Does Physician's Choice of When to Perform EHR Tasks Influence Total EHR Workload?

Umit Celik, Sandeep Rath, Saravanan Kesavan, Bradley Staats

University of North Carolina at Chapel Hill, Chapel Hill, North Carolina 27599

Umit_Celik@kenan-flagler.unc.edu, sandeep_rath@kenan-flagler.unc.edu.edu, skesavan@unc.edu, bstaats@unc.edu

Problem definition: Physicians spend more than 5 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 as 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 dataset 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.

Keywords: Electronic Health Record (EHR); task-switching; healthcare operations; service operations

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 (Graber et al. 2017, 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 US 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 US, 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).

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

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 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 states, "*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" due to 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 (2016) and Attiope (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. Figure 1 shows the same categories in our dataset, and we see large differences across physicians. 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 are times when secondary tasks may be completed. Doing EHR work before an appointment may help physicians conduct early task initiation (Batt and Terwiesch 2017), prepare for tasks during the appointment (Verbruggen et al. 2007, Altmann 2004), and efficiently capture key EHR details due to 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 as all (or most) information is available, and there is better recall after an appointment (KC 2014). However, it is also possible that time increases due to lower productivity from longer work hours (Caruso 2014) and task interruptions (Froehle and White 2014).

We focus on EHR tasks performed during idle time as the idle time between appointments is a decision variable for hospital management during appointment scheduling. So, idle time can potentially be used to 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, Attiope 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.

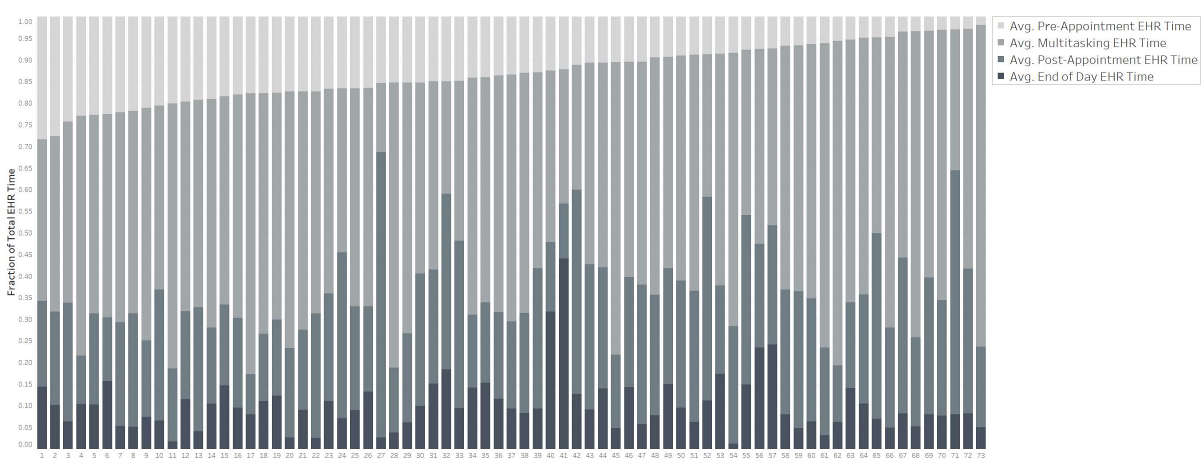
This topic is critical to improving healthcare operations, but it is also part of a more general discussion on how work should be done (Narayanan et al. 2009, KC et al. 2020, Pendem et al. 2022). Although much emphasis is placed on the primary tasks to be completed, such as patient treatment or surgery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

It is necessary to study secondary tasks separately as 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?

Figure 1: Average EHR Use at Different Parts of the Day for Each Physician



The first research question allows us to understand the operational impact of structuring secondary tasks. 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 (Tan and Netessine 2014), and task switching (Staats and Gino, Gurvich et al. 2019). 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 over 150,000 appointments across 74 physicians in the Family Medicine unit of a large Academic Medical Center in the US. Our dataset 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 as there is considerable heterogeneity in when EHR tasks are done 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 for two reasons. First, total EHR workload and EHR time spent during after-work hours significantly contribute to physician burnout (Tran et al. 2019). Second, these two measures have been identified as important aspects of hospital operational performance (Sinsky et al. 2020).

We categorize when physicians complete the secondary task of EHR use. There are four times during a day when physicians might complete EHR work for an appointment: before the appointment (what we label prework), during the appointment (what we label multitasking), after the appointment, but before the end of the day (what we label postwork) or after the workday (what we label end-of-day 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, as when they are performed significantly impacts total and after-work EHR time. Specifically, we find prework is a dominant strategy because it can reduce total time spent on EHR and end-of-day EHR work, whereas postwork can reduce end-of-day EHR work but increase total time spent on EHR.

We estimate that performing an additional five minutes of prework (about a one standard deviation increase) reduces the sum of multitasking, postwork, and end-of-day EHR work by 6.9 minutes. In other words, a 5-minute increase in prework in an appointment leads to a net reduction in total EHR time of 1.9 minutes for that appointment, a decrease of 10.5%. Approximately 0.9 minutes of this reduction is from the decrease in end-of-day EHR work, a decrease of 46%. In our setting, with 74 physicians who average 13 appointments per day, this translates into 31 fewer hours of total EHR work with 13 fewer hours in after-hour EHR work per day.

If a physician spends five additional minutes on postwork, then end-of-day work for that appointment decreases by 1.4 minutes, a reduction of 72%. This translates to a total reduction of 21 hours in after-hour EHR work per day for our setting. However, the total EHR workload goes up by 3.6 minutes per appointment, or 58 hours per day, across all physicians in our setting. To summarize, our results indicate that increasing prework helps reduce both total and end-of-day EHR work. Alternatively, increasing postwork reduces end-of-day 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 prework and postwork but focus more on postwork.

Our solution approach and results contribute in the following principal ways. First, the appointment scheduling literature has typically focused on the trade-off between idle buffer time between appointments, patient delays, and physician makespan when scheduling customer encounters. Appointment scheduling literature typically defines makespan as the sum of idle time and appointment time. According to this definition, increasing idle time between appointments reduces patient delay at the cost of increasing physician makespan (Robinson and Chen 2003). However, if we incorporate time spent on secondary tasks, makespan would need to be defined as the sum of idle time, appointment time, and end-of-day time spent on secondary tasks. In the presence of secondary tasks, physicians can perform these tasks during the idle time between appointments, leading to less end-of-day work and a lower makespan. Therefore, in the presence of secondary tasks, increasing idle time may not always have a detrimental effect on 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 dominant strategy leading to less time spent on secondary work and less time spent on secondary work after the end of the workday. These benefits potentially accrue due to task preparation and early-task initiation (Batt and Terwiesch 2017) by reducing the load from busier parts 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 due to increased interruptions. Prior findings in the literature related to task sequencing have not typically 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, 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, although at the cost of increasing total EHR time.

The paper is organized as follows. In Section 2, we discuss the related literature. Section 3 describes a physician's appointment and EHR activities in detail and motivates our study's relevant hypotheses.

Section 4 describes the data, the empirical strategy, and the results. In Section 5, we discuss the model and our empirical strategy. In Section 6, we present our findings and discuss possible alternative explanations. Finally, in Section 7, we discuss the implications of our findings and end with concluding remarks.

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 negative.

Technology-enabled channels of healthcare delivery, such as e-visits and telemedicine, increase physician workload (Bavafa et al. 2018, Bavafa and Terwiesch 2019), increase costs (Çakıcı and Mills 2021), and may worsen patient health disparities (Sunar and Staats 2022). Adopting IT technologies may also create legal vulnerabilities for physicians through increased information visibility (Kim et al. 2021) and may lead to lower physician productivity (Bhargava and Mishra 2014). Recent studies on EHR usage in clinical services literature have found an association between increasing EHR usage with increasing burnout and turnover (Sinsky et al. 2016, Melnick 2021) and lower patient satisfaction (Marmor et al. 2018). Lee et al. (2021) consider EHR documentation work from a queuing modeling perspective. They computationally evaluate different workflow policies for managing EHR work. They conduct a numerical evaluation of these workflow management policies' impact on patient wait time and physician overtime. 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, Tan and Netessine 2014, KC 2014, Freeman et al. 2017, Berry Jaeker et al. 2017, Gurvich et al. 2020). Gurvich et al. (2020) is a closely related paper to our context. They quantify the changeover time when the physicians switch 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. Progression of scheduled appointments creates idle time during the day, and we focus on physicians’ use of this idle time towards EHR tasks.

A related set of papers on multitasking are queuing models with one server or group of servers balancing two work queues (Gans and Zhou 2003, Legros et al. 2020). Legros et al. (2020) discuss service operators' switching between customer interaction and back-office tasks. They derive optimal threshold policies for using the interlude time between customer interactions. Further, they show that with task-switching costs and multiple interludes, back-office work should be concentrated on fewer, more extended, and later interludes. There are two primary differences in our context. First, in our context, physicians can also perform documentation work during the appointment in addition to the time between customer encounters which is not the case for tasks in Legros et al. (2020). Second, with EHR documentation work, as we observe from our results, not all work done in the interludes between appointments may have the same effect. We find that pre-appointment and post-appointment EHR work affect the total EHR workload differently.

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 find that early initiation of lab 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) find that a preference to complete easy tasks is related to lower throughput and learning in an ED. Ibanez et al. (2018) find that in addition to preferring to do easier tasks first, physicians also prefer to batch similar tasks together. They find this preference for easier and similar tasks negatively impacts productivity. In a related study, Feizi et al. (2022) found that ED physicians' preference for batching admissions leads to longer patient wait times. The preference to do easier tasks may be driven by task familiarity, as Niewoehner et al. (2022) find with physicians' selection of patients in an ED. They find that greater familiarity with patients increases physicians' patient pick-up rate, leading to shorter wait times with no negative impact on processing time or length of stay. 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, Ahmadi-Javid et al. 2017). 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, Wang et al. 2019), 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), Wetterneck et al. (2012), and Holman et al. (2016). We summarize the salient points below.

Patients typically book appointments a few days to a few months in advance. On the day of the appointment, the front desk staff collects basic information such as age and insurance information after the patient's arrival. Patients who fail to attend an appointment without prior notice are called no-shows. Literature estimates the prevalence of no-shows between 7-26% for Academic Medical Centers in the US (Dantas et al. 2018).

At the scheduled start time, when an examination room becomes available, the nurse receives and accompanies the patient to the room, where they perform a preliminary physical examination, including measuring weight and blood pressure. Following this, the physician, after they have concluded their previous visit, enters the examination room. After entering the room, the physician performs the following principal tasks: gathers patient information through discussion and questions, reviews patient information by reading from the EHR, documents patient information in the EHR system, performs a physical examination of the patient, looks up treatment and drug information, recommends treatment options after discussion with the patient, orders medication and tests, gives/communicates to patient prescription, information, or instructions, and finally concludes the appointment, sometimes by walking the patient to another location in the clinic.

As Holman et al. (2016) note, physicians do not perform these activities consistently in the same sequence, and task sequencing demonstrates significant variation depending on the patient's clinical conditions, the progression of the visit, and physician characteristics. For example, the physician may cycle through activities such as gathering, reviewing, looking up information, and communicating with the patient multiple times within the same 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 (Gottschalk et al. 2005). Surveys (Attipoe 2021) indicate that physicians perform some EHR activities such as finishing their notes, closing outpatient charts, and following up on lab results and patients' responses or comments after the end of the workday. Gottschalk et al. (2005) estimate that physicians performed 14.5% of visit-specific activities either before or after the appointment.

3.2 Hypothesis Development

We develop hypotheses on the impact of performing EHR activity in idle time between appointments. We first consider the causal impact of prework on the total time spent on the EHR system.

Prework includes reviewing patient demographic information, previous laboratory reports, and any previous communication from the patient or other caregivers (Wetterneck et al. 2012, Zhang et al. 2016).

There are three potential reasons prework may increase total EHR time. First, prework will increase task-switching from patient interactions to documentation. Switching time may increase physicians' EHR system time. Literature in operations management and psychology has identified the detrimental effects of task switching due to increased changeover time (Staats and Gino 2012, KC 2014, Gurvich et al. 2020). Second, idle time before an appointment may lead physicians to spend more time doing prework than usual, demonstrating 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).

Lastly, some prework tasks may be unnecessary, and the physician may need to rework in the patient's presence. Holman et al. (2016) give the following example of a patient encounter:

> *The PCP suggests a medication for one of the patient's problems, and the patient recognizes that the medication was tried previously and affected her negatively. The PCP again searches the patient's EHR, reviewing the patient's historical medications and laboratory values to confirm this and changes the patient's treatment recommendation.*

The above example indicates that clinical appointments benefit from service co-production between physicians and patients due to high variability in patient needs. Roels (2014) shows that when a task is less standard, it is optimal to increase interaction between the service provider and customer. Management literature has previously discussed the benefits of reduced rework with increasing customer engagement (Lengnick-Hall 1996).

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

- *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 2016).
- *I feel that preparation ahead of the visit is the key* (Zhang et al. 2016).

While some EHR work would 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 a busy time for the physician. They 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, Costa et al. 2013). 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.

Secondly, research in psychology has indicated that although switching costs are incurred when switching between tasks, the switching cost reduces (although it is not eliminated) when workers are given an opportunity to prepare for the switch (Verbruggen et al. 2007). 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). 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 in a more efficient manner. 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 we remarked in the discussion above, prework may increase the total EHR workload due to Parkinson's law, task-switching, and rework due to low service co-production. 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). Therefore, if prework increases the total EHR workload, it may also lead to increased after-work hours due to 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 do these additional tasks after the end of the workday (Attipoe 2021).

[2] Templates are customizable forms that help physicians collect and organize EHR data and reduce EHR documentation time (https://mobius.md/2021/12/07/what-are-ehr-templates/)

On the contrary, performing prework may reduce the end-of-day work since 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 end-of-day EHR work.*

Hypothesis 2b. *An increase in pre-appointment EHR work leads to more end-of-day 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, if the physicians stop doing the postwork of the focal appointment when the next patient is ready, then it would lead to an interruption in the EHR activity of the focal appointment. Froehle and White (2014) show that interruptions can induce forgetting in a worker leading to increased rework to complete the task. Second, similar to prework, introducing postwork may also lead to the detrimental effect of task switching from face-to-face appointment to EHR work, introducing changeover time when starting postwork EHR. Postwork EHR introduces changeover time like prework EHR, however, without 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 (KC et al. 2020, Ibanez et al. 2018). Therefore, the time taken to complete EHR work for the appointment may go up if the physician selects easier EHR tasks during the postwork period.

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 lead to improved efficiency in doing EHR work. Second, when compared to end-of-day work, the physician may have better recall during regular work hours and thus may be able to complete EHR tasks faster. Operations management literature has previously identified the productivity benefits of improved recall. Third, the physician may need to collaborate with the nurse or other care providers while filling in the information in EHR or may need technical assistance on the EHR system itself. In that case, it is preferable to complete tasks during regular work hours. After-work coordination and communication may need to be done asynchronously, as 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). Considering the effect of postwork on total EHR usage, we have the following hypotheses:

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

Hypothesis 3b. *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 as longer work hours have been associated with lower productivity (Caruso 2014). Given these factors, we hypothesize:

Hypothesis 4a. *An increase in post-appointment EHR leads to less end-of-day EHR workload.*

Hypothesis 4b. *An increase in post-appointment EHR leads to more end-of-day 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 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 due to 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, since 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) show that when there is time off between shifts, the time spent on secondary tasks goes up. Given these effects, we present the following hypotheses:

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

Hypothesis 5b. An *increase in the average idle time between preceding appointments leads to less 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. 2017, Meng et al. 2021, and Feizi et al. 2022). Physicians may also prefer the flexibility of working from home (Attipoe 2021) and may not utilize the idle time for postwork.

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. If physicians are averse to interruptions and incomplete work, they 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 utilize that to increase postwork. We present the following hypotheses:

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

Hypothesis 6b. *An increase in average idle time after an appointment leads to less post-appointment work.*

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

Table 1: Mechanisms of the effect of Prework and Postwork on Total and End-of-Day Time on EHR

<table>
<tr><th></th><th>TOTAL EHR WORK</th><th>End-of-Day EHR Work</th></tr>
<tr><td rowspan="2">Prework</td><td>Increase:
• 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 co-production (Lengnick-Hall 1996, Roels 2014)</td><td>Increase:
• Batching increases with workload (Ibanez 2018)</td></tr>
<tr><td>Decrease:
• Early task initiation (Batt and Terwiesch 2017)
• Lean changeover reduction through external setup (Shingo 1989, Costa et al. 2013)
• Task Preparation (Altmann 2004, Verbruggen et al. 2007)</td><td>Decrease:
• Lower workload through task preparation leading to less end of day work (Altmann 2004, Verbruggen et al. 2007)</td></tr>
<tr><td rowspan="2">Postwork</td><td>Increase:
• 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 (KC et al., 2020, Ibanez et al., 2018).</td><td>Increase
• Batching increases with workload (Ibanez 2018)</td></tr>
<tr><td>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 co-workers during regular work hours (Yang et al. 2022)</td><td>Decrease:
• Improved productivity through shorter workday length (Caruso 2014)</td></tr>
</table>

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 ranges from May 2017 through May 2019. We restrict our data to those days with at least five appointments in the day, as days with less than five appointments are not representative of the daily workload of the physicians. Our final data comprises 152,970 appointments from 74 physicians.

EHR systems record time stamps of activities performed. This data is called audit log data or event log data. This data tracks who logged in to the EHR system, what task was performed, when they did the task, and the patient record on which it was performed. This audit data is 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 (2017) compared EHR audit log data by two means, in-person observation, and audio recording. Sinha et al. (2021) and Arndt et al. (2017) validated EHR time stamp data with observed data. These studies find the difference between EHR time stamp data and observed data of EHR usage to be small and recommend using audit log data to study clinic workflow and EHR use by physicians.

We have two separate datasets of audit log data. The first dataset relates to the appointment progression. This data consists 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 dataset is EHR usage log data. This data has timestamps for each EHR action and the identifier for the patient whose records were being viewed or edited by the physician. This data consists 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 for each patient between two given time limits. Next, we define the different time windows when physicians perform EHR tasks.

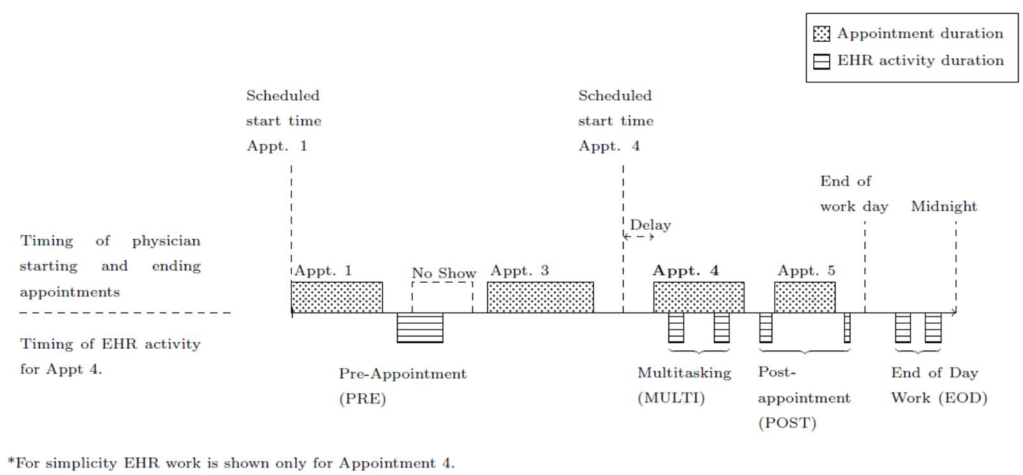
Prework (*PRE*) is the amount of time a physician spends on a patient's EHR record from 12:01 AM on the day of the appointment until the start of the face-to-face appointment. We ignore work done on EHR before 12:01 AM, as we observe that less than 0.01% of EHR work for an appointment is done on the 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-

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

face appointment and the end of the workday. End-of-day (*EOD*) EHR activity denotes time spent on EHR after the end of the workday. We define the end of the workday as 6 pm because it is the standard practice in our setting and several studies define regular work hours for physicians to be between 8 am and 6 pm (Arndt et al. 2017, Sinha et al. 2021). We repeat our analysis with the physician workday ending at 5 pm, as used by Bavafa and Terwiesch (2019), and also by computing the end of the workday to be the end of the last appointment. Our findings do not change for these alternate definitions for the end of the workday.

In Figure 2, 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 only show 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.

Figure 2: Representative diagram of timing of appointments and EHR work for a physician's day.



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 for each appointment, we have the EHR work done during the intervals for *PRE, MULTI, POST,* and *EOD.* Next, we describe the steps to compute the duration of EHR activity done by a physician within these time intervals.

First, we select the subset of EHR usage log data for the given Physician ID and Patient ID. Then we find all EHR activities where the activity time stamp falls within the start and end times of the required time interval. We order all these activities in increasing time. Let these activities be $(a_1, a_2, \dots, a_N)$ and the corresponding time stamps be $(t_1, t_2, \dots, t_N)$.

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 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, i.e., 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 as Arndt et al. (2017) validated that applying a 90-second cutoff supported observed data of physician EHR usage. Tai-Seale (2017) and Sinha et al. (2021) used a cutoff of 60 seconds. Both studies also validate 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.3.2), showing that our principal findings do not change. We compute *PRE, MULTI, POST*, and *EOD* using the above procedure. Next, we will describe the definition of each variable and present descriptive statistics.

4.3 Variable Definitions and Descriptive Statistics

In Table 1, 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 work day (*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*). We compute the duration between the end time of the index appointment and the start time of the subsequent appointment as the idle time after the index appointment. To compute the average idle time after the index appointment, we compute the average of all such idle times after the end of the index appointment. This variable will measure the time available to do post-appointment EHR tasks after an appointment. As *MULTI* may influence *MeanIdleAfter*, we model *MeanIdleAfter* as an endogenous 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, KC and Tushe 2021). 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'[4] 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. Additionally, we control for the appointment sequence because physicians' choices for allocating EHR tasks may vary for earlier and later appointments for the day. We include a control for the scheduled duration of the index appointment, as 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)*. **Other controls:** We include fixed effects for physicians to control for time-invariant physician characteristics. We also include the day-of-week effect.

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 am 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)*	Number of appointments scheduled for the day	13.26	4.205
(8)	*ApptSequence (integer)*	Scheduled sequence of the appointment	6.904	4.392
(9)	*DayTotalScheduled (mins)*	Total scheduled time of all appointments on 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 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 if 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

[4] https://ellessenne.github.io/comorbidity/

5. Econometric Model

Our observational dataset 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.

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 tasks to perform during idle time. While 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) find that patients and physicians having linguistic and cultural similarities correlate with more face-to-face time and total EHR time. These examples indicate that using observational data of EHR time stamps would be challenging for our analysis. 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 the idle time between appointments. Through this system of equations, we estimate the effect of *PRE* and *POST* on *TOTAL* and *EOD*.

5.1 Model Formulation and Identification

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

$$\boldsymbol{LogMULTI_i = \beta_{PRE,M}LogPRE_i + \alpha_{AD,MULTI}LogArrDelay_i + \alpha_{PD,M}LogPCPDelay_i + \alpha_{MLAG,M}LogLagMulti_i + \theta_M X_i + \epsilon_{MULTI,i}} \quad (2)$$

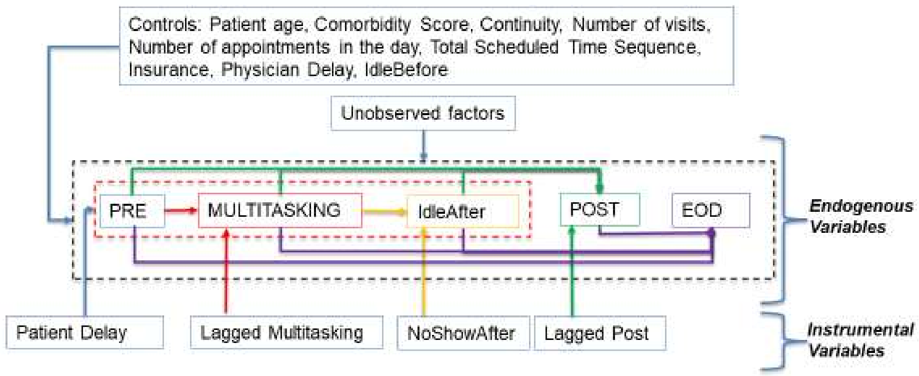
$$\boldsymbol{LogIdleAfter = \beta_{PRE,IA}LogPRE_i + \alpha_{AD,IA}LogArrDelay_i + \beta_{M,IA}LogMULTI_i + \alpha_{NA,IA}NoShowAfter + \theta_{IA}X_i + \epsilon_{IA,i}} \quad (3)$$

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

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

These equations model the relationship between *PRE*, *MULTI*, *MeanIdleAfter*, *POST*, and *EOD*. We perform a log transformation for all variables that are a duration of an activity or a time interval. We use log transformation because it has been used to model service time in healthcare (KC and Terwiesch 2009). Gurvich et al. (2020) show that documentation time by physicians follows a log-normal distribution. 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 ($\alpha_{AD,PRE}, \alpha_{PD,PRE}, \alpha_{IB,PRE}, \alpha_{MLAG,M}, \alpha_{NA,IA}, \alpha_{LP}$) 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. Figure 3 illustrates the block diagram for the system of equations.

Figure 3: Block Diagram of Causal Relationship



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 the 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, the physician may reduce the time spent on prework. We note that physicians being delayed due to 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).

We note that the system of equations above is recursive, where in each equation, only endogenous variables from the previous equations appear on the right-hand side (Wooldridge 2010). However, the system of equation 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 define the instrumental variables 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*) on the previous day, which has the same sequence 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 has the same sequence as the index appointment.

A valid instrument for a system of equations needs to satisfy specific requirements. First, it needs to be uncorrelated with all the error terms. Secondly, some of the exogenous variables must be excluded from some of the equations, i.e., not all exogenous variables can affect all of the endogenous variables directly. This requirement is called the exclusion requirement. For a system of equations to be identified, the exclusions must satisfy the order and rank conditions. 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. A detailed discussion of these requirements is available in Wooldridge (2010), Chapter 9. We discuss our choice of instrumental variables and their validity below.

First, for equation (1), we include patient arrival delay. If a patient arrives late for an appointment, that will give time for the physician to do additional prework. Similar to physician arrival delay, patient arrival delay may impact *MULTI* and the *IdleAfter* but is unlikely to be correlated with the error terms for the equations for *POST* or *EOD*. For equation (2), we include the logged transformation of *LagMULTI,* which is *MULTI* for the appointment on the previous day of the physician, which had the same sequence as the index appointment. Using lagged variables as instrumental variables is a common practice (Kesavan et al. 2014, Tan and Netessine 2014). We also used an alternate construction of *LagMULTI* by computing the average lagged multitasking EHR for the physician's appointments on the previous day. Our results remained the same.

Next, in equation (3), we use the indicator variable *NoShowAfter,* which denotes the presence of a no-show appointment after the index appointment. The information that an appointment is a no-show is available only at the start of that appointment. Therefore, it is unlikely that the presence of a no-show following the index appointment would be correlated with unobservable patient characteristics of the index appointment. Lastly, we used *LagLogPOST* for equation (4). *LagPOST* is the lagged variable for *POST* and is computed similarly to *LagMULTI.*

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. We use the Stata package 'checkreg3' (Baum 2007) to verify that all the equations satisfy the rank condition. 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.1). We cluster robust standard error by Physician and Date of Appointment.

As a 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.3.4), and we observe that parameter estimates show only minor differences from the 2SLS estimation. We also present results on tests of endogeneity (EC.3.5) 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 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 (2016), 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, if a physician arrives late to the index appointment, 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.

While the above-discussed effects are statistically significant, due to the logarithmic transformation of variables, the interpretation of these coefficients is not obvious. Furthermore, we want to estimate the marginal impact of *PRE* and *POST* on total EHR time spent, which is also not evident from these estimates. Therefore, next, we compute the marginal effects corresponding to these coefficients and the overall marginal effect of *PRE* and *POST* on *TOTAL*.

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)		-0.289^{***}		-0.0669	-0.305^{***}
		(0.0190)		(0.0436)	(0.0527)
Log(MULTI)			0.519^{***}	-0.0492	-0.260^{**}
			(0.0850)	(0.0452)	(0.0561)
Log(POST)					-0.854^{***}
					(0.124)
Log(MeanIdleBefore)	0.0723^{***}				
	(0.00278)				
Log(MeanIdleAfter)				0.745^{***}	0.236^{*}
				(0.0306)	(0.109)
Log(PCPDelay)	-0.173^{***}	0.165^{***}	-0.188^{***}		
	(0.00383)	(0.00411)	(0.0188)		
Log(PatientDelay)	0.0443^{***}	-0.0120^{***}	-0.0541^{***}		
	(0.00252)	(0.00177)	(0.00333)		
NoShowAfterAppt			0.141^{***}		
			(0.0160)		

Standard errors in parentheses Notes: N=152,970. 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 parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 Tables 4 and 5.

Table 4: Marginal Effects at Mean of Prework and Postwork on End of Day Work and Total EHR work

	EOD	TOTAL = (*PRE*+*MULTI*+*POST*+*EOD*)
PRE	-0.167	-0.391
POST	-0.317	0.683

Table 5: Marginal Effects at Mean Idle Time on Prework and Postwork EHR Work

	PRE	*POST*
MeanIdleBefore	0.0213	
MeanIdleAfter		0.412

We observe that a unit increase in *PRE* decreases *EOD* by 0.167 units and *TOTAL* by 0.391 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 5 minutes, then the sum of *MULTI, POST,* and *EOD* reduces by 6.9 minutes. In other words, a 5-minute increase in *PRE* reduces *TOTAL* by 1.9 minutes, a decrease of 10.4%. A 5-minute increase in *PRE* reduces *EOD* by 0.8 minutes, a decrease of 45%. In our setting, with 74 physicians who, on average, have 13 appointments per day, this translates into 21 fewer hours of end-of-day EHR work.

A unit increase in *POST* decreases *EOD* by 0.317 units, which leads to an overall increase in *TOTAL* of 0.683 units. Therefore, we find support for hypotheses 4a and 3b. The disadvantages of *POST* include the interruption effects of subsequent appointments, meaning that the reduction in *EOD* does not outweigh the additional work done during *POST.* If a physician spends 5 additional minutes doing *POST* for an appointment, *EOD* will decrease by 1.3 minutes, a reduction of 72%. However, the total EHR workload would go up by 3.6 minutes, an increase of 19.4%. We can observe that *POST* has a greater marginal effect on *EOD* as compared to the effect of *PRE* on *EOD.* This is possibly due to the fact that the physician has similar information regarding the patient visit when doing *POST* and *EOD.* Due to 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 end-of-day EHR activity time for physicians. While postwork reduces end-of-day EHR time significantly more than prework, postwork comes at the cost of increased overall EHR workload. Our results are interesting as they demonstrate the differential impact of doing the secondary task as a pre or postwork. In fact, while 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 strictly dominates postwork.

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 end-of-day EHR workload, more focus can be placed on increasing prework. If the focus is on decreasing end-of-day time, a greater emphasis can be placed on postwork. After-hours EHR work has been identified as a significant contributor to physician fatigue (Adler-Milstein et al. 2020) and burnout (Robertson et al. 2017). Therefore, while 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 if physicians would actually make use of the protected time to do EHR tasks. Due to the observational nature of our data, we can only provide insights into increases in unscheduled idle times. It is likely that physician behavior may change if physicians are informed of an increase in the idle time between appointments *ex-ante* and are offered encouragement to use this time towards *PRE* and *POST.* Further research is required into the effect of scheduled idle time on pre and post-appointment EHR time.

From our analysis of unscheduled idle time, we find that physicians show an increase in *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 increase of 5 minutes between the preceding appointment increases *PRE* by 7 seconds. On the other hand, an increase of 5 minutes between following appointments increases *POST* by 2 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 5a and 6a. While we find that prework is a dominating strategy; however, with increasing idle time, physicians spend more time on postwork than prework.

6.2 Alternative Explanation of 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 due to 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 (Olivia and Sterman 2001, 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* is a result of task reduction, 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 fully rule out the alternative explanation, 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.4)

7. Discussion and Conclusion

7.1 Discussion

Physician burnout is at an all-time high, with over 68% of physicians in the US reporting burnout in 2021.[5] In the U.S., the cost of physician turnover from burnout has been estimated to be between \$2.8bn to \$6.3bn 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 is a dominating strategy and 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, 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.

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

Increasing idle time between appointments increases both pre-appointment and post-appointment EHR workload. However, post-appointment EHR work increases to a greater degree.

Our findings are also relevant to several other service contexts. Service operators often must manage secondary tasks in addition to the primary task with customer interaction. Examples include data entry between calls for call center operators, working on insurance claim investigations between customer interactions for insurance agents, hand washing for surgeons, and collaboration with other physicians between inpatient rounds for hospitalists. These secondary tasks are related to the primary task; however, service operators have greater discretion when they choose to do them. Our results show when these secondary tasks are done during the day determines the total and after-hours secondary task workload.

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. EHR use literature 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 have different impacts on total and end-of-day EHR work. Pre-appointment EHR tasks reduce both total and end-of-day 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. While interviews with physicians have qualitatively indicated these factors, through our analysis, we are able to provide a rigorous quantitative analysis of the positive impact of pre-appointment EHR work. We also find that post-appointment EHR tasks significantly reduce end-of-day EHR. The marginal reduction of end-of-day 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 end-of-day EHR activities. Therefore, end-of-day 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 end-of-day 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 and may lead 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. Service designers can use these insights to create workflows for service operators managing primary and secondary tasks to improve server productivity and reduce after-work hours. 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. 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, greater emphasis can be placed on doing pre-appointment EHR tasks. If the objective is to reduce end-of-day EHR time, then increasing post-appointment EHR work would give a greater marginal benefit, although 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 effects both total time spent on secondary tasks and after-hours time, an important question is how does idle time affect physician makespan in the presence of secondary tasks like EHR. Since 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 *PRE* and *POST* reduce *EOD* and *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 conduct an analysis on the impact of increasing idle time between appointments on physician makespan, where makespan also includes the end-of-day time spent by the physician on EHR systems. Since makespan for a physician is a day-level measure, our unit of measure for this analysis is physician-day.

The components of our model are as follows: 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 end-of-day 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 end-of-day 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, i.e., ($PhysicianWorking = PhysicianMakespan - TotalDailyIdleTie$). 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.5).

Our econometric model is as follows, p indicates physician, 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 non-idle time of a physician's makespan.

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

There may be unobserved patient and appointment characteristics that may 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, consequently leading to less idle time following the appointment. Since mental health conditions correlate with higher EHR use, the end-of-day 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:

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

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.5). We find that if the total idle time increase by 5 minutes in a day, 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.

Idle time between appointments allows the service operator to perform EHR as prework and postwork. Our results in Section 6 show that prework and postwork can reduce after-hours work. Therefore, for at least small increases in idle time, the makespan for the physician reduces due to the reduction in after-hours work.

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 Department (ED), and surgery, may behave differently from primary care physicians when managing EHR workload. 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, whether they are in the clinic performing these tasks or at home is not observable. 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 end-of-day. Lastly, since 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 cut-off time of 90 seconds to remove the idle time between EHR tasks. This method has been validated through several other observational studies.

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 rigorously studied. We contribute to the literature on healthcare operations by analyzing detailed data on physician EHR usage. We find that pre-appointment EHR work is a dominating strategy reducing both total and after-hours EHR time. Post-appointment EHR work significantly reduces after-hours EHR work, however, 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 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 will provide insights to managers when creating schedules in the presence of a secondary task workload.

References

Adler-Milstein, J., Adelman, J. S., Tai-Seale, M., Patel, V. L., & Dymek, C. (2020). EHR audit logs: a new goldmine for health services research? Journal of biomedical informatics, 101, 103343.

Adler-Milstein, J., Zhao, W., Willard-Grace, R., Knox, M., & Grumbach, K. (2020). Electronic health records and burnout: time spent on the electronic health record after hours and message volume associated with exhaustion but not with cynicism among primary care clinicians. Journal of the American Medical Informatics Association, 27(4), 531-538.

Ahmadi-Javid, A., Jalali, Z., & Klassen, K. J. (2017). Outpatient appointment systems in healthcare: A review of optimization studies. European Journal of Operational Research, 258(1), 3-34.

Aksin, Z., Armony, M., & Mehrotra, V. (2007). The modern call center: A multi-disciplinary perspective on operations management research. Production and Operations Management, 16(6), 665–688.

Altmann, E. M. (2004). Advance preparation in task switching: What work is being done? Psychological Science, 15(9), 616-622.

American Medical Association (2019, November 14). New Research Intensifies AMA's call for improved EHR usability [Press Release] https://www.ama-assn.org/press-center/press-releases/new-research-intensifies-ama-s-call-improved-ehr-usability

Arndt, B. G., Beasley, J. W., Watkinson, M. D., Temte, J. L., Tuan, W. J., Sinsky, C. A., & Gilchrist, V. J. (2017). Tethered to the EHR: primary care physician workload assessment using EHR event log data and time-motion observations. The Annals of Family Medicine, 15(5), 419-426.

Attipoe, S. (2021). Electronic Health Record Work Outside of Work Hours: Patterns and Experiences Among Ambulatory-based Pediatricians at a Large Midwestern Pediatric Health System (Doctoral dissertation, The Ohio State University).

Austin, S. R., Wong, Y. N., Uzzo, R. G., Beck, J. R., & Egleston, B. L. (2015). Why summary comorbidity measures such as the Charlson comorbidity index and Elixhauser score work. *Medical care*, *53*(9), e65.

Bartel AP, Chan CW, Kim SH (2020) Should hospitals keep their patients longer? The role of inpatient care in reducing postdischarge mortality. Management Sci. 66(6):2326–2346.

Batt, R. J., & Terwiesch, C. (2017). Early task initiation and other load-adaptive mechanisms in the emergency department. Management Science, 63(11), 3531-3551.

Baum, C.F., (2007). checkreg3: Stata module to check identification status of simultaneous equations system. http://ideas.repec.org/c/boc/bocode/s456877.html

Bavafa, H., & Terwiesch, C. (2019). Work after work: The impact of new service delivery models on work hours. Journal of Operations Management, 65(7), 636-658.

Bavafa, H., Hitt, L. M., & Terwiesch, C. (2018). The impact of e-visits on visit frequencies and patient health: Evidence from primary care. Management Science, 64(12), 5461-5480.

Bernstein, F., & Kök, A. G. (2009). Dynamic cost reduction through process improvement in assembly networks. Management Science, 55(4), 552-567.

Berry Jaeker, J. A., & Tucker, A. L. (2017). Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity. Management Science, 63(4), 1042-1062.

Bhargava, H. K., & Mishra, A. N. (2014). Electronic medical records and physician productivity: Evidence from panel data analysis. Management Science, 60(10), 2543-2562.

Çakıcı, Ö. E., & Mills, A. F. (2021). On the role of teletriage in healthcare demand management. Manufacturing & Service Operations Management, 23(6), 1483-1504.

Caruso, C. C. (2014). Negative impacts of shiftwork and long work hours. Rehabilitation nursing, 39(1), 16-25.

Chen, R. R., & Robinson, L. W. (2014). Sequencing and scheduling appointments with potential call-in patients. Production and Operations Management, 23(9), 1522-1538.

Costa, A., Keane, M. M., Torrens, J. I., & Corry, E. (2013). Building operation and energy performance: Monitoring, analysis and optimisation toolkit. Applied energy, 101, 310-316.

Dai, H., Milkman, K. L., Hofmann, D. A., & Staats, B. R. (2015). The impact of time at work and time off from work on rule compliance: the case of hand hygiene in health care. *Journal of Applied Psychology*, *100*(3), 846.

Dantas, L. F., Fleck, J. L., Oliveira, F. L. C., & Hamacher, S. (2018). No-shows in appointment scheduling–a systematic literature review. *Health Policy*, *122*(4), 412-421.

De Jong, R. (2000). 15 An Intention-Activation Account of Residual Switch Costs. *Control of cognitive processes*, 357.

Dobson G, Pinker E, Van Horn RL (2009) Division of labor in medical office practices. Manufacturing and Service Oper. Management 11(3):525–537.

Feizi, A., Tucker, A., Berry Jaeker, J., & Baker, W. (2022). To batch or not to batch? impact of admission batching on emergency department boarding time and physician productivity. Forthcoming in Operations Research

Feldman, J., Liu, N., Topaloglu, H., & Ziya, S. (2014). Appointment scheduling under patient preference and no-show behavior. Operations Research, 62(4), 794-811.

Freeman, M., Savva, N., & Scholtes, S. (2017). Gatekeepers at work: An empirical analysis of a maternity unit. Management Science, 63(10), 3147–3167.

Froehle, C. M., & White, D. L. (2014). Interruption and forgetting in knowledge-intensive service environments. Production and Operations Management, 23(4), 704-722.

Gans, N., & Zhou, Y. P. (2003). A call-routing problem with service-level constraints. Operations Research, 51(2), 255-271.

Gawande, A. (2018). Why doctors hate their computers. The New Yorker, 12.

Gottschalk, A., & Flocke, S. A. (2005). Time spent in face-to-face patient care and work outside the examination room. The Annals of Family Medicine, 3(6), 488-493.

Graber, M. L., Byrne, C., & Johnston, D. (2017). The impact of electronic health records on diagnosis. Diagnosis, 4(4), 211-223.

Gupta, D., & Denton, B. (2008). Appointment scheduling in health care: Challenges and opportunities. IIE transactions, 40(9), 800-819.

Gurvich, I., O'Leary, K. J., Wang, L., & Van Mieghem, J. A. (2020). Collaboration, interruptions, and changeover times: Workflow model and empirical study of hospitalist charting. Manufacturing & Service Operations Management, 22(4), 754-774.

Gutierrez, G. J., & Kouvelis, P. (1991). Parkinson's law and its implications for project management. *Management Science*, *37*(8), 990-1001.

Han, S., Shanafelt, T. D., Sinsky, C. A., Awad, K. M., Dyrbye, L. N., Fiscus, L. C., ... & Goh, J. (2019). Estimating the attributable cost of physician burnout in the United States. Annals of internal medicine, 170(11), 784-790.

Hasija, S., Pinker, E., & Shumsky, R. A. (2010). OM practice—Work expands to fill the time available: Capacity estimation and staffing under Parkinson's law. *Manufacturing & Service Operations Management*, *12*(1), 1-18.

Holman, G. T., Beasley, J. W., Karsh, B. T., Stone, J. A., Smith, P. D., & Wetterneck, T. B. (2016). The myth of standardized workflow in primary care. *Journal of the American Medical Informatics Association*, *23*(1), 29-37.

Hydari, M. Z., Telang, R., & Marella, W. M. (2019). Saving patient Ryan—can advanced electronic medical records make patient care safer?. *Management Science*, *65*(5), 2041-2059.

Ibanez MR, Clark JR, Huckman RS, Staats BR (2018) Discretionary task ordering: Queue management in radiological services. Manage. Sci. 64(9):4389–4407.

Karr-Wisniewski, P., & Lu, Y. (2010). When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity. Computers in Human Behavior, 26(5), 1061-1072.

KC, D. S, Staats BR, Kouchaki M, Gino F (2020) Management Science Task Selection and Workload: A Focus on Completing Easy Tasks Hurts Performance. 66(10):4397–4416.

KC, D. S. (2014). Does multitasking improve performance? Evidence from the emergency department. Manufacturing & Service Operations Management, 16(2), 168-183.

KC, D. S., & Terwiesch, C. (2009). Impact of workload on service time and patient safety: An econometric analysis of hospital operations. Management science, 55(9), 1486-1498.

KC, D. S., & Terwiesch, C. (2012). An econometric analysis of patient flows in the cardiac intensive care unit. Manufacturing & Service Operations Management, 14(1), 50-65.

KC, D., & Tushe, S. (2021). The effects of multisiting on productivity and quality. *Manufacturing & Service Operations Management*, *23*(4), 803-818.

Kesavan, S., Staats, B. R., & Gilland, W. (2014). Volume flexibility in services: The costs and benefits of flexible labor resources. Management Science, 60(8), 1884-1906.

Kim, Y., Ayvaci, M., Raghunathan, S., & Ayer, T. (2021). When IT Creates Legal Vulnerability: Not Just Overutilization but Underprovisioning of Health Care Could be a Consequence. Available at SSRN 3487639.

Kong, Q., Li, S., Liu, N., Teo, C. P., & Yan, Z. (2020). Appointment scheduling under time-dependent patient no-show behavior. Management Science, 66(8), 3480-3500.

Lee, S., Bain, P. A., Musa, A. J., & Li, J. (2021). A Markov chain model for analysis of physician workflow in primary care clinics. *Health Care Management Science*, *24*(1), 72-91.

Legros, B., Jouini, O., Akşin, O. Z., & Koole, G. (2020). Front-office multitasking between service encounters and back-office tasks. European Journal of Operational Research, 287(3), 946-963.

Lengnick-Hall, C. A. (1996). Customer contributions to quality: A different view of the customer-oriented firm. Academy of management review, 21(3), 791-824.

Liu, N., Ziya, S., & Kulkarni, V. G. (2010). Dynamic scheduling of outpatient appointments under patient no-shows and cancellations. Manufacturing & Service Operations Management, 12(2), 347-364.

Marmor, R. A., Clay, B., Millen, M., Savides, T. J., & Longhurst, C. A. (2018). The impact of physician EHR usage on patient satisfaction. Applied clinical informatics, 9(01), 011-014.

Melnick, E.R., Fong, A., Nath, B., Williams, B., Ratwani, R.M., Goldstein, R., O'Connell, R.T., Sinsky, C.A., Marchalik, D. and Mete, M., (2021). Analysis of electronic health record use and clinical productivity and their association with physician turnover. JAMA Network Open, 4(10), pp.e2128790-e2128790.

Meng, L., Batt, R. J., & Terwiesch, C. (2021). The impact of facility layout on service worker behavior: An empirical study of nurses in the emergency department. Manufacturing & Service Operations Management, 23(4), 819-834.

Narayanan, S., Balasubramanian, S., & Swaminathan, J. M. (2009). A matter of balance: Specialization, task variety, and individual learning in a software maintenance environment. Management science, 55(11), 1861-1876.

Niewoehner, R. J., KC, D. S., & Staats, B. R. (2022). Physician Discretion and Patient Pick-up: How Familiarity Encourages Multitasking in the Emergency Department. Forthcoming in Operations Research.

Office of the National Coordinator for Health Information Technology. 'Office-based Physician Electronic Health Record Adoption,' Health IT Quick-Stat #50. https://www.healthit.gov/data/quickstats/office-based-physician-electronic-health-record-adoption. January 2021.

Oliva, R., & Sterman, J. D. (2001). Cutting corners and working overtime: Quality erosion in the service industry. Management Science, 47(7), 894-914.

Parkinson, C. N. (1955). From the archive: Parkinson's Law. The Economist, 38.

Pendem, P. K., Green Jr, P. I., & Staats, B. R. (2022). The Microstructure of Work: Understanding Productivity Benefits and Costs of Interruptions. *Manufacturing & Service Operations Management*.

Rathert C, Porter TH, Mittler JN, Fleig-Palmer M (2019) Seven years after Meaningful Use: Physicians' and nurses' experiences with electronic health records. Health Care Manage. Rev. 44(1):30–40.

Robertson, S. L., Robinson, M. D., & Reid, A. (2017). Electronic health record effects on work-life balance and burnout within the I3 population collaborative. Journal of graduate medical education, 9(4), 479-484.

Robinson, L. W., & Chen, R. R. (2003). Scheduling doctors' appointments: optimal and empirically-based heuristic policies. IIE Transactions, 35(3), 295-307.

Roels, G. (2014). Optimal design of coproductive services: Interaction and work allocation. Manufacturing & Service Operations Management, 16(4), 578-594.

Sauré, A., Begen, M. A., & Patrick, J. (2020). Dynamic multi-priority, multi-class patient scheduling with stochastic service times. European Journal of Operational Research, 280(1), 254-265.

Shan Wang, Nan Liu, Guohua Wan (2019) Managing Appointment-Based Services in the Presence of Walk-in Customers. Management Science 66(2):667-686

Shingo, S. (1989). A Study of the Toyota Production System from an Industrial Engineering Viewpoint. Cambridge, Mass., Productivity Press.

Sinha, A., Stevens, L. A., Su, F., Pageler, N. M., & Tawfik, D. S. (2021). Measuring electronic health record use in the pediatric ICU using audit-logs and screen recordings. *Applied Clinical Informatics*, *12*(04), 737-744.

Sinsky CA, Rule A, Cohen G, Arndt BG, Shanafelt TD, Sharp CD, Baxter SL, et al. (2020) Metrics for assessing physician activity using electronic health record log data. J. Am. Med. Informatics Assoc. 27(4):639–643.

Sinsky, C., Colligan, L., Li, L., Prgomet, M., Reynolds, S., Goeders, L., Westbrook, J., Tutty, M. and Blike, G., (2016). Allocation of physician time in ambulatory practice: a time and motion study in 4 specialties. Annals of internal medicine, 165(11), pp.753-760.

Staats, B. R., & Gino, F. (2012). Specialization and variety in repetitive tasks: Evidence from a Japanese bank. Management science, 58(6), 1141-1159.

Stanford Medicine; The Harris Poll (2018) How Doctors Feel About Electronic Health Records National Physician Poll by The Harris Poll 2 Background, Objectives, and Methodology. :1–33.

Sunar, N., & Staats, B. R. (2022). Telemedicine for Inclusive Care: Remedy for Socioeconomic Health Disparities?. Available at SSRN 4103887.

Tai-Seale, Ming, Cliff W. Olson, Jinnan Li, Albert S. Chan, Criss Morikawa, Meg Durbin, Wei Wang, and Harold S. Luft. (2017) "Electronic health record logs indicate that physicians split time evenly between seeing patients and desktop medicine." *Health affairs* 36, no. 4: 655-662.

Tan, T. F., & Netessine, S. (2014). When does the devil make work? An empirical study of the impact of workload on worker productivity. Management Science, 60(6), 1574-1593.

Tran, B., Lenhart, A., Ross, R., & Dorr, D. A. (2019). Burnout and EHR use among academic primary care physicians with varied clinical workloads. *AMIA Summits on Translational Science Proceedings*, *2019*, 136.

Verbruggen, F., Liefooghe, B., Vandierendonck, A., & Demanet, J. (2007). Short cue presentations encourage advance task preparation: a recipe to diminish the residual switch cost. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(2), 342.

Wetterneck, T. B., Lapin, J. A., Krueger, D. J., Holman, G. T., Beasley, J. W., & Karsh, B. T. (2012). Development of a primary care physician task list to evaluate clinic visit workflow. *BMJ quality & safety*, *21*(1), 47-53.

Wooldridge JM (2010) Econometric Analysis of Cross Section and Panel Data (MIT Press).

Yang, L., Holtz, D., Jaffe, S., Suri, S., Sinha, S., Weston, J., ... & Teevan, J. (2022). The effects of remote work on collaboration among information workers. *Nature human behaviour*, *6*(1), 43-54.

Youn, S., Geismar, H. N., & Pinedo, M. (2022). Planning and scheduling in healthcare for better care coordination: Current understanding, trending topics, and future opportunities. *Production and Operations Management*.

Young, R., Burge, S., Kumar, K., Wilson, J., & Ortiz, D. (2018). A time-motion study of primary care physicians' work in the electronic health record era. *Family medicine*, *50*(2), 91-99.

Zellner, A., & Theil, H. (1992). Three-stage least squares: simultaneous estimation of simultaneous equations. In Henri theil's contributions to economics and econometrics (pp. 147-178). Springer, Dordrecht.

Zhang J, Chen Y, Ashfaq S, Bell K, Calvitti A, Farber NJ, Gabuzda MT, et al. (2016) Strategizing EHR use to achieve patient-centered care in exam rooms: A qualitative study on primary care providers. J. Am. Med. Informatics Assoc. 23(1):137–143.

Does Physician's Choice of When to Perform EHR Tasks Influence Total EHR Workload?

Electronic Companion

EC.1. 2SLS Estimation Procedure

1. Express *PRE, MULTI, POST, MeanIdleAfter, and EOD* as individual linear equations of all the exogenous variables, i.e., those discussed as control and instrumental variables above.
2. Estimate each of those equations independently by OLS.
3. Using the coefficients of the above variables, generate predicted variables $\widehat{PRE}, \widehat{MULTI}, \widehat{POST}, \widehat{MeanIdleAfter}, \widehat{EOD}$.
4. Use $\widehat{PRE}, \widehat{MULTI}, \widehat{POST}, \widehat{MeanIdleAfter}, \widehat{EOD}$ in equations (1)-(5) and estimate using OLS, this gives the final estimated coefficients.

EC.2 Derivation of Marginal Effects at Means

$$\frac{dMULTI}{dPRE} = \beta_{PRE,M} \frac{\overline{MULTI}}{\overline{PRE}} \quad (1)$$

$$\frac{dBreakAfter}{dPRE} = \beta_{PRE,BA} \times \frac{\overline{BreakAfter}}{\overline{PRE}} + \beta_{M,BA} \times \frac{\overline{BreakAfter}}{\overline{MULTI}} \times \frac{dMULTI}{dPRE} \quad (2)$$

$$\frac{dPOST}{dPRE} = \beta_{PRE,POST} \times \frac{\overline{POST}}{\overline{PRE}} + \beta_{MULTI,POST} \times \frac{\overline{POST}}{\overline{MULTI}} \times \frac{dMULTI}{dPRE} + \beta_{BA,POST} \times \frac{\overline{POST}}{\overline{BreakAfter}} \times \frac{dBreakAfter}{dPRE} \quad (3)$$

$$\frac{dEOD}{dPRE} = \beta_{PRE,EOD} \times \frac{\overline{EOD}}{\overline{PRE}} + \beta_{MULTI,EOD} \times \frac{\overline{EOD}}{\overline{MULTI}} \times \frac{ddMULTI}{ddPRE} + \beta_{BA,EOD} \times \frac{\overline{EOD}}{\overline{BreakAfter}} \times \frac{dBreakAfter}{dPRE} + \beta_{POST,EOD} \times \frac{\overline{EOD}}{\overline{POST}} \times \frac{dPOST}{PRE} \quad (4)$$

Effect of prework on total EHR:

$$\frac{d(PRE + MULTI + POST + EOD)}{dPRE} = 1 + \frac{dMULTI}{dPRE} + \frac{dPOST}{dPRE} + \frac{dEOD}{dPRE}$$

Effect of postwork on total EHR:

$$\frac{d(PRE + MULTI + POST + EOD)}{dPOST} = 1 + \frac{dEOD}{dPOST}$$

EC.3 Robustness Tests

EC.3.1. Repeating the analysis with EHR time cutoff for 60 seconds

We show in Tables EC.3.1 and EC.3.2 the results of the regressions using 60 seconds and 120 seconds as the cutoff. We observe that the results are similar to our main analysis using a 90-second cutoff. In Table EC.3.3 we show the marginal effects from using the three different cutoffs. We observe that our principal results do not change materially for different cutoffs.

Table EC.3.1: Summary Regression Results for Simultaneous Equation Model Equations for 60 seconds cutoff (1)-(5)

	(1) Log(PRE)	*(2) Log(MULTI)*	*(3) Log(MeanIdleAfter)*	*(4) Log(POST)*	*(5) Log(EOD)*
Log(PRE)		-0.256^{***}		-0.0563	-0.119^{***}
		(0.0178)		(0.0391)	(0.0457)
Log(MULTI)			1.134^{***}	-0.138^{***}	-0.121^{***}
			(0.107)	(0.0413)	(0.0)
Log(POST)					-0.481^{***}
					(0.0737)
Log(MeanIdleBefore)	0.0703^{***}				
	(0.00270)				
Log(MeanIdleAfter)				0.563^{***}	-0.116^{*}
				(0.0208)	(0.0533)
Log(PCPDelay)	-0.170^{***}	0.155^{***}	-0.177^{***}		
	(0.00374)	(0.00401)	(0.0185)		
Log(PatientDelay)	0.0470^{***}	-0.0104^{***}	-0.0529^{***}		
	(0.00276)	(0.00171)	(0.00324)		
NoShowAfterAppt			0.0392^{***}		
			(0.0158)		

Standard errors in parentheses
it: Notes: N=152,970. The time cut-off for an EHR action is **60 seconds**. 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 parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EC.3.2. Repeating the analysis with EHR time cutoff for 120 seconds

Table EC.3.2: Summary Regression Results for Simultaneous Equation Model Equations with 120 seconds cutoff (1)-(5)

	(1) Log(PRE)	*(2) Log(MULTI)*	*(3) Log(MeanIdleAfter)*	*(4) Log(POST)*	*(5) Log(EOD)*
Log(PRE)		-0.283^{***}		-0.00104	-0.335^{***}
		(0.0189)		(0.0384)	(0.0460)
Log(MULTI)			0.480^{***}	-0.0705	-0.334^{***}
			(0.0871)	(0.0394)	(0.0496)
Log(POST)					-0.489^{***}
					(0.0738)
Log(MeanIdleBefore)	0.0728***				
	(0.00283)				
Log(MeanIdleAfter)				0.588^{***}	-0.123^{*}
				(0.0220)	(0.0558)
Log(PCPDelay)	-0.173^{***}	0.167^{***}	-0.184^{***}		
	(0.00392)	(0.00412)	(0.0193)		
Log(PatientDelay)	0.0443^{***}	-0.0107^{***}	-0.0522^{***}		
	(0.00258)	(0.00179)	(0.00329)		
NoShowAfterAppt			0.0392^{***}		
			(0.0159)		

Standard errors in parentheses
it: Notes: N=152,970. The time cut-off for an EHR action is 120 seconds. 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 parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.3.3: Robustness Check Summary - Comparison of marginal effects for different cutoffs

TIME CUT-OFF	***INDEPENDENT VARIABLE***	***(1) TOTAL = (PRE+MULTI+POST+EOD)***	***(2) EOD***
90 seconds	*PRE*	-.3667641*** (.1016148)	-.1702313*** (.0371355)
60 seconds	*PRE*	-.3643146*** (.093679)	-.1513459*** (.0293003)
120 seconds	*PRE*	-.3589106*** (.0941201)	-.1509205*** (.029788)
90 seconds	*POST*	.6863219*** (.0453456)	-.3136781*** (.0453456)
60 seconds	*POST*	.8235743*** (.027041)	-.1764257*** (.027041)
120 seconds	*POST*	.820298*** (.0271308)	-.179702*** (.0271308)

Notes: EHR time calculated based on 90 seconds, 60 seconds and 120 seconds cut-offs. The coefficients represent the effect of one unit increase in PRE and POST on TOTAL and EOD. All models include Physician FE, Patient Controls, and Scheduling Controls as described in Section 4. Robust standard errors, in parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EC.3.3. End of day defined as end of the last appointment of the day

Table EC.3.4: 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)		-0.366^{***} (0.0171)		-0.268^{***} (0.0394)	-0.134^{*} (0.0533)
Log(MULTI)			1.268^{***} (0.0749)	-0.296^{***} (0.0404)	-0.0796 (0.0546)
Log(POST)					-0.631^{***} (0.0955)
Log(MeanIdleBefore)	0.0724^{***} (0.00278)				
Log(MeanIdleAfter)				0.431^{***} (0.0276)	0.171^{**} (0.0537)
Log(PCPDelay)	-0.173^{***} (0.00383)	0.154^{***} (0.00395)	-0.349^{***} (0.0172)		
Log(PatientDelay)	0.0441^{***} (0.00252)	-0.0116^{***} (0.00252)	-0.0607^{***} (0.00322)		
NoShowAfterAppt			0.119^{***} (0.0195)		

Standard errors in parentheses
it: Notes: N=152,970. The time end of day EHR time starts after the end of the last appointment of the day. 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 parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EC.3.4. Three Stage Least Squares (3SLS) Estimation

Table EC.4.5: 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)		-0.334^{***}		0.248^{***}	-0.308^{***}
		(0.0185)		(0.0403)	(0.0516)
Log(MULTI)			0.519^{***}	-0.221^{***}	-0.239^{**}
			(0.0809)	(0.0422)	(0.0551)
Log(POST)					-0.577^{***}
					(0.112)
Log(MeanIdleBefore)	0.0694^{***}				
	(0.00275)				
Log(MeanIdleAfter)				0.821^{***}	0.110
				(0.0298)	(0.100)
Log(PCPDelay)	-0.174^{***}	0.157^{***}	-0.188^{***}		
	(0.00383)	(0.00403)	(0.0179)		
Log(PatientDelay)	0.0415^{***}	-0.0111^{***}	-0.0551^{***}		
	(0.00250)	(0.00174)	(0.00320)		
NoShowAfterAppt			0.104^{***}		
			(0.0137)		

Standard errors in parentheses
it: Notes: N=152,970. The results are for 3SLS. 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 parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.3.6: Marginal Effects at Mean of Prework and Postwork on End of Day Work and Total EHR work with 3SLS

	EOD	TOTAL = (*PRE*+*MULTI*+*POST*+*EOD*)
PRE	-0.206	-0.414
POST	-0.214	0.786

EC.3.5. Test of Endogeneity

We perform Durbin-Wu-Hausman test for endogeneity on equations (2) – (5) to determine of *MULTI, POST, MeanIdleAfter, EOD* are endogenous. The test results support endogeneity for all equations with $p < 0.0001$. We also perform test of weak instruments. We provide below the F-statistics to test for the significance of excluded instruments.

Equation Number	F-Statistics for Significance of Excluded Instruments
(2)	635.95
(3)	1646.02
(4)	276.32
(4)	265.13

EC.4 Relationship between *PRE* and Total EHR Word Count

EC. 4.2 Summary Statistics

Table EC.4.1: Summary Statistics of Word Count Analysis

	Variable	Description	Mean	Std.Dev.
(1)	Total Word Count	Total word count entered by physician for the appointment	2186.23	2195.23
(2)	*PRE*	EHR usage between 12:01 am on the day of the appointment till the time the physician enters the examination room for the appointment	2.16	4.39
(3)	*MULTI*	EHR usage between the time the physician enters the examination room for the appointment and ends the appointment	10.06	6.24
(4)	*POST*	EHR usage from the end of the appointment until the end of the workday	5.38	5.89
(5)	*EOD*	EHR usage from the end of the workday until midnight of the day of the appointment	1.98	4.277

EC. 4.1 Model

$$Log(TOTAL\ WORD\ COUNT) = Log(PRE) + Log(MULTI) + LOG(POST) + LOG(EOD) + Controls$$

EC. 4.3 Regression Results

Table EC.4.2: Summary Regression Results for Word Count Analysis

	(1) Log(Total Word Count)
Log(PRE)	
	0.010***
	(0.001143)
Log(MULTI)	
	0.0368***
	(0.0025)
Log(POST)	
	0.0195***
	(0.0015)
Log(EOD)	0.0167***
	(0.001292)

Standard errors in parentheses
it: Notes: N=80,339. 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 parenthesis, are clustered by Physician and Date of Appointment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EC.5 Effect of Total Daily Idle Time on Makespan

EC.5.1 Summary Statistics

Table EC.5.1: Descriptive Statistics at the Day Level

	Variable	Description	Mean	Std.Dev.
	Endogenous Variables			
(1)	Physician Makespan (mins)	Total makespan on a day by physician	437.36	147.4
(2)	Physician Working (mins)	Total non-idle part of physicians day	323.94	115.2
(3)	Total Idle Time (mins)	EHR usage between 6 am on the day of the appointment till the time the physician enters the examination room for the appointment	111.5	89.09
	Control Variables			
(4)	Average complexity (CCI score)	Number of appointments scheduled for the day	2.174	1.853
(5)	Average Age	Average age of patients in a day	53.36	15.19
(6)	Average Scheduled appointment time (mins)	Average scheduled time of all appointments on the day	23.53	5.715
(7)	Number of Appts In Day	Charlson comorbidity score	11.63	4.431
	Instrumental Variable			
(8)	Number of no-shows	Number of no-shows in a day	0.713	0.946

Notes: N=15,613. Unit of analysis is a physician day. Other control variables not in the table: Physician FE, Patient Gender, Patient Insurance

EC.5.1 Regression Results

Table EC.5.2: Summary Regression Results for Day-Level Analysis of Duration of Workday for Physician

	Log(PhysicianMakespan)
Log ($TotalDailyIdleTime$)	-0.390***
	(0.0531)
Log(DayTotalScheduled)	0.00155***
	(0.000156)
TotalApptsInDay	0.0668***
	(0.00724)

Notes: N=13,383. The unit of analysis is a day of a physician. Robust standard errors, in parenthesis, are clustered by physician. Other control variables not in table: Physician FE, daily average patient age, fraction of Medicare patients in day, fraction of Medicaid patients in day, fraction of patients with continuity in visits * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EC.5.2 Computation of Marginal Effect at Mean

From Equation (6):

$$Log(PhysicianWorking) = \beta_{I,W} Log\big(TotalDailyIdleTime_{pj}\big) + \boldsymbol{\gamma Y_{pj}} + \delta_{pj}$$

From the definition of *PhysicianMakespan* and *PhysicianWorking:*

$$PhysicianMakespan = PhysicianWorking + TotalDailyIdleTime$$

Taking first derivative of the above two equations and substituting:

$$\frac{dPhysicianMakespan}{dTotalDailyIdleTime} = \beta_{I,W} \frac{\overline{PhysicianWorking}}{\overline{TotalDailyidleTime}} + 1$$

Substituting the values, we have $\frac{dPhysicianMake}{dTotalDailyIdleTime} = -0.11$. Therefore, a 5 minute increase in total daily idle time will lead to a decrease of 0.55 minutes in physician makespan