to the lean concept of changeover reduction by doing external setup tasks when the machine is stopped (Shingo 1989). Lean changeover reduction focuses on minimizing downtime and increasing efficiency during the transition between tasks or processes using smaller batch sizes. EHR tasks such as reviewing patient records and selecting templates[2] in the EHR system can be thought of as setup tasks, and performing them before the appointment would help reduce the time spent on EHR during the appointment.

Second, research in psychology has indicated that although switching costs are incurred when switching between tasks, the switching cost is reduced (although it is not eliminated) when workers are given an opportunity to prepare for the switch. Task preparation may be considered as the activation of mental structures in anticipation of their future use, such as collecting one's thoughts before a lecture or collecting tools before a manual task, making the process progress more efficiently (Altmann 2004). Third, if the physicians stop doing the prework of the focal appointment when the next patient is ready, it will lead to an interruption in the EHR activity of the focal appointment. Froehle and White (2014) showed that interruptions can induce workers' forgetting, leading to increased task rework.

Therefore, doing some prework, such as reviewing patient records, would help the physician be mentally prepared and help them do the multitasking part of EHR work more efficiently. Given that prework could potentially lead to an increase or decrease in total EHR work, we propose the following hypotheses.

Hypothesis 1a. *An increase in pre-appointment EHR work leads to less total time spent on EHR.*

Hypothesis 1b. *An increase in pre-appointment EHR work leads to more total time spent on EHR.*

Physician burnout from EHR activities is related to total EHR workload and after-work hours (Sinsky et al. 2016, Attipoe 2021). In our second hypothesis, we try to measure the effect of prework on EHR workload after the end of the day. As discussed above, prework may increase the total EHR workload because of Parkinson's law, task-switching, and rework that is due to low service coproduction. Prior studies have found that knowledge workers often batch similar tasks, and this batching behavior is positively associated with increasing workload (Ibanez et al. 2018). Task batching involves grouping similar or related tasks and completing them in a single, focused effort. This approach increases efficiency by reducing context switching and optimizing workflow, improving productivity, and reducing overall time spent completing tasks. Therefore, if prework increases the total EHR workload, it may also lead to increased after-work hours because of the batching of EHR tasks to the end of the day. Also, with an increasing workload, physicians may prefer not to be rushed during clinic hours and to do these additional tasks after the end of the workday (Attipoe 2021). On the contrary, performing prework may reduce the after-hours work because the physician is more prepared for the appointment. This may lead to reduced errors in EHR work during the appointment and, therefore, less EHR work during after-work hours. We hypothesize the following.

Hypothesis 2a. *An increase in pre-appointment EHR work leads to less after-hours EHR work.*

Hypothesis 2b. *An increase in pre-appointment EHR work leads to more after-hours EHR work.*

We next consider the effect of postwork on the total EHR workload. After the conclusion of the appointment, the physician performs several actions on the EHR system. These are typically tasks such as writing after-visit notes, ordering tests, sending medication orders to pharmacies, and communicating with the patient over secure communication about the summary of the visit and any recommendations. A physician may choose to complete this work as postwork in the idle time between appointments or wait until the end of the day.

There are three reasons postwork would lead to an increase in total EHR time. First, similar to prework, if the physicians stop doing the postwork of the focal appointment, then it would increase the time taken to complete the remaining EHR work due to forgetting and rework (Froehle and White 2014). Second, like prework, introducing postwork may also lead to the detrimental effect of task switching from face-to-face appointments to EHR work. Postwork EHR introduces changeover time like prework EHR; however, it does not have the advantages of task preparation. Lastly, physicians may prefer easier tasks when selecting EHR tasks to perform during the post-appointment time. Selecting easier tasks has been associated with lower productivity (Ibanez et al. 2018, KC et al. 2020).

There are three advantages to performing EHR tasks during idle time after an appointment. First, shifting EHR-related activity to after the appointment may help reduce information overload (Karr-Wisniewski and Lu 2010) for the physician during the appointment. Doing dedicated EHR work during idle time without interference from patient interaction may improve efficiency in doing EHR work. Second, compared with after-hours work, the physician may have better recall during regular work hours and thus may be able to complete EHR tasks faster. Third, the physician may need to collaborate with the nurse or other care providers while filling in the information in EHR, or he or she may need technical assistance on the EHR system itself. In that case, completing tasks during regular work hours is preferable. After-work coordination and communication may need to be done asynchronously because not everyone is available. Recent studies on work from home of information workers have shown that increased asynchronous communication leads to slower information sharing (Yang et al. 2022). Lastly, similar to prework, physicians' actions when doing postwork may also demonstrate Parkinson's Law and may fill available time with more postwork than required, thus increasing the total EHR time.

Both prework and postwork reduce EHR work from busy patient interaction time during the appointment. Although postwork is not an example of early-task initiation, it can be considered a shift of work from the busy multitasking time with patients by delaying some activities and performing them during breaks after the appointment. Considering the effect of postwork on total EHR usage, we have the following hypothesis.

Hypothesis 3. *An increase in post-appointment EHR work leads to more total EHR workload.*

As discussed above, postwork may increase the total EHR workload, and as discussed previously, workers tend to batch tasks with increasing workload, which may increase after-work hours. On the other hand, postwork helps shift work from after-work hours and may improve EHR productivity because longer work hours have been associated with lower productivity (Caruso 2014). Given these factors, we hypothesize the following.

Hypothesis 4. *An increase in post-appointment EHR leads to less after-hours EHR workload.*

Physicians have considerable discretion on how they choose to distribute EHR activity before, after, or during appointments or after the end of the workday (Zhang et al. 2016, Attipoe 2021). In the following two hypotheses, we consider whether increasing the idle time between appointments would lead to changes in the amount of prework and postwork.

We first consider the effect of idle time on prework. Research in psychology has demonstrated that when presented with an opportunity to prepare for upcoming tasks to reduce task-switching costs, workers may fail to do so. This may happen because of a lack of motivation, fatigue, or lack of feedback on the performance benefits of preparation (De Jong 2000). Short breaks can benefit productivity (Pendem et al. 2022), and physicians may wish to take benefit of these short breaks to rejuvenate themselves rather than work on EHR. Lastly, because there is a possibility that the upcoming appointment may be a no-show, the physician may not do prework to avoid wasted effort.

On the other hand, increasing the idle time before an appointment may lead to the physician spending more time on prework. The physician may be aware of the productivity benefits of prework and may do so when given an opportunity. The physician may prefer to spend more face time with the patient and perform more prework EHR work when the idle time before an appointment increases. In the context of hand hygiene, Dai et al. (2015) showed that when there is time off between shifts, the time spent on secondary tasks increases. Given these effects, we present the following hypotheses.

Hypothesis 5. *An increase in the average idle time between preceding appointments leads to more pre-appointment EHR time for the focal appointment.*

Increasing idle time after an appointment may not lead to any increase in postwork. Physicians may procrastinate any remaining EHR tasks for the appointment to the end of the day and utilize idle time for rejuvenation. Secondly, the physician may prefer to batch EHR tasks to the end of the day. Batching of tasks by healthcare professionals has been observed in other healthcare contexts, such as radiology and the emergency department (Ibanez et al. 2018, Feizi et al. 2023). Surveys of physicians such as Zhang et al. (2016) indicate that some physicians like to do EHR work after the day's appointments are over. One potential reason could be that if physicians do not switch between face-to-face work and EHR work, it will save them task-switching time. Also, communication with the patients may be more efficient without interruption from EHR work. Other reasons could be that sometimes test results ordered during the day may be available later in the day, and writing after-visit notes toward the end of the day allows them to have complete information when completing after-visit notes. Also, the EPIC EHR system often logs out the physician after a period of inactivity (Tai-Seale et al. 2017). Therefore, if the physician switches between patient work and EHR work during the workday, they may incur multiple logout events and would need to incur time and effort in logging back into the system. Finally, physicians may also prefer the flexibility of working from home (Attipoe 2021) and may not utilize the idle time for postwork. Therefore, there may be efficiency in "batching" EHR work to the end of the day.

On the other hand, several factors may lead to increasing postwork with increasing idle time between appointments. First, an increase in idle time between appointments may increase the likelihood of completing a patient's EHR-related tasks and not getting interrupted by the following appointment. Physicians who are averse to interruptions and incomplete work may increase postwork activity if more time becomes available. Additionally, physicians may prefer to end the day early, spend more face time with the patients, and take advantage of better recall immediately after the appointment. Thus, with additional idle time after the appointment, physicians will increase postwork. We present the following hypotheses.

Hypothesis 6. *An increase in average idle time after an appointment leads to more post-appointment work for the focal appointment.*

We tabulate the mechanisms through which prework and postwork may affect total and after-hours time spent on EHR in Table 1.

4. Data

4.1. Data Description

We test our hypotheses using data from the family medicine unit of one of the largest academic medical centers in the United States. The family medicine unit delivers primary care services in an outpatient setting. All physicians are required to use the same EHR system provided by Epic Systems Inc.[3] Our data range from May 2017 through May 2019. We restrict our data to those days with at least five appointments in the day, because days with fewer than five appointments are not representative of the daily workload of the physicians. Our final data comprise 152,970 appointments from 74 physicians.

EHR systems record time stamps of activities performed. These data are called audit log data or event log data. These data track who logged in to the EHR system, what task was performed, when the person did the task, and the patient record on which it was

Table 1. Mechanisms of the Effect of Prework and Postwork on Total and After-Hours Time on EHR

	Total EHR work	After-hours EHR work
Prework	**Increase (H1b):** • Task switching (Staats and Gino 2012, KC 2014, Gurvich et al. 2020) • Parkinson's law (Parkinson 1955, Gutierrez and Kouvelis 1991, Hasija et al. 2010) • Rework and service coproduction (Lengnick-Hall 1996, Roels 2014) • Task interruption (Froehle and White 2014)	**Increase (H2b):** • Batching increases with workload (Ibanez et al. 2018)
	Decrease (H1a): • Early task initiation (Batt and Terwiesch 2017) • Lean changeover reduction through external setup (Shingo 1989) • Task preparation (Altmann 2004)	**Decrease (H2a):** • Lower workload through task preparation leads to less after-hours work (Altmann 2004)
Postwork	**Increase (H3):** • Task interruption (Froehle and White 2014) • Task switching (Staats and Gino 2012, KC 2014, Gurvich et al. 2020) • Preference for easier tasks during task selection (Ibanez et al. 2018, KC et al. 2020) • Parkinson's law (Parkinson 1955, Gutierrez and Kouvelis 1991, Hasija et al. 2010)	**Increase** • Batching increases with workload (Ibanez et al. 2018)
	Decrease • Improved productivity due to reduced information overload (Karr-Wisniewski and Lu 2010) from face-time • Better recall after the appointment • Improved coordination and communication with coworkers during regular work hours (Yang et al. 2022)	**Decrease (H4):** • Improved productivity through shorter workday length (Caruso 2014)
	Prework	**Postwork**
MeanIdleBefore	**Increase:** Physician prefers face-to-face time with the patient and uses idle time for EHR work. Increased idle time between shifts increases time on secondary tasks (Dai et al. 2015) **Decrease/No Increase:** Lack of motivation, fatigue, or lack of feedback on the performance benefits of preparation (De Jong 2000), physicians seeking productivity increase from short breaks (Pendem et al. 2022), and the upcoming appointment may be a no-show, preference for batching tasks to end of day (Zhang et al. 2016, Attipoe 2021)	
MeanIdleAfter		**Increase:** Increase the likelihood of completing a patient's EHR-related tasks. The physician prefers face-to-face time with the patient and uses idle time for EHR work, physicians taking advantage of improved recall. Increased idle time between shifts increases time on secondary tasks (Dai et al. 2015) **Decrease/No Increase:** Procrastination, batching (Ibanez et al. 2018, Feizi et al. 2023), preference for after-hours work, and work from home (Zhang et al. 2016, Attipoe 2021)

performed. These audit data are recorded because of the HIPAA requirements to audit inappropriate access (Adler-Milstein et al. 2020). Several studies have validated the measurement of EHR use from audit log data through other means. Tai-Seale et al. (2017) compared EHR audit log data through in-person observation and audio recording. Arndt et al. (2017) validated EHR time stamp data with observed data. These studies found the difference between EHR time stamp data and observed data of EHR usage to be small and recommended using audit log data to study clinic workflow and EHR use by physicians.

We have two separate data sets. The first data set relates to the appointment progression. These data consist of the following fields for each appointment: *Patient ID*, *Physician ID*, *Date of appointment*, *Age of patient*, *Gender of patient*, *Patient insurance provider*, *Scheduled start time of appointment*, *Start time of patient check-in at the front desk*, *Time patient enters an examination room*, *Time nurse leaves the examination room*, *Time physician enters the examination room*, *Diagnosis codes for visit*, and *Time physician ends the appointment*. The second data set is EHR usage log data. These data have timestamps for each EHR action and the identifier for the patient whose records were being viewed or edited by the physician. These data consist of the following: *Physician ID*, *Patient ID*, *EHR activity starting timestamp*, and *EHR activity name*. Given physician ID, patient ID, appointment time stamps, and EHR activity time stamps, we can combine the two data sets to get the time spent on EHR activity by the physician for each patient between two given time limits. Next, we define the different time windows when physicians perform EHR tasks.

Prework (*PRE*) is the amount of time a physician spends on a patient's EHR record from 12:01 a.m. on the day of the appointment until the start of the face-to-face appointment. We ignore work done on EHR before 12:01 a.m. because we observe that less than 0.01% of EHR work for an appointment is done on the previous day. Multitasking (*MULTI*) EHR time is spent on EHR tasks while the physician is in the examination room with the patient. Postwork (*POST*) EHR activity is done between the end of the face-to-face appointment and the end of the workday. After-hours (*EOD*) EHR activity denotes time spent on EHR after the end of the workday. We define the end of the workday as 6 p.m. because it is the standard practice in our setting, and several studies have defined regular work hours for physicians to be between 8 a.m. and 6 p.m. (Arndt et al. 2017). We repeat our analysis with the physician workday ending at 5 p.m., as used by Bavafa and Terwiesch (2019), and also by computing the end of the workday to be the end of the last appointment and one hour after the end of the last appointment of the day. Our findings do not change for these alternate definitions for the end of the workday.

In Figure 1, we show the representative timing of these EHR activities. The blocks above the central horizontal line represent the time physicians spend with patients in the room. We show five appointments; the second appointment is a no-show, and the fourth appointment has a delayed start, starting after its scheduled start time. For simplicity, we show only EHR activities of appointment 4. We show the timing of EHR activity in the blocks below the horizontal line. As discussed above, we can observe that physicians divide their EHR activity into prework (*PRE*), postwork (*POST*), multitasking work with the patient in the room (*MULTI*), and EHR work at the end of the day (*EOD*). We next describe the procedure of computing the time spent on EHR activity between given time intervals.

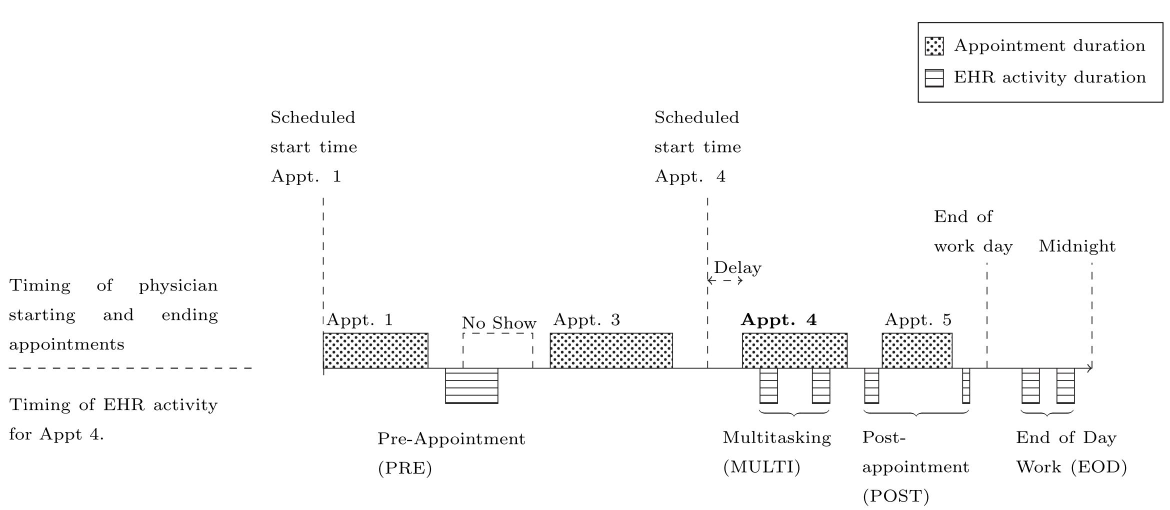
4.2. Data Transformation

Our unit of analysis is an appointment, and we analyze the timing of EHR usage relative to the appropriate appointment. For this, we transform the data so that we have the EHR work done during the intervals for PRE, MULTI, POST, and EOD for each appointment. We describe the data transformation steps below.

First, we find all EHR activities where the activity time stamp falls within the start and end times of the required time interval for the given physician ID and patient ID. We order all these activities in increasing time. Let these activities be $(a_1, a_2, \ldots, a_N)$ and the corresponding time stamps be $(t_1, t_2, \ldots, t_N)$.

Next, we compute the duration of the activity a_i by computing $t_{i+1} - t_i$. The timestamp for each activity is created by the EHR internal system when the physician

Figure 1. Representative Diagram of Timing of Appointments and EHR Work for a Physician's Day



*For simplicity EHR work and scheduled start time is shown only for Appointment 4.

interacts with the system. However, there is no direct way to ascertain how long the physician was active on the EHR system for a particular task. The physician may have the EHR open while engaging in other activities, such as talking to the patient or a colleague. To eliminate idle time where the system is open without any activity, we applied a cutoff of 90 seconds; that is, for activity a_i, if $t_{i+1} - t_i$ exceeds 90 seconds, we set it to 90 seconds. We used a 90-second cutoff because Arndt et al. (2017) validated that applying a 90-second cutoff supported observed data of physician EHR usage. Tai-Seale et al. (2017) used a cutoff of 60 seconds. They also validated the measurement from EHR audit logs against data from actual observations of physicians. To demonstrate that our results are not sensitive to this cutoff threshold, we repeat our analysis for cutoff values of 60 seconds, 90 seconds, and 120 seconds. We present these results in the electronic companion (EC.5), showing that our principal findings do not change. Using the above procedure, we compute PRE, MULTI, POST, and EOD.

4.3. Variable Definitions and Descriptive Statistics

In Table 2, we present the summary statistics. We have two dependent variables for our analysis. The first is the total time spent on EHR on an appointment on the day of the appointment (*TOTAL*). The second dependent variable of interest is the time physicians spend on EHR systems after the end of the workday (*EOD*).

We have four principal endogenous variables for our analysis: *PRE*, *MULTI*, *POST*, and *EOD*. Our last variable of interest is the average idle time between appointments after the index appointment (*MeanIdleAfter*). This variable is computed by dividing the total idle time after the index appointment by the number of appointments after the index appointment. Mathematically, for appointment i, $MeanIdleAfter_i = \frac{\text{Total idle time after appointment } i}{\text{Number of appointments after } i}$. This variable will measure the time available to do post-appointment EHR tasks after an appointment, scaled by the number of remaining appointments. Because *MULTI* may influence *MeanIdleAfter*, we model *MeanIdleAfter* as an endogenous

Table 2. Descriptive Statistics at the Appointment Level

	Variable	Description	Mean	Std. dev.
	Endogenous variables			
(1)	*TOTAL (mins)*	Total time spent on EHR for the index appointment	18.81	9.394
(2)	*PRE (mins)*	EHR usage between 12:01 a.m. on the day of the appointment till the time the physician enters the examination room for the appointment	2.441	4.698
(3)	*MULTI (mins)*	EHR usage between the time the physician enters the examination room for the appointment and ends the appointment	9.355	6.184
(4)	*POST (mins)*	EHR usage from the end of the appointment until the end of the workday	5.124	5.693
(5)	*EOD (mins)*	EHR usage from the end of the workday until midnight of the day of the appointment	1.893	4.153
(6)	*MeanIdleAfter (mins)*	Average idle time between all appointments following the index appointment	9.269	12.97
	Control variables			
(7)	*TotalApptsInDay (integer)*	No. of appointments scheduled for the day	13.26	4.205
(8)	*ApptStartHour (integer)*	Start hour of the appointment	*11.27*	*2.72*
(9)	*DayTotalScheduled (mins)*	Total scheduled time of all appointments in the day	269.1	99.19
(10)	*ApptScheduledLength (mins)*	Scheduled duration of the index appointment	23.13	9.296
(11)	*CCI (Score range: 0–13)*	Charlson comorbidity score	0.499	1.054
(12)	*PCPDelay (minutes)*	Time duration between the scheduled start of the appointment and the time the physician enters the examination room	0.44	0.48
(13)	*MeanIdleBefore (mins)*	Average idle time between all appointments preceding the index appointment	6.754	7.686
	Instrumental variables			
(13)	*ArrDelay (mins)*	Patient arrival delay. The time difference between the scheduled start time of the appointment and patient check-in time	2.41	7.19
(13)	*LagMULTI (mins)*	Lagged average of *MULTI* by appointment sequence	9.355	6.194
(14)	*NoShowAfter (indicator)*	Variable indicating whether there is a no-show for an appointment following the index appointment	0.218	0.413
(15)	*LagPOST (mins)*	Lagged average of *POST* by appointment sequence	5.102	5.695

Notes. $N = 152{,}970$. Unit of analysis is an appointment. Other control variables not in the table: physician FE, patient gender, patient age, patient insurance, patient continuity indicator, and day of week.

variable. Finally, we include the following control variables:

Patient controls: Patient characteristics such as clinical complexity may determine how much time physicians spend outside clinical hours and during appointments on EHR systems (Zhang et al. 2016, Arndt et al. 2017). Therefore, we control for several patient-level factors, such as gender, age, and whether the patient has Medicaid, Medicare, or private insurance. We control for patient continuity by including an indicator variable if the patient has last visited the same physician previously. We control for patient complexity by including a variable for the Charlson Comorbidity Index (CCI), which is used frequently in the literature (Austin et al. 2015). CCI measures the one-year mortality of patients by incorporating the acuity of several severe medical conditions and is expressed as an integer between 0 and 13. We use the *R* package "comorbidity" to convert the diagnosis codes of a visit to CCI scores.

Workload and scheduling controls: The clinical workload of the physician may influence the choice to allocate EHR work during work hours or after the end of the day. Therefore, we include the total number of appointments scheduled and the total scheduled duration of all appointments on the day. We also control for the appointment's start hour because the physician's EHR behavior may change as the day progresses because of factors such as fatigue. We include a control for the scheduled duration of the index appointment because that may influence the physician's choice to increase multitasking EHR activity during the appointment. We also control for the average idle time between appointments preceding the index appointment (*MeanIdleBefore*). This variable is computed by dividing the total idle time before the index appointment by the number of appointments before the index appointment. Mathematically, for appointment i, $MeanIdleBefore_i = \frac{\textit{Total idle time before appointment } i}{\textit{Number of appointments before } i}$. This variable measures the time available for pre-appointment EHR before an appointment, scaled by the number of preceding appointments. Additionally, we include a control for physician delay because the physician EHR use behavior may change if the physician runs late for an appointment.

Other controls: We include fixed effects for physicians to control for time-invariant physician characteristics. We also include the day-of-week effect.

5. Econometric Model

Our observational data set on physician EHR use is detailed and granular, allowing us to perform a process-level analysis. The patient ID labels EHR activity for a particular patient's record. This allows us to connect the appointment progression and patient characteristics with the EHR use, giving us a view into when EHR tasks were performed for a particular appointment. In order to estimate effects related to the hypotheses discussed in Section 3.2, we need to identify the causal relationship between *PRE*, *POST*, *TOTAL*, *EOD*, *MeanIdleBefore*, and *MeanIdleAfter*. Before modeling this causal relationship, we perform a model-free analysis of the effect of increasing idle time before and after an appointment on *PRE*, *POST*, and *TOTAL*. A no-show before or after the appointment is an exogenous shock that increases the idle time between appointments. We compare the means between two sets of two groups: with and without a no-show before the appointment and with and without a no-show after the appointment. We present these results in the electronic companion in EC 2.1. We find that a no-show before the appointment is associated with increased prework and after-hours EHR work and decreased total EHR work. On the other hand, a no-show after the appointment is associated with an increase in postwork and total EHR work but a decrease in after-hours EHR work. Although this mean comparison motivates the primary analyses of the paper that an increase in idle time before and after the appointment has varying effects on the prework, postwork, total EHR workload, and after-hours EHR workload, this is not conclusive evidence of the causal effect of prework and postwork on total and after-hours EHR.

The central challenge in using observational data to identify causal effects in our analyses arises from physicians' endogenous choice of when and how much EHR work to perform during idle time. Whereas we control for factors such as daily workload and patient complexity, other unobservable patient factors may affect the total time on EHR and the work done during idle time. For example, if a patient expresses a severe mental health condition during the appointment, the physician would be more likely to spend face time with the patient than do EHR work while the patient is in the room (Zhang et al. 2016). This would likely increase *POST* and *EOD* while reducing *MULTI*. A patient having a severe mental health condition is also correlated with increased EHR usage by the physician (Young et al. 2018). Young et al. (2018) found that patients and physicians having linguistic and cultural similarities correlate with more face-to-face time and total EHR time. Therefore, linguistic and cultural similarities may increase the duration of the appointment, reducing the idle time after the appointment (*MeanIdleAfter*). Linguistic and cultural similarities may also increase the information the patient may convey to the physician, thus increasing *POST* and *EOD*. Therefore, we model *MeanIdleAfter* as an endogenous variable.

These examples indicate that using observational data of EHR timestamps without accounting for endogeneity would lead to biased estimates. We address this problem by setting up an identifiable system of simultaneous equations accounting for the simultaneity bias among our key variables of interest. Through this system of equations, we model the relationship between *PRE*, *MULTI*, *POST*, *EOD*, and *MeanIdleAfter*. Through this system of equations, we estimate the effect of *PRE* and *POST* on *TOTAL* and *EOD*.

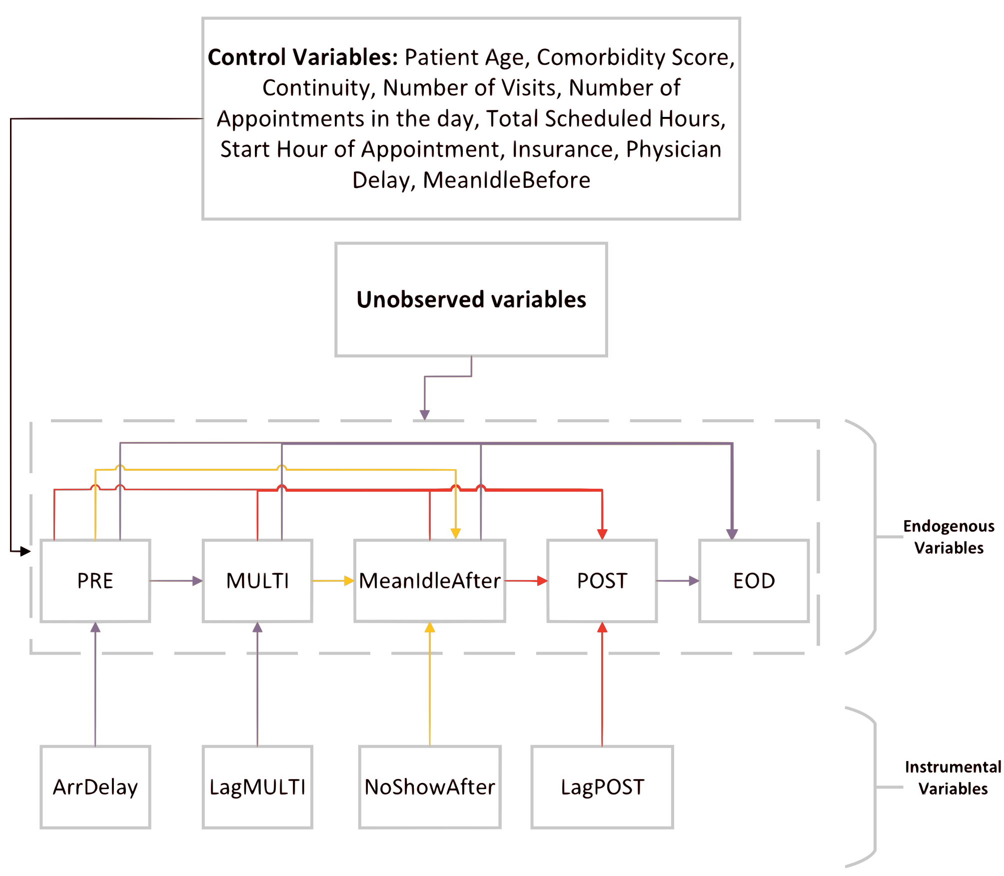
5.1. Model Formulation and Identification

First, we perform an OLS estimation of the effect of *PRE* and *POST* on *TOTAL* and *EOD*. For conciseness, we present the results of this estimation in the electronic companion (EC.2.2). We find that the marginal effect of *PRE* and *POST* on *TOTAL* is positive. However, as discussed above, in the presence of endogeneity due to unobserved patient characteristics, these OLS results are likely biased; thus, we propose an instrumental variable approach.

Figure 2 shows the relationship between the endogenous, control, and instrumental variables. Because *PRE*, *MULTI*, *MeanIdleAfter*, *POST*, and *EOD* relate to the progression of EHR work and duration of the index appointment, they are likely causally related; that is, *MULTI* may be affected by *PRE*. Similarly, *POST* may be affected by *PRE*, *MULTI*, and *MeanIdleAfter*. *EOD* may be affected by *PRE*, *MULTI*, and *POST*. We have represented this relationship by the "Endogenous variables" box in Figure 2. As noted above, unobserved patient-related variables may simultaneously affect these variables, which we denote by the box titled "Unobserved variables." Next, the control variables are indicated in the "Control Variables" box. Finally, because we adopt an instrumental variable approach to mitigate these unobserved variables, we include instrumental variables that affect the individual endogenous variable but would not be affected by the unobserved variables. This we denote by the group of variables called "Instrumental variables" in Figure 2. We next present the simultaneous equation model describing the relationship between the endogenous, control, and instrumental variables. *EOD* does not require an instrumental variable because it does not appear on the right-hand side of the system of equations. Please note that Figure 2 is only representative of the model. For conciseness, we have not represented all model relationships. For example, *MeanIdleBefore* is a control variable for only (1) and not (2)–(5).

A set of simultaneous equations represents the above model. In a simultaneous equation model, multiple economic variables are modeled together, considering

Figure 2. (Color online) Model Schematic



their interdependencies. Because of the nature of the problem, the simultaneous equation model is a recursive model. A recursive model is a special case of a system of equations where the right-hand side of the first equation contains no endogenous variables and the right-hand side of the kth equation involves only the endogenous variables from the previous $k-1$ equations (Wooldridge 2010). This is true in our case because there is no simultaneous relationship between the endogenous variables. For example, because of the sequential nature of tasks, *PRE* can affect *MULTI*, *POST*, and *EOD*. However, *MULTI*, *POST*, and *EOD* cannot affect *PRE*.

The model equations are given below:

$$LogPRE_i = \alpha_{AD,PRE} LogArrDelay_i + \alpha_{IB,PRE} LogMeanIdleBefore + \boldsymbol{\theta_{PRE} X_i} + \epsilon_{PRE,i} \quad (1)$$

$$LogMULTI_i = \beta_{PRE,M} LogPRE_i + \alpha_{MLAG,M} Log(LagMulti_i) + \boldsymbol{\theta_M X_i} + \epsilon_{MULTI,i} \quad (2)$$

$$LogMeanIdleAfter = \beta_{PRE,IA} LogPRE_i + \beta_{M,IA} LogMULTI_i + \alpha_{NA,IA} NoShowAfter + \boldsymbol{\theta_{IA} X_i} + \epsilon_{IA,i} \quad (3)$$

$$LogPOST_i = \beta_{PRE,POST} LogPRE_i + \beta_{MULTI,POST} LogMULTI_i + \beta_{IA,POST} LogMeanIdleAfter_i + \alpha_{LP} Log(LagPOST_i) + \boldsymbol{\theta_{POST} X_i} + \epsilon_{POST,i} \quad (4)$$

$$LogEOD_i = \beta_{PRE,EOD} LogPRE_i + \beta_{MULTI,EOD} LogMULTI_i + \beta_{IA,EOD} LogMeanIdleAfter_i + \beta_{POST,EOD} LogPOST_i + \boldsymbol{\theta_{EOD} X_i} + \epsilon_{EOD,i} \quad (5)$$

These equations model the relationship between *PRE*, *MULTI*, *MeanIdleAfter*, *POST*, and *EOD*. We perform a log transformation for all variables that are the duration of an activity or a time interval, namely, *PRE*, *ArrDelay*, *PCPDelay*, *MeanIdleBefore*, *MULTI*, *LagMULTI*, *MeanIdleAfter*, *POST*, *LagPOST*, and *EOD.* We use log transformation because it has been used to model service time in healthcare (Gurvich et al. 2020).

The estimates ($\beta_{PRE,M}, \beta_{PRE,IA}, \beta_{M,IA}, \beta_{PRE,POST}, \beta_{MULTI,POST}, \beta_{IA,POST}, \beta_{PRE,EOD}, \beta_{MULTI,EOD}, \beta_{IA,EOD}, \beta_{POST,EOD}$) give the relationship among the endogenous variables. The parameters ($\alpha_{AD,PRE}, \alpha_{IB,PRE}, \alpha_{MLAG,M}, \alpha_{NA,IA}, \alpha_{LP}$) are the coefficients of the exogenous variables. All other controls, such as patient controls, workload, and scheduling controls, are collected together in $\boldsymbol{X_i}$, and the coefficients corresponding to these controls are ($\theta_{PRE}, \theta_M, \theta_{IA}, \theta_{POST}, \theta_{EOD}$). Finally, ($\epsilon_{PRE,i}, \epsilon_{MULTI,i}, \epsilon_{IR,i}, \epsilon_{POST,i}, \epsilon_{EOD,i}$) are the error terms for each equation. We first consider Equation (1). With increasing idle time before an appointment, physicians would have more time to do prework. If this coefficient is positive, that would indicate that physicians utilize idle time before an appointment to perform tasks on the EHR system before face-to-face time with the patient. If the physician is delayed for an appointment, then the physician may reduce the time spent on prework. We note that physicians being delayed because of the previous appointment will be exogenous to physician EHR use for the index appointment. Next, in Equation (2), we model the time spent on the EHR system while the patient is in the room to depend on prework and physician delay.

The time physicians multitask on EHR may influence the idle time between subsequent appointments. From this, we have Equation (3). Depending on the effect of previous work done on EHR (*PRE*, *MULTI*) and the amount of idle time available between appointments after its conclusion, the physician may choose to perform some postwork. We model this by Equation (4). Finally, depending on the effect of previous EHR tasks, the remaining EHR task is done after the end of the workday (*EOD*). We model this by Equation (5).

As noted above, the system of Equations (1)–(5) is recursive, where for each equation, only endogenous variables from the previous equations appear on the right-hand side (Wooldridge 2010). A special case of the recursive system of equations is a fully recursive system of equations where the error terms are pairwise uncorrelated. A fully recursive system of equations can be estimated by equation-by-equation OLS regression. However, the system of Equations (1)–(5) is not fully recursive because, as we discussed above, there may be unobserved patient characteristics that may influence both total EHR time spent on an appointment and the distribution of EHR tasks to *PRE*, *MULTI*, *POST*, and *EOD*. Therefore, we cannot assume that the error terms ($\epsilon_{PRE,i}, \epsilon_{MULTI,i}, \epsilon_{IR,i}, \epsilon_{POST,i}, \epsilon_{EOD,i}$) are pairwise uncorrelated. Consequently, for the system to be identified, we include instrumental variables in addition to the variables discussed above. We describe the instrumental variables in detail below:

Patient Arrival Delay (*ArrDelay*): This is the delay in patient arrival, computed by the time difference between the appointment's scheduled start time and the patient's check-in time.

Lagged Multitasking (*LagMULTI*): This is the time spent on EHR by the physician during an appointment (*MULTI*) seven days before the index appointment, which starts at the same hour of the day as the index appointment.

No Show After Appointment (*NoShowAfter*): Indicator variable if one of the scheduled appointments after the index appointment is a no-show.

Lagged Postwork (*LagPOST*): We compute this variable by taking the time spent on EHR by the physician after an appointment (*POST*) on the previous day, which occurs seven days before the index appointment and starts at the same hour of the day as the index appointment.

A valid instrument for a system of equations needs to satisfy specific requirements. First, the instrumental variable should be correlated with the endogenous variable but should not be directly related to the outcome variable except through its effect on the endogenous variable. Second, the instrumental variable should be exogenous, that is, not influenced by the outcome variable or any unobserved factors that affect the outcome. This ensures that the instrumental variable is not subject to reverse causality or omitted variable bias. We note that the patient arrival delay gives the physician additional time to perform prework and is likely not influenced by unobservable patient characteristics described above. The presence of a no-show after the index appointment will directly influence *MeanIdleAfter* by increasing the idle time after the appointment. Because the no-show is due to the absence of a different patient and the information that an appointment is a no-show is available only at the start of that appointment, it is unlikely to be influenced by the unobserved patient characteristics of the index appointment.

We use lagged variables as instruments for *LogMULTI* and *LogPOST.* Using lagged variables as instrumental variables is a common practice (Kesavan et al. 2014). For *Log(LagMULTI)* and *Log(LagPOST)* to be appropriate IVs, we need evidence that these variables should satisfy relevance and exclusion criteria. For relevance criteria, *MULTI* and *POST* for an appointment in the past, starting at the same hour as the focal appointment, should be correlated with *MULTI* and *POST* of the focal appointment. Results from prior literature demonstrate that physicians exhibit significant learning effects. Holmgren et al. (2021) found that with every month of experience, physicians become more efficient with EHR systems. Therefore, past EHR usage would be correlated with present EHR usage behaviors. In our data, we also find similar learning effects with respect to total EHR, multitasking EHR, and postwork EHR. We present these results of the learning curve in EHR usage in the electronic companion (EC 3.4). Physicians also demonstrate fatigue effects within a day. Khairat et al. (2020) found that as the day progresses, physicians become less efficient. Therefore, physician EHR use for a past appointment starting at the same hour of the day would be correlated with the index appointment. This implies that lagged variables of EHR use would likely be relevant instrumental variables. Because the primary cause of endogeneity is unobserved patient characteristics, the EHR use for an appointment in the past would not be correlated with the error terms for the index appointment. Therefore, lagged EHR use variables such as *Log(LagMULTI)* and *Log(LagPOST)* would satisfy the exogeneity requirement of instrumental variables. In order to mitigate any workload spillover effects from the previous day, we select a period of seven days for these lagged variables.

When applying instrumental variables to a system of equations, some exogenous variables must be excluded from some of the equations; that is, not all exogenous variables can directly affect all endogenous variables. This requirement is called the exclusion requirement. The exclusions must satisfy the order and rank conditions for a system of equations to be identified. The order condition for an equation states that the number of excluded exogenous variables from the equation must be greater than or equal to the number of included right-hand-side endogenous variables. The rank condition requires that the matrix of all structural equations of the model have full rank. Wooldridge (2010, chapter 9), presents a detailed discussion of these requirements.

We can verify through observation that our system of equations satisfies the order condition because, for all equations, the number of excluded exogenous variables from the equation is greater than the number of included right-hand-side endogenous variables. To verify that all the equations satisfy the rank condition, we use the Stata package "checkreg3" (Baum 2007). Our estimation procedure is based on the two-stage least squares (2SLS) estimation procedure for simultaneous equations described in Wooldridge (2010). We describe the estimation steps in the electronic companion (EC.3). We cluster robust standard error by physician and date of appointment.

As part of our robustness tests, we also show results from estimating our model using the three-stage least squares (3SLS) estimator (Zellner and Theil 1992) (EC.5.4), and we observe that parameter estimates show only minor differences from the 2SLS estimation. We present the simultaneous equation model coefficients without the instrumental variables (EC.2) and results on endogeneity tests (EC.5.5) and show that the results support endogeneity in the system of equations. In the next section, we discuss our results and their managerial relevance.

6. Results and Discussion

In Table 3, we present the estimated parameters of our system of equations. The dependent variables label the columns, and the column numbers correspond to Equations (1)–(5). The right-hand-side variables of the

Table 3. Summary Regression Results for Simultaneous Equation Model Equations (1)–(5)

	(1) *Log(PRE)*	(2) *Log(MULTI)*	(3) *Log(MeanIdleAfter)*	(4) *Log(POST)*	(5) *Log(EOD)*
Log(PRE)		−0.406*** (0.0208)	−0.545*** (0.127)	0.134 (0.0808)	−0.267** (0.0960)
Log(MULTI)			1.157*** (0.245)	0.590*** (0.153)	−0.184 (0.177)
Log(POST)					−0.607*** (0.114)
Log(MeanIdleBefore)	0.0679*** (0.00341)				
Log(MeanIdleAfter)				0.497*** (0.0379)	−0.0826 (0.0938)
Log(PCPDelay)	−0.172*** (0.00427)	0.139*** (0.00629)	−0.441*** (0.0328)	−0.123*** (0.0240)	−0.0198 (0.0266)
Log(PatientDelay)	0.0443*** (0.00273)				
NoShowAfterAppt			0.403*** (0.0320)		
N	154,192	148,842	148,842	148,842	148,842

Notes. Standard errors in parentheses The unit of analysis is an appointment. All models include physician FE, patient controls, and scheduling controls, as described in Section 4. Robust standard errors, in parentheses, are clustered by physician and date of appointment.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

corresponding equations label the rows. We have rows for all endogenous variables and, for conciseness, include only a subset of the exogenous variables. From the estimates of Equation (1), we observe that as the idle time before an appointment increases, the physicians increase *PRE*. A small but significant increase in *PRE* is also observed when patients check in after their scheduled appointment start time. This also suggests that when physicians have time available before an appointment, they are likely to increase *PRE.* When physicians are delayed, they reduce *PRE*. This suggests that a more congested schedule with less idle time for physicians would lead to physicians reducing *PRE.*

From Equation (2), we observe that an increase in *PRE* leads to a reduction in *MULTI.* As comments by Sinsky et al. (2016) and the literature on task preparation and early-task initiation suggest, this could be due to the advantages of early-task initiation and task preparation. In column (3), we observe that a no-show after an appointment increases the idle time between appointments. However, suppose a physician arrives late to the index appointment. In that case, the effect of physician delay persists beyond the completion of the index appointment by reducing the idle time following the appointment. Finally, from estimates for *LogEOD* in column (5), we observe that increasing *PRE*, *MULTI*, and *POST* reduces EHR work from after-work hours. Next, we compute the marginal effects corresponding to these coefficients and the overall marginal effect of *PRE* and *POST* on *TOTAL.*

6.1. Marginal Effects and Managerial Relevance

From Equation (5), we compute the marginal effect of *PRE* and *POST* on *EOD*. In the electronic companion, we show the computation of the overall marginal effect of *PRE* and *POST* on *TOTAL* from the coefficients of the system of equations. From Equations (1) and (4), we compute the marginal effect of *MeanIdleBefore* and *MeanIdleAfter* on *PRE* and *POST*. We present these in Table 4.

We observe that a unit increase in *PRE* decreases *EOD* by 0.114 units and *TOTAL* by 1.457 units. Therefore, we find support for Hypotheses 1a and 2a. The advantages of *PRE*, such as task preparation and early task initiation, outweigh the additional time spent doing *PRE* and any task changeover time introduced by doing more prework between appointments. The managerial relevance of these estimates is that if a physician increases *PRE* for an appointment by two minutes, then the sum of *MULTI*, *POST*, and *EOD* reduces

Table 4. Marginal Effects at Mean

Marginal effect	Value	Relevant hypothesis	Relevant equations
$\frac{dTOTAL}{dPRE}$	−1.457 (0.1410)	1a, 1b	(2), (3), (4), (5)
$\frac{dEOD}{dPRE}$	−0.114 (037)	2a, 2b	(5)
$\frac{dTOTAL}{dPOST}$	0.785 (0.028)	3	(4), (5)
$\frac{dEOD}{dPOST}$	−0.214 (0.028)	4	(5)
$\frac{dPRE}{dMeanIdleBefore}$	0.0196 (0.014)	5	(1)
$\frac{dPOST}{dMeanIdleAfter}$	0.275 (0.000)	6	(4)

Notes. Values in parentheses indicate standard errors. The relevant equations column indicates the equations used to derive the expression for the particular marginal effect, and full expressions are as derived in EC 4.

by 4.8 minutes. In other words, a two-minute increase in *PRE* reduces *TOTAL* by 2.8 minutes, a decrease of 15.5%. A two-minute increase in *PRE* reduces *EOD* by 0.228 minutes, a decrease of 12%. In our setting, with 74 physicians who, on average, have 13 appointments per day, increasing prework by two minutes per appointment would translate into 3.64 fewer hours of after-hours EHR work and 44 fewer hours of total EHR work.

A unit increase in *POST* decreases *EOD* by 0.214 units, which leads to an overall increase in *TOTAL* of 0.785 units. Therefore, we find support for hypotheses 4 and 3. The disadvantages of *POST* include the interruption effects of subsequent appointments, meaning that the reduction in *EOD* does not outweigh the additional time taken during *POST*. If a physician spends two additional minutes doing *POST* for an appointment, then *EOD* will decrease by 0.4 minutes, a reduction of 22%. However, the total EHR workload would go up by 1.6 minutes, an increase of 8.8%. We can observe that *POST* has a greater marginal effect on *EOD* than PRE. This is possibly because the physician has similar information regarding the patient visit when doing *POST* and *EOD*. Because of this, *POST* and *EOD* efforts are substitutable to a greater extent than *PRE* and *EOD*.

From the above results, we estimate that increasing prework has the potential to significantly reduce both total and after-hours EHR activity time for physicians. Whereas postwork reduces after-hours EHR time significantly more than prework, postwork comes at the cost of increased overall EHR workload. Our results are interesting because they demonstrate the differential impact of doing the secondary task as a prework or postwork. Although prior literature on managing primary and secondary tasks, such as Legros et al. (2020) and EHR documentation tasks (Gurvich et al. 2020), has not differentiated prework and postwork, in our context, we find that prework can reduce both total and after-hours EHR work, whereas postwork can reduce after-hours work but increase total EHR work.

Given the relative advantages of prework and postwork, hospital administrators may consider providing protected time for EHR tasks, depending on the outcomes required. If the objective is to reduce both total and after-hours EHR workload, more focus can be placed on increasing prework. If the focus is on decreasing after-hours time, a greater emphasis can be placed on postwork. After-hours EHR work has been identified as a significant contributor to physician fatigue and burnout (Robertson et al. 2017). Therefore, although postwork may increase total EHR work, its impact on reducing after-hours EHR work may still make postwork attractive.

While considering increasing protected time for EHR tasks, an important consideration would be whether physicians would actually use the protected time to do EHR tasks. Because of the observational nature of our data, we can provide insights only into increases in unscheduled idle times. Physician behavior may likely change if physicians are informed of an increase in the idle time between appointments ex ante and are offered encouragement to use this time toward *PRE* and *POST*. Further research is required into the effect of scheduled idle time on pre- and post-appointment EHR time.

Our analysis of unscheduled idle time shows that physicians increase *PRE* and *POST* with increasing idle time before and after an appointment. We note that the overall marginal effect of *MeanIdleBefore* on *PRE* is smaller than that of *MeanIdleAfter* on *POST*. An average increase of five minutes between the preceding appointment increases *PRE* by 5.9 seconds. On the other hand, an average increase of five minutes between following appointments increases *POST* by 1.4 minutes. Our data suggest that physicians increase both *PRE* and *POST* when presented with unscheduled increases in idle time. Therefore, we find support for Hypotheses 5 and 6. Although we find that prework can reduce both total and after-hours EHR, we also find that with increasing idle time, physicians spend more time on postwork than prework.

6.2. Alternative Explanation of the Relationship Between Prework and Total EHR Time

In our analysis, increasing prework reduces total EHR time. There are two possible explanations for this. The first explanation is that physicians are more productive with increasing prework because of task preparation and early task initiation advantages. An alternative explanation is that prework may be a load-based response mechanism; therefore, the negative association between *PRE* and *TOTAL* may be due to task reduction. Previous literature has identified the relationship between increased load and eroding service standards (KC and Terwiesch 2012). To assess this question, we examine a different measure of EHR work: word count. Given the patient identifying information in the provider notes, we are not able to access them directly. However, we obtained precise word counts of the progress notes, patient instructions, and all other notes entered by the physician for each appointment. We use this word count as a proxy measure of EHR quality. If the decrease in *TOTAL* from increasing *PRE* results from task reduction, then we should find a negative association between EHR word count and *PRE*. Controlling for all workload, physician, and patient characteristics described in Section 4.3, we find that an increase in *PRE* is associated with an increase in the total word count. Although careful qualitative analysis of all notes would be necessary to rule out the alternative explanation fully, this finding helps mitigate concerns that the negative relationship between *PRE* and *TOTAL* is from task reduction. We provide the result of this analysis in the electronic companion (EC.6)

7. Discussion and Conclusion

7.1. Discussion

Physician burnout is at an all-time high, with more than 68% of physicians in the United States reporting burnout in 2021.[4] In the United States, the cost of physician turnover from burnout has been estimated to be between \$2.8 billion and \$6.3 billion per year (Han et al. 2019). Several studies have identified the significant impact of EHR workload on physician burnout. However, operational suggestions for reducing this workload have been relatively unexplored. We investigate the impact of the structure of EHR work during a physician's day. We find that doing EHR work in preparation for the upcoming appointment can reduce a physician's total and after-hours time on EHR. Doing EHR work after an appointment can significantly reduce after-hours EHR time; however, this comes at the cost of increasing the total EHR workload. We find that idle time between appointments is an important driver of how physicians structure their daily EHR workload. Increasing idle time between appointments increases both pre-appointment and post-appointment EHR workload. However, post-appointment EHR work increases to a greater degree.

We make the following four principal contributions. First, we contribute to physician EHR use literature by quantifying the impact of pre- and post-appointment EHR work during idle time between appointments. The literature on EHR use has focused on the overall impact of increasing EHR workload. We add to this literature by measuring the impact of the structure of EHR work during the day. We find that pre-appointment and post-appointment EHR tasks impact total and after-hours EHR work differently. Pre-appointment EHR tasks reduce both total and after-hours EHR workload. This suggests that the advantages of pre-appointment EHR tasks, such as better preparation and early task initiation, outweigh the costs of increased task switching from documentation to face-to-face activities. Although interviews with physicians have qualitatively indicated these factors, we can provide a rigorous quantitative analysis of the positive impact of pre-appointment EHR work. We also find that post-appointment EHR tasks significantly reduce after-hours EHR. The marginal reduction of after-hours EHR time is greater from increasing post-appointment EHR tasks than from increasing pre-appointment EHR tasks. This is likely because the physician has similar information regarding the appointment when doing post-appointment and after-hours EHR activities. Therefore, after-hours EHR time can be easily substituted by post-appointment EHR. However, increasing post-appointment EHR tasks leads to an increase in total time spent on EHR. This suggests that the disadvantages of post-appointment EHR work, such as interruption due to following appointments and task switching, outweigh the advantages of reducing the after-hours EHR workload.

Second, we contribute to task selection literature in operations management, which has discussed the structure of work and the trade-offs involved in strategies such as multitasking, batching, and early-task initiation. Many of these studies have focused on the workload from the primary task. However, like the EHR workload for physicians, in many services, the workload due to secondary tasks is significant, and we study the operational impact of the structure of secondary tasks. Our findings show that the total time spent on secondary tasks depends on how service operators structure secondary work before, during, and after an appointment. Doing secondary tasks before an appointment may help reduce the time spent on secondary tasks by taking advantage of task preparation and early task initiation. Increasing secondary tasks after an appointment significantly reduces after-work hours; however, post-appointment secondary tasks may be interrupted by the following appointment, leading to an overall increase in total time spent on secondary tasks due to interruption-driven inefficiencies.

In addition to contributing to theory, our findings have important implications for practice. The impact of the structure of secondary tasks on operational performance, such as makespan and after-work hours, will have relevance in a wide variety of service contexts. Service designers can use these insights to create workflows for service operators such as call center agents, surgeons, and insurance claim investigators who manage primary and secondary tasks to improve server productivity and reduce after-work hours. For clinics, these insights will help healthcare administrators in primary care create EHR workflows and appointment schedules that reduce burnout due to EHR workload. The idle time between appointments can be increased to increase both pre-appointment and post-appointment EHR time. The varying effects of pre and post-appointment EHR work suggest that the recommended use of idle time would depend on the clinic's objective. If the objective is to reduce the total EHR workload, then greater emphasis can be placed on doing pre-appointment EHR tasks. If the objective is to reduce after-hours EHR time, then increasing post-appointment EHR work would give a greater marginal benefit, albeit at the cost of increasing total EHR time.

Our results have significant implications for the theory and practice of appointment scheduling. Scheduling literature for services has typically focused on customer interaction time and has not incorporated the workload from these secondary tasks. In the appointment-scheduling literature, an increase in idle time is often associated with an increase in makespan.

However, as we observe from our results, idle time between appointments may be used to perform pre- and post-appointment secondary tasks. Given our findings that prework and postwork affect both total time spent on secondary tasks and after-hours time, an important question is how idle time affects physician makespan in the presence of secondary tasks like EHR. Because makespan is a day-level measure for a physician, we perform the following analysis to answer this question.

7.2. Impact of Increasing Idle Time Between Appointments on Physician Makespan

Our results show that increasing idle time increases *PRE* and *POST*. We also observe that *PRE* and *POST* reduce *EOD* and that *POST* increases *TOTAL*. So, the overall effect of performing EHR tasks in idle time on *TOTAL* is not obvious. To estimate the combined effect of increasing idle time, we analyze the impact of increasing idle time between appointments on physician makespan, where makespan also includes the after-hours time spent by the physician on EHR systems. Because makespan for a physician is a day-level measure, our unit of measure for this analysis is physician-day.

Our outcome of interest is the makespan for a physician (*PhysicianMakespan*). We define makespan as the sum of face time with patients, idle time between appointments, and after-hours EHR time. We compute this by calculating the time difference between the end of the last appointment of a physician's day and the start of the first appointment. Then, we add the total after-hours EHR work for the physician's appointments. Our primary independent variable is the amount of idle time between appointments (*TotalDailyIdleTime*). We compute the idle time between two consecutive appointments by the time difference between an appointment's end and the subsequent appointment's start. We then sum these idle times for all appointments of a physician's day to get *TotalDailyIdleTime*. We define the variable *PhysicianWorking* as the difference between makespan and the idle time, that is, (*PhysicianWorking* = *PhysicianMakespan* − *TotalDailyIdleTime*). We control for the number of appointments scheduled in the day, the total scheduled duration of appointments, the average age of patients on the day, average patient complexity (as measured by CCI) of the day, the average number of patients having Medicare insurance, day of the week, and physician fixed effects. The summary statistics of all variables are in the electronic companion (EC.7).

Our econometric model is as follows. p indicates physician, and j indicates day. The vector $\boldsymbol{Y_{pj}}$ represents the control variables, and δ_{pj} indicates the error term. The coefficient $\beta_{I,W}$ signifies the effect of increasing a physician's total idle time in a day on the nonidle time of a physician's makespan.

$$Log(PhysicianWorking_{pj}) = \beta_{I,W} Log(TotalDailyIdleTime_{pj}) + \boldsymbol{\gamma Y_{pj}} + \delta_{pj} \tag{6}$$

There may be unobserved patient and appointment characteristics that influence both total idle time and physician makespan. For example, as discussed before, if a patient has a serious mental health condition and discusses that with the physician during the appointment, it may lead to more time spent with the patient in the room, leading to less idle time following the appointment. Because mental health conditions correlate with higher EHR use, the after-hours EHR time would be higher, leading to a longer makespan. We use the instrumental variables approach to circumvent the possibility that *TotalDailyIdleTime* may be endogenous. We use the number of no-shows on the physician's day as our instrumental variable. We estimate our modeling using the 2SLS procedure. The first stage is given by

$$Log(TotalDailyIdleTime_{pj}) = \beta_{B,DL} NumberofNoShows_{pj} + \boldsymbol{\gamma Y_{pj}} + \phi_{pj} \tag{7}$$

We show the results of regression analysis and the computation of the marginal effect of total daily idle time on physician makespan in the electronic companion (EC.7). We find that if the total idle time increases by five minutes in a day, then the physician makespan decreases by 0.55 minutes. Therefore, pre- and post-appointment EHR time may be increased through increasing idle time without negatively impacting makespan. Subsequently, we also show the impact of *TotalDailyIdleTime* on the two components of physician makespan, the face-to-face time with patients and total daily after-hours EHR work. We find that *TotalDailyIdleTime* reduces both face-to-face time and total after-hours EHR work. Therefore, the improvement obtained from increasing idle time during the day would not lead to physicians performing fewer appointments in the day. We show this result in EC 7.4.

Idle time between appointments allows the service operator to perform EHR as prework and postwork. Our results in Section 6 show that prework can reduce both total and after-hours EHR time, and postwork can reduce after-hours work. Increasing idle time between appointments can lead to lower after-hours work and may reduce daily makespan. Therefore, increasing idle time between appointments may be an effective strategy for reducing EHR workload. However, the detrimental effect of idle time may outweigh the EHR-related benefits if the physician's makespan increases. For this, the results in this section show that increasing idle time between appointments leads to lower makespan, lower face-to-face time, and lower after-hours

EHR work. Although the mechanism through which idle time negatively affects makespan cannot be directly identified in this analysis, the results show that small increases in idle time may be recommended for reducing the after-hours EHR workload without increasing the daily makespan.

7.3. Limitations

Our study has some limitations. First, our analysis is from a primary care setting. Physicians in other settings, such as inpatients, emergency departments (ED), and surgery, may behave differently from primary care physicians when managing EHR workloads. Physicians in an inpatient and ED setting do not have scheduled appointments and often do not have the opportunity to perform prework. Therefore, our findings may not be valid in that context. Secondly, when physicians perform tasks after work, their location is not observable because physicians use virtual private networks (VPN) to connect to EHR systems when located outside the clinic. To demarcate after-hours work, we rely on the current practice in our setting and prior literature (Bavafa and Terwiesch 2019) to set a standard time for the end of the day. We also repeat our analysis for alternative definitions of after-hours. Lastly, because we utilize EHR audit logs to measure physician EHR use, it will be an approximate measure of time spent on the EHR system. We use a cutoff time of 90 seconds to remove the idle time between EHR tasks. This method has been validated through several other observational studies. We also repeat our analysis for different values of the cutoff time.

7.4. Conclusion

Several recent studies in healthcare literature have determined that workload due to EHR contributes significantly to physician burnout. However, the operational implications of physician EHR usage behavior have not been studied rigorously. We contribute to the literature on healthcare operations by analyzing detailed data on physician EHR usage. We find that pre-appointment EHR work can reduce both total and after-hours EHR time. Post-appointment EHR work significantly reduces after-hours EHR work; however, it comes at the cost of increasing total EHR time. We find that when the idle time between appointments increases, physicians increase pre- and post-appointment EHR work. However, they focus more on post-appointment EHR work. To assess the overall impact of increasing the idle time between appointments, we find that in the presence of secondary tasks like EHR, a physician's makespan may be reduced by increasing the idle time between appointments. Our findings also contribute broadly to operations management literature by studying the implications of the structure of secondary work on workload and makespan. Our results have implications for the theory of task selection and appointment scheduling. Additionally, our results provide insights to managers when creating schedules in the presence of a secondary task workload.

Endnotes

[1] https://www.healthit.gov/faq/what-electronic-health-record-ehr.

[2] Templates are customizable forms that help physicians collect and organize EHR data and reduce EHR documentation time (https://mobius.md/2023/06/21/what-are-ehr-templates/).

[3] https://www.epic.com/.

[4] https://www.healthcareitnews.com/news/physician-burnout-all-time-high-says-ama.

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