The Impact of Surgeon Daily Workload and its Implications for Operating Room Scheduling

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In many service systems, workload can have a substantial impact on service time and quality. Such effects are especially important in healthcare systems which often involve multiple people and operate under resource and time constraints. In this study, we investigate this relationship in the context of cardiac surgery. Using a detailed data set of more than 5,600 cardiac operations in a large hospital, we quantify how surgeon daily workload (e.g., the number of operations performed by the focal surgeon) affects surgery duration and patient outcomes. To handle the endogeneity of surgeon daily workload, we construct instrument variables using hospital operational factors, including the block schedule of surgeons. We find high daily workload for the focal surgeon is associated with longer incision times and worse patient outcomes. Specifically, increased daily workload leads to longer post-surgery length-of-stay in ICU and hospital as well as higher likelihoods of reoperation and readmission for their patients. These results highlight the potential negative impact of high surgeon workload which may result in surgeon fatigue and operational constraints. We develop a surgical scheduling model that incorporates the estimated impact of surgeon workload. We solve the model and show that our proposed schedule can substantially reduce total incision time and post-surgery length-of-stay.

Key words: healthcare delivery, empirical operations management, behavioral operations, operating room scheduling, surgeon workload, quality of care

1. Introduction

The relationship between system workload and service performance has drawn increasing attention in the operations management community. Traditional operations management models generally assume service time is fixed and independent of the system workload (see e.g., Wolff (1989) and Dallery and Gershwin (1992)). However, a growing body of empirical research shows that the service time of human-involved systems can be endogenously impacted by the overall workload (e.g. Schultz et al. (1998), Staats and Gino (2012), and Tan and Netessine (2014)). Such effects are particularly important in healthcare, where resources are often constrained and timely access to medical services can have a substantial impact on

patient satisfaction and clinical outcomes. The system workload has been shown to affect service time in different healthcare settings, such as intensive care units (ICUs) (Kc and Terwiesch 2012), patient transportation and cardiac surgery (Kc and Terwiesch 2009), as well as emergency departments (Kc 2014, Batt and Terwiesch 2016). While some studies found that service time can increase with workload levels (Green and Nguyen 2001, Tan and Netessine 2014), the opposite pattern, i.e., service time decreasing in workload levels, has also been observed (Kc and Terwiesch 2009, Chan et al. 2012). Different mechanisms have been proposed to explain the observed patterns, such as rushing, task-reduction, and multitasking (see, e.g., Batt and Terwiesch (2016)). Partially reconciling the two patterns, some recent studies show that the service time can react non-monotonically to workload levels. These studies have found an inverted-U shaped pattern, i.e., service time first increases and then decreases in the workload measures (see, e.g., Tan and Netessine (2014), Batt and Terwiesch (2016), and Berry Jaeker and Tucker (2017)). Beyond service time, the effect of hospital's workload on the quality of care has also been investigated in both the operations management and medical community. There is empirical evidence that increased workload can lead to worse medical outcomes, such as higher mortality and readmission rates (e.g., Kc and Terwiesch (2009), Kc and Terwiesch (2012), and Needleman et al. (2011)). Such negative effects have been explained by the mental strain of healthcare workers (Kuntz et al. 2015) and the delay in treatment received by patients (Chalfin et al. 2007).

In this paper, we empirically investigate the impact of workload on service time and quality in the context of cardiac surgery. We focus on the daily workload of surgeons, e.g., the number of operations performed by the focal surgeon on a given day. In most of the existing literature, workload is measured on a system level, usually as the bed occupancy in different hospital units at the time of patient's admission (e.g., Kc and Terwiesch (2012), Kuntz et al. (2015), and Kim et al. (2015)). Different from these works, our study considers a novel type of workload; namely we measure the workload for individual surgeons on each day. To the best of our knowledge, we are the first to study the impact of surgeon daily workload in the field of operations management. Note this is in contrast to the literature on surgical volume over longer time horizons. In these works, increased volume has been associated with improved outcomes due to more surgery experience (e.g. Kc and Staats (2012)).

It is common for a cardiac surgeon to do multiple operations a day. In our study hospital, the median surgeon daily workload is two operations, and the maximum is four operations. On average, each operation takes more than seven hours to complete. Although some parts of the operation can be done by other members of the medical team, performing multiple operations a day is still a heavy physical and cognitive burden for the surgeon. With long working hours, surgeons can suffer from physical and mental fatigue, which may lead to worse medical outcomes (see, e.g., Janhofer et al. (2019)). In addition, high surgeon workload may strain operational resources. For example, there may be less experienced staff for operations performed in the late evening, and the bed flow could be slower outside of the normal working hours if auxiliary resources are not available. In this study, our goal is to understand the effect of surgeon workload,

which is important for hospitals to improve their surgical outcomes and system performance. Due to data limitation, we do not aim to fully differentiate the factors leading to such effect, e.g., surgeon fatigue versus operational constraints.

In this paper, we examine the impact of surgeons' daily workload using a data set of cardiac surgery from a large academic medical center. Our data comes from the Society of Thoracic Surgeons (STS) Adult Cardiac Surgery Database for our partner hospital and contains detailed information of more than 5,600 cardiac operations that are performed over a horizon of four years. We measure the impact of surgeon daily workload on multiple outcomes. First, we examine how surgeon daily workload affects the surgery duration of each case, as measured by its incision time. This sheds light on the relationship between workload and service time in the context of cardiac surgery, i.e., whether the incision time increases or decreases when the surgeon performs more cases in a day. Next, we analyze the effects of surgeon daily workload on the patient's post-surgery length-of-stay (LOS) in the ICU and in the hospital. The post-surgery LOS is important for the hospital as it affects the demand for downstream resources (e.g., ICU and ward beds) and overall throughput efficiency. Finally, we check the impact of surgeon workload on the likelihood of adverse post-operation events for their patients, including reoperation, readmission, and mortality. We also examine whether the treatment effect of surgeon workload is heterogeneous for different types of patients. For example, urgent and emergent patients are generally more severe than the elective patients, thus their surgical outcomes may be more sensitive to surgeon daily workload.

Our detailed data set allows us to control for a variety of demographic, risk, and operative factors that may also affect the surgical outcomes. However, we still face a major challenge in identifying the true effect of surgeon daily workload. That is, the surgeon daily workload is endogenous. This is because there are likely risk factors that are considered by the surgeons when they schedule their cases, but these factors are not observable in the data. These unobservable factors will affect both the surgeon daily workload and the surgical outcomes, thus violating the exogeneity condition for identification. For example, a surgeon may schedule more cases by packing in low risk, "easy" cases. If these measures of low risk are unobservable in the data, this will generate a negative bias in the estimated causal effect of surgeon daily workload. We handle the endogeneity bias by utilizing an instrument variable (IV) approach. The IV method has been widely used in healthcare operations management for patient admission decisions (e.g., Kc and Terwiesch (2011), Kc and Terwiesch (2012), and Kim et al. (2015)). We now apply it in the context of cardiac surgery to control for the endogeneity in surgeon workload.

A valid IV in our study should influence the surgical outcomes only via the surgeon daily workload. We construct two instrument variables by leveraging operational factors in cardiac surgery. The first IV is the number of cases performed by other cardiac surgeons on the same day. As many resources are shared by surgeons in the cardiac department, more operations performed by other surgeons tend to limit the daily workload of the focal surgeon. We then construct another IV using novel operational data, which is the block

schedule of surgeons. Specifically, we define the second IV as the number of days until the next scheduled block of the focal surgeon. This IV is based on the following surgeon behavior: the surgeon may "squeeze in" more cases if his or her next scheduled block is far away. We validate the two IVs empirically with our data and show they are essential for correctly estimating the effect of surgeon daily workload.

We find higher daily workload for surgeons is associated with longer incision time of the operation and worse outcomes for the patients. Specifically, adding one more case to a surgeon's daily workload increases the incision time by 26 minutes for each case performed by the surgeon in the day. This is a 9% relative increase. Besides, surgeon daily workload leads to longer post-surgery LOS of patients in both the ICU and the hospital: when the surgeon needs to do one more case in a day, the affected patients are expected to stay in the ICU (resp. hospital) for 1.03 (resp. 1.41) more days after their operations. In addition, we find higher daily workload increases the patient's likelihood of reoperation and readmission. These consistent results highlight the negative impacts of high daily surgeon workload.

We further show there is substantial heterogeneity in the effect of daily workload for elective and non-elective patients. The non-elective patients refer to those categorized as urgent, emergent, and salvage status. We find the effect of surgeon daily workload on incision time is statistically significant for the elective patients, but not for the non-elective ones. On the contrary, the effects on post-surgery LOS (in both ICU and hospital), reoperation, and readmission are significant only for non-elective patients. One possible explanation for such heterogeneity in treatment effect is that the operations for non-elective patients are more time-constrained, thus their incision time is less impacted by surgeon's workload. On the other hand, the non-elective patients are generally more severe, and their surgical outcomes (post-LOS, reoperation, and readmission) are more sensitive to surgeon workload.

Based on the empirical results, we develop a surgery scheduling model that incorporates the effect of surgeon daily workload. Operating rooms are expensive medical resources and generate up to a half of hospital's revenues (McDermott et al. 2017), and accordingly the literature on surgical scheduling is large (see, e.g., Keskinocak and Savva (2020)). In most of the existing literature, the surgery duration and patient outcomes are assumed to be exogenous with deterministic or stochastic distributions. However, as shown by our study, they can endogenously depend on surgeon daily workload. We thus propose a scheduling model that accounts for such effect. In our model, the objective is to minimize the total expected incision time, post-LOS, or ICU time of the patients in our sample. We consider the intervention of changing the dates of the operations in order to mitigate the negative impact of high daily workload for a surgeon. We formulate and solve the model as a mixed-integer quadratic programming problem. Using our estimated effects, we show the new schedules from our model can reduce the total post-LOS and ICU time by up to 3.5% and 5.4% respectively, which are economically substantial for the hospital. This highlights the benefits of accounting for the impact of surgeon daily workload in surgery scheduling.

In summary, we make the following contributions in this paper.

- **Impact of surgeon daily workload:** We empirically estimate the causal impact of surgeon daily workload on surgery duration and patient outcomes using a detailed data set of cardiac surgery. We find surgeon workload increases surgery duration and leads to worse patient outcomes (post-surgery LOS, reoperation, and readmission). The effects are highly heterogeneous for different patient outcomes and different types of patients. Our result highlights the important impact of surgeon daily workload on the operations and clinical outcomes of cardiac surgery. It also provides a potential mechanism for hospitals to focus on in order to improve their surgery operations and patient outcomes.
- **Estimation methodology:** To address the endogeneity bias in surgeon daily workload, we propose two novel IVs using operational factors in the cardiac surgery department. The first IV is based on the resource sharing by surgeons in the department. The second IV leverages the surgeons' block schedule data to capture the "squeeze-in" behavior that affects the surgeon workload. We validate the two IVs empirically and show they are essential for estimating the effect of surgeon workload without bias.
- **Surgery scheduling:** Our findings suggest that surgeon daily workload can substantially affect the surgery duration and patient outcomes. However, such impacts are largely ignored in the previous literature. Thus, we develop a surgery scheduling model that incorporates the impacts of a surgeon's daily workload. Using the estimated effects, we show that accounting for such effects in surgery scheduling can substantially reduce the total incision time and patient's LOS.

The rest of the paper is organized as follows. The next section is a brief overview of related literature. Section 2 describes the data and clinical setting of our study. In Section 3, we develop the econometric framework and estimation methodology. Section 4 provides the main empirical findings. We discuss our surgery scheduling model in Section 5. Section 6 concludes the paper and discusses future directions. The appendices include variable definitions and supplementary tables.

1.1. Literature Review

Our study is related to four streams of literature: (1) the effect of system workload on service rate and quality, (2) volume-outcome relationship, (3) the impact of surgeon fatigue, and (4) operating room scheduling.

While traditional models usually assume a constant and exogenous service rate, there is rich literature, both analytical and empirical, that focuses on the relationship between system workload and service rate. The dynamic queueing control literature has derived optimal service rates that balance the costs of acceleration and waiting time (e.g., George and Harrison (2001)). In reality, such optimal policies are not always feasible for human workers. To examine how human workers actually behave under varying workload, various empirical research has been conducted using observational data in real-world settings, and the results are mixed. Kc and Terwiesch (2009) show that workers for patient transport and cardiac surgery increase their service rate under high workload. Kc and Terwiesch (2012) and Chan et al. (2012) find hospitals are likely to discharge patients early when ICU occupancy is high, i.e., decreasing the service time. The opposite

direction of the impact is also observed empirically. For example, Green and Nguyen (2001) show patient's LOS can increase when patient load becomes higher. The seemingly opposite effects of workload can be partially reconciled by an inverted-U shape pattern between service time and workload. That is, the service time first increases and then decreases with the workload level. Empirical evidence for this inverted-U shape pattern is found using restaurant chain data in Tan and Netessine (2014), and in the healthcare setting in Batt and Terwiesch (2016) and Berry Jaeker and Tucker (2017). Different mechanisms have been proposed to explain the impact of workload on service time. For example, the decrease in the service time can be explained by server speedup (Staats and Gino 2012, Kc and Terwiesch 2009, Tan and Netessine 2014), task reduction (Oliva and Sterman 2001, Kuntz et al. 2015), or early task initiative between stages (Batt and Terwiesch 2016). On the other hand, the slowdown in service time can be caused by multitasking (Tan and Netessine 2014, Freeman et al. 2017), mental fatigue (Kuntz et al. 2015), and increase in patient's average severity level (Berry Jaeker and Tucker 2017). On the analytical side, Delasay et al. (2016) develop a state-dependent queueing model to capture the adaptive mechanisms leading to the nonlinear pattern between service rate and workload. Delasay et al. (2019) provide a general framework that incorporates different effects of workload on service time.

There is also a rich literature studying the effect of workload on servers' behavior and quality. Green et al. (2013) find the nurse absenteeism is positively correlated with the expected future workload. Hopp et al. (2007) use an analytical queueing model to show increasing servers may worsen congestion when servers have discretion over task completion time. Freeman et al. (2017) find that gatekeeper-providers would alter their service configuration and referral decisions in response to their workload. In multiple healthcare settings, the quality of care is found to suffer under high workload, such as higher mortality and readmission rate (Kc and Terwiesch 2009, 2012, Kuntz et al. 2015), as well as longer LOS and higher likelihood of transfer-up (Kim et al. 2015). The positive linkage between hospital workload and mortality is also observed in the medical literature (e.g., Schilling et al. (2010) and Neuraz et al. (2015)). The negative impact on quality is particularly significant when the workload is already high. This suggests a safety tipping point in occupancy level, after which the service time increases and the quality of care deteriorates (Kuntz et al. 2015, Berry Jaeker and Tucker 2017). Our study contributes to this line of literature by considering a novel type of workload in healthcare setting, i.e., number of operations performed in a day. We find a surgeon's high workload is associated with longer surgery duration and worse patient outcomes, providing consistent evidence for the negative impact of very high workload level. We also show such effects are highly heterogeneous across different patients and outcomes.

Next, our work is related to the literature on volume-outcome relationship in healthcare management. In the medical community, there is vast evidence supporting a positive relationship between a surgeon's (or a hospital's) volume and surgical outcomes (see, e.g., Falcoz et al. (2014), Bashir et al. (2017), and Modrall et al. (2018)). The volume in these studies usually refers to the number of operations performed by

the surgeon in a relatively long period (e.g., the past one year). The volume-outcome relationship has also drawn attention in the field of operations management. Research in different empirical settings has been conducted to investigate the driver and mechanism behind the relationship, e.g., learning and specialization. For example, Kc and Terwiesch (2011) show that after controlling for selective patient admissions, the benefit of specialization disappears at the hospital level, but it still exists at the operating unit level in terms of a shorter patient's LOS. Kc and Staats (2012) disentangle the volume-outcome relationship by dividing experience into focal and related categories. They find a surgeon's focal experience has a greater impact on surgical outcome than related experience. Clark and Huckman (2012) identify the existence of complementarities resulting from cospecialization in focal and related segments, i.e., hospitals with greater specialization in related areas have a higher marginal benefit from specialization in the focal area. Using transaction data from a Japanese bank, Staats and Gino (2012) show specialization improves the performance in the short-term (single-day), while variety increases worker productivity in a longer-term (across days). Recent work by Wang and Pourghannad (2020) shows the effects of surgical volume on surgery duration is heterogeneous across patients. Complementing this line of research, we investigate the impact of a surgeon's short-term volume, i.e., number of cases performed in a day, on surgery duration and surgical outcomes.

Our work also relates and contributes to the literature on surgeon fatigue. As the work of a surgeon is highly demanding both physically and mentally, the potential negative impact of surgeon fatigue has long been a focus of the medical community (see a recent survey in Janhofer et al. (2019)). Long working hours and, consequently, suboptimal amount of rest can cause different types of fatigue for surgeons, including muscular fatigue (Dorion and Darveau 2013), mental fatigue (McCormick et al. 2012), and decision fatigue (Stewart et al. 2012). Under different medical settings, multiple studies have shown surgeon fatigue is associated with worse surgical outcomes (see, e.g., Halldorson et al. (2009), Shanafelt et al. (2010), and Thomas et al. (2012)). However, other studies have found no significant impact from surgeon fatigue on surgical outcomes (Ellman et al. 2005, Bagrodia et al. 2012, Govindarajan et al. 2015). In general, the medical literature does not have a clear conclusion on the relation between surgeon fatigue and worse patient outcomes. Our work sheds light on this important problem using a detailed empirical data set of cardiac surgery and rigorous econometric analysis. We acknowledge that there may be other factors (e.g., fewer staff and limited resources in the evening) that contribute and/or explain the effects of surgeon workload; however, surgeon fatigue is one plausible explanation for our findings. As an important difference from existing medical literature, which focuses primarily on correlations rather than trying to tease out causal effects, we use IVs to control for the endogeneity in surgeon daily workload and generate causal estimates. This accounts for the possibility that surgeons will schedule less severe cases when they know their workload is high. Ignoring such endogeneity may make it difficult, or even impossible, to identify the true effect.

We also contribute to the literature of operating room scheduling. Operating rooms are big cost centers and revenue generators of the hospital. However, efficient management of operating rooms often faces operational difficulties such as low utilization, late starts, overtime costs, and unexpected cancellations (Doebbeling et al. 2012). The literature on operating room scheduling is huge. Some review of the current research, challenges, and future directions of this field can be found in Cardoen et al. (2010), May et al. (2011), and Samudra et al. (2016) among many others. Different objectives are considered in operating room scheduling, including minimizing costs (Denton et al. 2010), maximizing profit (Freeman et al. 2016), maximizing utilization (Gupta 2007), reducing patient wait times (Zenteno et al. 2015), and smoothing downstream census (Zenteno et al. 2016). Combinations of these objectives are also considered (e.g., Min and Yih (2010), Gul et al. (2011), and Li et al. (2017)). From a different aspect, Olivares et al. (2008) apply a structural estimation method on observational data to identify how the hospital actually balances the costs of reserving too much versus too little operating room capacity for cardiac surgery. However, most of the existing literature assumes the surgery duration, either deterministic or stochastic, to be exogenous and independent of surgeon workload. To the best of our knowledge, we are the first to develop a scheduling model that incorporates the effects of surgeon daily workload. A recent example of endogenous surgery duration is the recent work by Wang and Pourghannad (2020), in which the surgery duration is affected by the attending surgeon's past volume. They then develop a surgery scheduling model that minimizes the total duration of all operations. Our work differs from theirs in several important aspects. First, we focus on the impact of surgeon daily workload, and apply an IV method to address the endogeneity bias. Next, our model considers the assignment of operations to available days, which is different from their decisions of matching patients and surgeons. In addition, we examine clinical outcomes in addition to surgery duration, including patient post-LOS and ICU time.

2. Data and Clinical Setting

In this study, we use cardiac surgery data from a large academic hospital over the period of July 2015 to July 2019. The data comes from two sources. The first one is the cardiac surgery data collected from the Society of Thoracic Surgeons (STS) Adult Cardiac Surgery Database.[1] The STS data contains detailed information of patient demographics, risk factors, preoperative status, operative procedures and timelines, as well as postoperative events for all cardiac operations occurred in the sample period in our partner hospital. This comprehensive data set allows us to control for the severity of patients and complexity of operations when analyzing the impact of daily workload. The STS data contains basic patient demographics such as gender, age, and race. It also includes risk factors such as a patient's status for liver illness, lung disease, diabetes control, and renal failure. The preoperative section records whether the patient experienced heart

[1] https://www.sts.org/registries-research-center/sts-national-database/adult-cardiac-surgery-database/data-collection

failure, cardiogenic shock, or myocardial infarction (MI) before the operation. We also obtain from the STS data each patient's hospital admission date, surgery date, and discharge date. Thus, we can compute the patient's LOS before and after the operation. For each operation, we can determine its operating room (OR) time and incision time from the STS data using the timestamps of its OR entry and exit, as well as skin incision start and end. We also have the surgeon's identifier for each case, which enables us to control for surgeon-specific differences in outcomes (e.g. Wang and Pourghannad (2020)). Finally, the STS data contains multiple outcomes of each operation, such as the time spent in ICU, reoperation, readmission, and mortality.

The second data source is the block schedule of surgeons provided by the cardiac department of our partner hospital. The hospital employs a block booking framework to schedule their cardiac surgery. Under the block booking, surgeons are assigned with fixed time slots (blocks) and dedicated resources (e.g., OR and staff) to perform their operations. The block schedule is decided in advance by the management board and adjusted infrequently, e.g., each quarter or twice a year. The block scheduling framework is widely accepted in the US as it is convenient for surgeons and hospitals to employ (Erdogan and Denton 2010). Each block in our data specifies the date, OR number, and the surgeon assigned – e.g., OR 1 is assigned to Surgeon A on October 1st, 2016. We note that in most cases in our study, each OR is assigned to only one surgeon for the entire day. That is, OR sharing by multiple surgeons is rare (only 3%). There are in total eight ORs for cardiac operations. However, some blocks of these ORs are assigned to other departments in the hospital (e.g., the pediatrics department). This is also documented in the block schedule data.

In principle, the block schedule data allows us to determine for each operation whether it happens in or out of the block schedule. Here "in block schedule" means the operation is performed in an OR that is assigned to the surgeon on the operation date. However, the data has two limitations. First, a significant proportion of the block schedule data is missing: out of the 48 months (resp. 5,604 cases) in our surgery data, we only have the block schedule data for 22 months (resp. 2,499 cases). Thus, we would need to impute the block schedule information for the missing periods. We provide the details of the imputation in Section 3.1.2. We emphasize that the missing block data is due to the absence of administrative staff in the department (e.g., personal or medical leave), thus it does not introduce any selection of patients or operations. Second, we do not have the location information (the OR number) for each operation in our data. Because of this limitation, we can only determine the block status on the surgeon-day level, i.e., whether a surgeon is assigned a block in one of the ORs on a specific day. We then use this block status for all the cases performed by the surgeon on that day. We verify with our partner hospital that this is a reasonable assumption.

2.1. Data Selection

In this section, we describe the data cleaning process and provide some summary statistics of the final sample in our study.

We start from 5,604 cases from the STS data. We first drop 20 cases that are cancelled before or during the operation. We then drop 232 cases from seven "infrequent" surgeons in our sample. These surgeons performed a very small number of cases during the four years in the sample period. They are dropped for the following two reasons. First, these surgeons are more likely to only perform unusual procedures that require special expertise. Second, the small sample size of these surgeons does not allow us to effectively control for surgeon fixed effects. Thus, we focus on the cases from the other eight surgeons, each of which performed at least 200 cases in the sample period. This leaves us with a sample of 5,352 cases in total, which consists of 95.5% of the initial sample.

In the final full sample of our study, we have the block schedule information for 2,492 of the cases (46.5%). We refer to these cases as the block sample. As we explained above, we can determine the block status on the surgeon-day level. In the 1,744 surgeon-day pairs with block information, 1,343 (77%) of them are in block schedule, i.e., the surgeon has a block assignment on that day, while the remaining 401 (23%) pairs happen out of schedule. Given a surgeon operates in a day, on average, the surgeon performs 1.4 (resp. 1.2) cases a day if he or she is in (resp. out of) block schedule. In total, we have 2,010 cases classified as in block schedule, 482 as out of block schedule, and 2,860 cases of which we do not have block schedule information and use imputed block information in our analysis. We run robustness checks on the block sample for the cases with complete block schedule information only, as discussed in Section 4.3.

2.2. Patient Risk Factors

The STS data set provides a comprehensive set of risk factors of each patient, which allows us to control for the patient's severity and condition. Table 1 reports the summary statistics of patients' gender, age, and critical status for both the full sample and the block sample. Specifically, a patient is classified as critical if he or she experiences a cardiogenic shock or syncope before the operation. In Appendix A, we provide a detailed description of other factors included in our econometric framework and their summary statistics.

Table 1 Summary Statistics of Patients for the Full Sample and Block Sample (Full Sample: N = 5,352, Block Sample: N = 2,492)

	Full Sample			Block Sample		
	Mean	Median	Std	Mean	Median	Std
Gender: Male	0.675	-	-	0.671	-	-
Age	64.73	66.00	12.56	65.06	66.00	12.33
Critical	0.103	-	-	0.102	-	-

The cardiac operations are divided into four main risk categories (surgery status) in increasing order of patient severity and urgency in need of operation: elective, urgent, emergent, and salvage. The elective cases are those operations that can be deferred without increased risk; the urgent cases are supposed to

be performed during the same clinical stay to reduce further risk; the emergent and salvage cases refer to the situation that requires emergent operations with no delay upon the outbreak.[2] The surgery status has important implications on the surgical scheduling. While the hospital has relatively high flexibility in scheduling the elective cases, the schedules of urgent cases are more difficult to change, and the hospital has little control over the timing of emergent and salvage cases. In Table 2 below, we provide the summary statistics for the four categories in both the full sample and the block sample. We have two findings from the statistics. First, a significant proportion of the operations are urgent or emergent cases, which consist of 53.5% of the full sample and 52.3% of the block sample. The numbers of elective and urgent cases are almost the same. Second, the distributions of the four status are very similar for the full and block samples.

Table 2 Statistics of Surgery Status in Full and Block Sample

	Full Sample		Block Sample	
Status	Number	Ratio	Number	Ratio
Elective	2479	46.3%	1184	47.5%
Urgent	2488	46.5%	1124	45.1%
Emergent	374	7.0%	180	7.2%
Salvage	11	0.2%	4	0.2%

In addition to the surgery status, we also obtain the procedure information for each case from the STS data, i.e., which types of procedures are performed during the operation. To control for differences across different types of procedures, we classify the operations to different types as follows. First, there are eight standard types for the most commonly performed cardiac operations. For them, we directly use the classification provided by the STS data: coronary artery bypass graft (CABG), aortic valve replacement (AVR), mitral valve replacement (MVR), mitral valve repair (MVr), and their combinations CABG+AVR, CABG+MVR, CABG+MVr, and AVR+MVR. For the non-standard procedures which do not fall in one of the eight types above, we define their surgery types based on the actual procedures performed. The detailed definitions of the non-standard types are provided in Appendix A. In total, we have 14 procedure types for the cases in our data. There are 3,420 cases (63.9%) that belong to one of the eight standard types, and 1,932 cases (36.1%) that belong to one of the six non-standard types.

We compute the pre-surgery LOS (pre-LOS) for each patient as the number of days between the hospital admission and the operation, and the post-surgery LOS (post-LOS) as that between the operation and the hospital discharge. The OR time of each case is calculated as the time elapsed between its OR entry and OR exit. As shown in Figure 1, the OR time can be decomposed to three stages: pre-incision time, incision time, and post-incision time. The incision stage corresponds to the time between skin incision start and end,

[2] See page 154 in the training manual: https://www.sts.org/sites/default/files/Training%20Manual%20V2-9%20June%202020.pdf

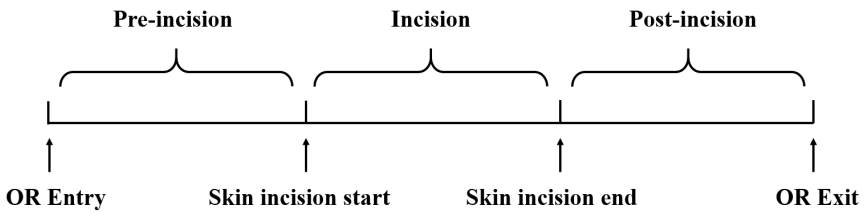

Figure 1 OR Timeline for a Cardiac Operation (not drawn to scale)

and the pre-incision (resp. post-incision) stage refers to the time before (resp. after) it. Different tasks are performed in the three stages. The pre-incision stage includes pre-operative tests, positioning the patient in OR, and anesthesia. The post-incision stage includes closing the incision and cleaning up. In cardiac operations, these tasks can be largely performed by medical staff or surgical fellows without the presence of the focal surgeon. On the other hand, the incision stage requires relatively high level of participation of the surgeon. Thus, the incision time is a more accurate measure for a surgeon's working time than the total OR time.

We present the summary statistics for the pre-incision measures including pre-LOS and pre-incision time by the four surgery status in Table 3. We can see that the elective cases have relatively short pre-LOS. This is because most of the elective patients are admitted one day before or on the same day of their operations. We also see a fairly consistent pre-incision time spent in the OR across Elective, Urgent, and Emergent patients. This is likely due to the fact that, for these patients, pre-incision time is very protocol-driven where the patient goes through standard preparation before the surgeon actually cuts the patient. On the other hand, the pre-incision time for Salvage patients is shorter. Although the sample size is very small, this may be indicative of the highly time-sensitive nature of these procedures.

Table 3 Summary Statistics of Pre-incision metrics by Surgery Status

Status	Num Obs.	Pre-surgery LOS (days)	Pre-incision time (hours)
Elective	2479	1.16 (2.92)	1.48 (0.28)
Urgent	2488	4.90 (9.83)	1.51 (0.31)
Emergent	374	15.32 (30.11)	1.48 (0.45)
Salvage	11	8.09 (7.54)	1.18 (0.51)
All	5352	3.9 (11.19)	1.49 (0.31)

2.3. Surgery Metrics and Patient Outcomes

We now report the summary statistics for the surgical metrics and outcomes in Table 4. First, we see that the average incision and OR time are longer for the urgent and emergent cases than that for the elective cases. This is not surprising as the non-elective cases tend to be more complicated and thus take longer

time to perform. On average, the incision stage consists of 67% of the total OR time. Second, the elective cases have the shortest post-LOS, while the emergent cases have the longest. This reflects the fact that the patients of the elective cases are generally less severe than those of the urgent and emergent cases and follow typical post-surgery protocols. Third, the total time in ICU accounts for both the initial ICU visit and the potential revisits and is longer for the more complex cases. For patient outcomes, we focus on three binary ones: reoperation, readmission to the hospital, and mortality. Reoperation includes all causes for a patient to return to OR: bleeding, valve dysfunction, MI, aortic disease, and other cardiac and non-cardiac reasons. However, we exclude reoperations within 24 hours after operation due to acute bleeding because these acute reoperations increase the surgeon's workload on the same day, but they are not documented in the STS data[3]. Mortality is defined as death in 30 days after the operation regardless of the location (e.g., in hospital or at home). Not surprisingly, we see that the urgent cases on average are associated with worse outcomes than the elective ones, and the emergent cases have the worst average outcomes among the three categories.

Table 4 Summary Statistics of Surgery Metric and Patient Outcomes

	Elective	Urgent	Emergent	Salvage	All
OR time (hours)	6.79 (1.79)	7.24 (1.99)	8.31 (2.59)	8.28 (2.60)	7.11 (1.99)
Incision time (hours)	4.52 (1.56)	4.88 (1.76)	5.80 (2.31)	5.96 (2.27)	4.78 (1.75)
Post-LOS (days)	8.77 (7.89)	13.28 (18.55)	25.88 (22.28)	20.55 (12.15)	12.09 (15.58)
Total ICU (days)	3.61 (5.55)	5.88 (11.36)	13.29 (17.35)	15.59 (13.03)	5.37 (10.09)
Reoperation	0.0347	0.076	0.251	0.364	0.070
Readmission	0.0891	0.104	0.118	0.200	0.098
Mortality	0.0157	0.031	0.061	0.455	0.027
Number	2479	2488	374	11	5352

3. Econometric Framework

We now develop the econometric framework for identifying the effect of daily workload on surgery duration and outcomes. For each case i, denote its surgeon and surgery date by s and t respectively. $Workload_{ist}$ is the daily workload of case i's surgeon s on day t. Since each case i maps to a unique pair of surgeon s and day t, we use $Workload_i$ and remove the subscript st for all variables for brevity. We consider two measures for the surgeon daily workload. The first measure $NumCases_i$ is the total number of cases excluding i performed by surgeon s on day t. The second measure $SumInc_i$ represents the total incision time of cases excluding i by surgeon s on day t. The summary statistics of the two daily workload measures are reported in Table 5 below. We see that it is very common for a surgeon to perform multiple cases on the

[3] This happens for 108 out of the 5352 cases, consisting of 22% of all cases that return to OR for reoperation.

same day: the median of $NumCases_i$ is one for both the full sample and the block sample. That is, for at least half of the cases i in our sample, i's surgeon s performs at least two cases in total on day t. This is also reflected by the average of $SumInc_i$, which is 3.27 (resp 3.14) hours for the full (resp. block) sample. Note that if the surgeon performs only one case in a day, we would have $NumCases_i$ and $SumInc_i$ equal to zero by their definitions. We also note that the two daily workload measures are highly correlated. The correlation is 0.91 and 0.92 for the full and block samples, respectively. We choose $NumCases_i$ as the workload measure in the main specification because it is easier to interpret the results. We also conduct the full set of analyses described below using $SumInc_i$ as the workload measure. The results are qualitatively similar and are provided in the appendix.

Table 5 Summary Statistics of Daily Workload for Full and Block Sample (Full Sample: N = 5,352, Block Sample: N = 2,492)

	Full Sample			Block Sample		
Workload	Mean	Median	Std	Mean	Median	Std
$NumCases_i$	0.69	1.00	0.69	0.66	1.00	0.65
$SumInc_i$	3.27	3.17	3.58	3.14	3.10	3.38

We control for a variety of demographic, medical, and operative factors as explanatory variables in our estimation as described in Section 2.2. We also include five operational variables: dummy variables for the weekday of the week, month, and year of the operation, the pre-LOS, and the block schedule status (in-schedule, out-of-schedule, or unknown). A detailed description of the independent variables used in our estimation can be found in Appendix A. We represent these variables and a constant by X_i for case i. To estimate the effect of daily workload, we consider the following regression models. Let dependent variable y_i be one of the surgical metrics or patient outcomes described in Section 2.3. For continuous y_i, we employ the linear model:

$$y_i = X_i\beta + \gamma Workload_i + \varepsilon_i, \tag{1}$$

where ε_i is the error term. For binary y_i, we use the following Probit model:

$$\begin{aligned} y_i^* &= X_i\beta + \gamma Workload_i + \varepsilon_i, \\ y_i &= \mathbf{1}\{y_i^* > 0\}, \end{aligned} \tag{2}$$

where y_i^* is a latent variable, $\mathbf{1}\{\}$ is the indicator function, and the error term ε_i follows a normal distribution. We use equations (1) and (2) to estimate γ, which is the effect of daily workload on y_i averaged across all cases by the surgeon in a day.

As a naive approach, we can estimate the coefficients in (1) and (2) by ordinary least squares (OLS) or maximum likelihood estimation (MLE) and interpret the estimated γ as the effect of daily workload on the

dependent variable y_i. However, this approach ignores the endogeneity in the daily workload of surgeons. That is, the surgeon daily workload can be affected by patients' severity factors that are unobserved in the data but are considered by the surgeons (e.g., a patient's cognitive state). For example, the surgeon may schedule more cases in a day if the unobserved severity factors are lower and imply shorter incision times. Consequently, both the dependent variable (e.g., incision time) and the daily workload (e.g., number of other cases) are affected by regressor X_i as well as the unobserved severity factors. If we ignore this endogeneity problem, the estimated coefficients will be biased. In the example described above, ignoring the unobserved severity factor introduces a negative bias to the estimate of γ, as the unobserved severity level is negatively correlated with the daily workload and positively correlated with incision time. Thus, using OLS to estimate (1) may yield a negative γ even if the true effect is positive. The same reasoning applies to MLE without accounting for the endogeneity of $Workload_i$. To address the endogeneity bias, we employ the instrumental variable (IV) method to obtain consistent estimates of the coefficients. We construct two IVs using the operational data from the cardiac department. We introduce the two IVs and explain their validity in next section.

3.1. Instrument Variables

We propose two novel IVs using operational data and demonstrate their validity in this section. The two IVs are both computed on the surgeon-day level, i.e., they are the same across the cases performed by a surgeon on the same day.

3.1.1. Total Cases by Other Surgeons The first IV we consider is $TotOther_i$, the total number of cases performed by other surgeons on the same day as case i. The relevance condition is satisfied for this IV because the number cases by other surgeons can affect the daily workload of the focal surgeon through *resource sharing* across surgeons. Many resources in the cardiac department are shared across surgeons, including OR time, medical staff such as nurses and anesthesiologists, medications, and equipment such as ventilators, etc. Thus, more cases performed by other surgeons on the same day tends to limit the workload of the focal surgeon. As such, we expect $TotOther_i$ to be negatively correlated with the focal surgeon daily workload. To test the relevance condition, we conduct a simple linear regression of $NumCases_i$ ($SumInc_i$) on $TotOther_i$, while controlling for patient demographic, medical risk, operative, and operational covariates[4]. We find that the coefficient for $TotOther_i$ is -0.074 (-0.369) for $NumCases_i$ ($SumInc_i$) with p-values smaller than 0.0001 (for both). Hence, we find that the total number of cases by other surgeons does, indeed, explain variation in the daily workload of the focal surgeon.

We next consider whether $TotOther_i$ likely satisfies the exogeneity condition. The surgeons in the cardiac department at our study hospital have substantial ownership of their patients and schedule. They rarely coordinate with other surgeons beyond whether there is OR time when scheduling their own cases and it

[4] We also include a second IV in the regression, which will be introduced in next section.

is entirely the discretion of the focal surgeon which operations to prioritize amongst his/her own patients. That is, an individual surgeon has little control over other surgeons' patients and scheduling. This suggests that the workload of other surgeons should be uncorrelated with the unobserved severity factors of the focal surgeon's patients. We also checked whether the IV is correlated with the *observed* measures of severity. Table 18 in Appendix D summarizes the correlation between the IV and 21 observed severity factors. The magnitude of all correlations is smaller than 0.1, and the average (absolute) correlation is 0.022. Thus, the correlation between the IV and observable severity factors is very weak[5].

3.1.2. Gap to Next Block Schedule We construct a second IV using the block schedule data. We consider the following behavioral observation: if a surgeon has to wait for a long period of time for the next scheduled block, the surgeon may be motivated to squeeze more cases into the current day. Thus, we expect the gap to next block (in days) of the focal surgeon, $GapNext_i$, to be positively correlated with the surgeon daily workload. In other words, $GapNext_i$ satisfies the relevance condition. Moreover, the block schedule of each surgeon is fixed in advance and adjusted very infrequently (twice a year). Thus, it is unlikely for $GapNext_i$ to be correlated with the unobserved severity factors of the surgeon's current patients. This suggests that the exogeneity requirement for $GapNext_i$ is likely to be satisfied.

Block Schedule Imputation: For the periods with the block schedule data available, we can directly compute $GapNext_i$ for each case. However, the block schedule data is missing for a significant proportion of the sample horizon as described in Section 2.1. For the periods without the block schedule data, we construct $GapNext_i$ as follows. First, we impute the block schedule on the surgeon-day level using a logistic regression. Then, we calculate the *expected* $GapNext_i$ based on our imputation. This enables us to maintain the entire sample for estimation. Simply dropping the missing periods would reduce our sample size by 53%, though we consider a robustness check with this subsample in Section 4.3. The results are qualitatively similar.

We impute the block schedule information for the surgeon-day pairs that appear in our sample. Let $Y_{s,t}$ be a binary variable which takes value one if surgeon s has an assigned block on day t (i.e., in block schedule), and zero otherwise (i.e., out of block schedule). We estimate $Y_{s,t}$ using a logistic model, i.e.,

$$\ln\left[\frac{\Pr(Y_{s,t}=1|X'_{s,t})}{\Pr(Y_{s,t}=0|X'_{s,t})}\right] = X'_{s,t}\beta + e_{s,t}, \tag{3}$$

where $X'_{s,t}$ is a set of independent variables and $e_{s,t}$ denotes the error term. The regressor $X'_{s,t}$ contains 23 independent variables (plus a constant term) for surgeon s on day t. For example, it includes the numbers of elective, urgent, and emergent cases by the focal and other surgeons on day t. As we are imputing instead of forecasting $Y_{s,t}$, the regressor $X'_{s,t}$ also contains variables that depend on the "future" information after

[5] We also checked this by regressing each observable severity factor on $TotOther_i$, as well as other risk, operative, and operational factors in model (1). The coefficient of $TotOther_i$ is significant at 0.05 level for only one of the 21 factors

day t, e.g., the number of days worked by surgeon s in the current calendar week. A complete description of the independent variables in $X'_{s,t}$ can be found in Appendix B.

We estimate the logit model (3) using the surgeon-day pairs in the block sample, for which the values of $Y_{s,t}$ are known. We then use the estimated model to impute the block schedule for the periods where the block schedule is missing. With the fitted probability $\Pr(Y_{s,t} = 1|X'_{s,t})$, we calculate the expected gap to next block as:

$$GapNext_i = \sum_{l=1}^{T-1} \left[\prod_{j=1}^{l-1} (1 - p_{t+j}^{(blk)}) p_{t+l}^{(blk)} \right] \times l + \prod_{j=1}^{T-1} (1 - p_{t+j}^{(blk)}) \times T, \tag{4}$$

where

$$p_{t+l}^{(blk)} := \Pr(Y_{s,t+l} = 1|X'_{s,t+l}).$$

Here t denotes the surgery date of case i; $p_{t+l}^{(blk)}$ is the probability that case i's surgeon has a block on day $t+l$; T is the truncation level for the maximum expected gap. We set it to be 14 days in our computation, as we find from the block schedule data that it is rare for a surgeon to stay idle without any block assignment in two consecutive weeks. The calculation in (4) is based on an implicit assumption that whether a surgeon has a block assignment is independent across days. Thus, the term $\prod_{j=1}^{l-1}(1 - p_{t+j}^{(blk)})p_{t+l}^{(blk)}$ represents the probability that the first block assignment after day t occurs on day $t+l$. Note that for the periods with block schedule data, the corresponding $GapNext_i$ can also be computed by (4) with $p_{t+l}^{(blk)}$ set to zero or one according to the block schedule.

Imputation Results: We briefly discuss the results for the block schedule imputation model (3), and the IV $GapNext_i$ constructed by (4) for the periods without block information. We estimate model (3) using the periods with block schedule information. The weekends are dropped as all blocks are assigned on weekdays. This leaves us with 1680 surgeon-day pairs in the block sample for estimation. We use the McFadden's R-squared to measure the model's performance, which is defined as

$$R^2 = 1 - \frac{\ln(l^{mod})}{\ln(l^{null})},$$

where l^{mod} is the likelihood from the estimated model, l^{null} is the likelihood from the null model with only an intercept. In addition, we also compute the Area Under Curve (AUC) from the fitted model.

In Table 6, we report the estimated coefficients and average marginal effects (AME) for select variables in model (3). The McFadden's R-squared of the estimated model is 0.31 and the AUC from the model classification is 0.86. Both measures show the imputation model fits the block schedule data well. We only report the variables with p-value smaller than 0.05 if they are not surgeon or weekday dummies.

We make the following observations. First, more elective and urgent cases by other surgeons on the same day ($ElecOth_{s,t}$ and $UrgOth_{s,t}$) decreases the probability that the focal surgeon is assigned a block schedule. This reflects the resource sharing among surgeons in the department on the same day. On the other hand, more elective cases ($ElecCur_{s,t}$) and patients admitted ($AdmCur_{s,t}$) by the focal surgeon increases

Table 6 Select Coefficients in the Logistic Model (3)

N = 1,680, R-squared=0.31

Variable	Coefficient	AME
$ElecOth_{s,t}$	-0.206^{***}	-0.020^{***}
	(0.059)	(0.006)
$UrgOth_{s,t}$	-0.140^{*}	-0.014^{*}
	(0.062)	(0.006)
$ElecCur_{s,t}$	1.297^{***}	0.126^{***}
	(0.300)	(0.028)
$AdmCur_{s,t}$	0.332^{***}	0.032^{**}
	(0.099)	(0.010)
$NumCurWeek_{s,t}$	-0.293^{*}	-0.029^{*}
	(0.141)	(0.014)
$DistNext_{s,t}$	-0.125^{**}	-0.012^{**}
	(0.045)	(0.004)
$StartLate_{s,t}$	-1.457^{***}	-0.205^{**}
	(0.351)	(0.065)
$WDElecRatio_{s,t}$	6.598^{***}	0.643^{***}
	(0.790)	(0.081)

Standard errors are reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. Select coefficients for schedule imputation model (3).

the probability of being in the block schedule, i.e., $\Pr(Y_{s,t} = 1)$. Next, a late start after 8AM ($StartLate_{s,t}$) by the focal surgeon s decreases the probability of being in the block schedule. This suggests that surgeons tend to start operation early when in their block schedules.

The surgeon's recent workload also has explanatory power for $\Pr(Y_{s,t} = 1)$. For example, the number of days worked in the current calendar week ($NumCurWeek_{s,t}$) and the distance to the next work day ($DistNext_{s,t}$) are negatively associated with $\Pr(Y_{s,t} = 1)$. Finally, $WDElecRatio_{s,t}$ denotes the proportion of elective cases by the focal surgeon in $[t - 180, t + 180]$ that fall on the same weekday as t. We see that its coefficient and AME are positive and statistically significant. This can be explained by the fact that the blocks are usually assigned on specific weekdays for each surgeon, and more than 90% of elective cases are performed in their surgeons' block schedule. Thus, a higher ratio $WDElecRatio_{s,t}$ increases the probability of block schedule for the focal surgeon.

With the estimated schedule imputation model, we compute the expected gap to next block $GapNext_i$ following (4). To test the relevance condition, we conduct a simple linear regression of $NumCases_i$ ($SumInc_i$) on $GapNext_i$, while controlling for the patient demographic, medical risk, operative, and operational covariates, as well as the first IV $TotOther_i$. We find that the coefficient for $GapNext_i$ is 0.006 (0.044) for $NumCases_i$ ($SumInc_i$) with p-value 0.084 (0.005).[6] Hence, we find that the total number

[6] The higher statistical significance level of $GapNext_i$ for $SumInc_i$ can be explained as $SumInc_i$ has more variation than $NumCases_i$ which takes integer values only.

of cases by other surgeons does, indeed, explain the variation in the total workload of the focal surgeon. In addition, as shown by Table 18 in Appendix D, the correlation between $GapNext_i$ and the *observed* measures of severity is very weak. The largest (average) absolute correlation is 0.084 (0.036).[7]

The summary statistics of the two IVs are shown in Table 7 for both the full sample and the block sample. We see that, in aggregate, the other surgeons on average perform 4.1 cases on the operation day of the focal surgeon and the average (resp. median) gap to next block schedule is 3.46 days (resp. 2.21 days) for the full sample. Moreover, the standard deviation of $GapNext_i$ is 3.04 days, reflecting significant variation. This is because the blocks of each surgeon are distributed unevenly across days. We also notice that the statistics of $GapNext_i$ is very similar for the full sample and the block sample. This supports the effectiveness of our schedule imputation model as the distribution of $GapNext_i$ imputed by the model is close to that calculated directly from the block data.

Table 7 Summary Statistics of the IVs for Full and Block Sample
(Full Sample: N = 5,352, Block Sample: N = 2,492)

	Full Sample			Block Sample		
IV	Mean	Median	Std	Mean	Median	Std
$TotOther_i$	4.11	4.00	1.78	4.18	4.00	1.77
$GapNext_i$	3.46	2.21	3.04	3.40	2.00	3.22

3.2. Estimation Methods

We estimate the effect of daily workload in models (1) and (2) using the two IVs introduced above. We describe the estimation methods below.

For continuous dependent variable y_i, we estimate the linear model (1) using the two-stage least squares (TSLS) regression. The TSLS estimation is conducted as follows. In the first stage, we regress the daily workload on the exogenous variables X_i and the two IVs using OLS:

$$Workload_i = X_i\beta + \eta_1 TotOther_i + \eta_2 GapNext_i + \xi_i. \tag{5}$$

The first stage regression measures the impact of the two IVs on a surgeon's daily workload. For the two IVs to affect the daily workload (i.e., the relevance condition), at least one of η_1 and η_2 should be statistically different from zero. Then in the second stage, we replace $Workload_i$ in (1) with its fitted values from (5) and estimate γ by OLS. Note that the standard errors in the second stage need to be adjusted as we are plugging in estimates of $Workload_i$.

[7] When regressing each observable severity factor on $GapNext_i$ and other risk, operative, and operational factors in model (1), we find the coefficient of $GapNext_i$ is significant at 0.05 level for only two of the 21 factors.

For binary dependent variable y_i, we use the full information maximum likelihood estimation method to estimate the effect γ in the probit model (2) (Woodridge 2010, Cameron and Trivedi 2013). Specifically, the models for the daily workload in (5) and the outcome in (2) are estimated jointly under the assumption that the error terms (ε_i, ξ_i) follow a bivariate normal distribution. To capture the endogeneity in daily workload, we allow ε_i and ξ_i to be correlated. Thus, there can be unobserved severity factors that affect both the surgical outcomes and the daily workload.

We find that the distributions of incision time, post-LOS, and total ICU time have long tails on the right end, thus we winsorize them by their 97.5th percentiles to mitigate the impact of extreme values. Our estimation results are robust to other choices of winsorization levels. In addition, for both the linear and probit models in (1) and (2), we cluster the standard errors by the surgeon's identifier to account for the potential correlation across cases of the same surgeon.

4. Estimation Results

This section provides the main estimation results regarding the effects of surgeon daily workload on surgery duration and outcomes. We first provide the results estimated from the full sample in Section 4.1. Then we analyze the heterogeneity in the effects for elective and non-elective patients in Section 4.2.

4.1. Effect of Daily Workload on Surgery Duration and Patient Outcomes

In Table 8, we report the estimated effects of surgeon daily workload, with $Workload_i$ measured by $NumCases_i$ in (1) and (2). The results using $SumInc_i$ as the daily workload measure are qualitatively similar and are reported in Table 20 of Appendix D. Since the IV varies at the surgeon-day level, the estimated γ here captures the effect averaged across all the cases performed by the surgeon in a day.

For the three continuous dependent variables, incision time, post-LOS, and total ICU time, we show the estimated γ in (1) and its standard errors. For the three binary dependent variables, reoperation, readmission, and mortality, we report the estimated average marginal effects (AME) of daily workload as they are easier to interpret. The estimated coefficient γ in (2) for the three binary outcomes are provided in Table 22 of Appendix D. Panel A in Table 8 reports the estimation results from the TSLS and full information MLE with the two IVs, as described in Section 3.2. For comparison, we also show in Panel B the results when we ignore the endogeneity problem using simple OLS to estimate (1) and MLE to estimate (2).

First, we see from the "Incision time" column in Panel A of Table 8 that higher daily workload tends to increase the incision time of the cases performed by the focal surgeon. In particular, adding one more case increases the incision time of each case performed by the surgeon by 0.43 hours (26 minutes) on average. This translates to a 9% relative increase of the average incision time. The effect is statistically significant at the 5% level. On the other hand, if we ignore the endogeneity in daily workload and estimate the model by OLS, the result becomes the opposite as shown in the "Incision time" column in Panel B: the coefficient is significantly negative. This shows that it is essential to address the endogeneity in the daily workload as

Table 8 Estimated Effects of Daily Workload (Number of Other Cases) on Surgery Duration and Patient Outcomes: Full Sample

	Continuous y_i: Coefficients			Binary y_i: AME		
	Incision time	Post-LOS	Total ICU time	Reoperation	Readmission	Mortality
Panel A: Full	0.430^{*}	1.408^{*}	1.031^{*}	0.030^{**}	$0.065^{\dagger}$	0.010
	(0.217)	(0.565)	(0.482)	(0.011)	(0.039)	(0.011)
Num Obs.	5345	5344	5319	5345	5116	5081
Panel B: Full (w/o IV)	-0.102^{**}	-0.020	-0.002	-0.002	-0.000	0.010^{*}
	(0.039)	(0.147)	(0.086)	(0.004)	(0.008)	(0.004)
Num Obs.	5345	5344	5319	5345	5116	5081

The estimated effects of surgeon daily workload (number of other cases) on surgery duration and patient outcomes for the full sample. We report the estimated coefficients in (1) for the three continuous dependent variables, and the AME from (2) for the three binary dependent variables. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

surgeons may schedule more cases a day if the unobserved severity factor implies shorter incision times, resulting in a negatively biased estimate of the effect.

A priori, it is not clear how a surgeon's daily workload may impact the incision time. First, surgeons may "speed up" the operations when they have more cases to perform in a day, leading to a shorter incision time. This type of speedup effect is found in, e.g., Kc and Terwiesch (2009). On the other hand, surgeons may take more time to complete their tasks due to fatigue and operational constraints associated with high daily workloads. For example, in a different setting, Berry Jaeker and Tucker (2017) finds patient's LOS increases in occupancy once the occupancy level exceeds a tipping point. After addressing the endogeneity bias with proper IVs, our empirical results here support the second mechanism, i.e., higher daily workload of surgeons leads to longer incision times.

A possible explanation for the mechanism is as follows. First, unlike patient transporting and patient LOS studied in Kc and Terwiesch (2009), cardiac operations are complex and delicate procedures, it is very difficult for surgeons to speed up in their operations. Second, given they are such demanding tasks, performing multiple cases a day could cause fatigue of surgeons, both physically and mentally, thus leading to longer incision time. In addition, when a surgeon needs to do multiple cases in a day, some of them may have to be performed outside of normal working hours. Thus, they are more likely to be associated with fewer medical staff and less experienced nurses, as well as constrained resources and delay in bed flow. For example, one "on-call" anesthesiologist may have to cover multiple operations performed in the night. For these reasons, the impact of surgeon fatigue and other operational constraints outweighs the potential channels for speedup, and causes longer incision time on average when more cases are performed. Due to the limitation of our data, we are not able to fully identify the factors that lead to the longer incision times. That said, our results provide clear evidence for the negative impact of high surgeon daily workload.

Recall that the coefficient γ in (1) measures the effect of daily workload on each case averaged across all cases performed by the surgeon on that day. We acknowledge that the effect is likely to vary across the cases, e.g., the surgeon's workload naturally has a larger impact on the last case of the day. However, as we do not have the information on how the operations are scheduled within a day, we cannot effectively control for the potential endogeneity in the sequencing of operations. Thus, we choose to estimate the effect averaged across all cases performed by the surgeon in a day. As a potential future direction, it would be practically important to estimate the effect of surgeon daily workload for individual cases. This requires more data on the scheduling and sequencing of operations within a day.

On the other hand, we note that model (1) suggests that the hospital may be able to achieve substantial improvements in its performance by "smoothing" surgeon workload across days. For example, if we reschedule a surgeon with two cases in one day to two separate days, the expected total incision time for these two cases would decrease by $(0.43 \times 1 - 0.43 \times 0) \times 2 = 0.86$ hours. We leverage this insight to propose a surgical scheduling model that captures such effects in Section 5.

We now consider the effect of daily workload on patient outcomes, including two continuous outcomes, post-LOS and total ICU time, and three binary outcomes, reoperation, readmission, and mortality. In the "post-LOS" and "total ICU time" columns in Panel A of Table 8, we find that higher daily workload increases the post-LOS and total ICU time. Specifically, adding one more case increases the total ICU time and post-LOS by 1.05 and 1.45 days, respectively, for the cases performed by the surgeon on the same day. This is equivalent to a 12% increase for post-LOS and a 19% increase for total ICU time. Without using the IVs, the effect is insignificant for both outcomes. The results here suggest increased surgeon daily workload is associated with longer post-surgery recovery time for patients. As we discussed for incision time, the negative effect can be attributed to multiple potential factors, including surgeon fatigue due to long working hours, as well as other constraints due to operating later in the day. For example, patients who are sent to ICU in the night may have to wait longer before extubation, as it is considered safer to keep them asleep until the intensivist or respiratory therapist is available. This may also increase their ICU time.

The effect on total ICU time and post-LOS is important to consider when managing patient flow. Longer post-surgery LOS will result in increased demand for downstream units and resources and reduce the system throughput. This can lead to overcrowding in the perioperative environment and delay in operations (Zenteno et al. 2016). Additionally, the ICU is often congested and extremely expensive to operate (e.g., Halpern (2011)). Given almost all patients (99%) in our sample are sent to the ICU after operation, understanding the factors that impact their ICU recovery time provides an important potential solution for managing ICU congestion. As we discussed for incision time, smoothing the surgeon's workload across days can reduce the total expected ICU time and post-LOS, i.e., the time needed for recovery of the patients. For example, our estimation results imply moving two cases performed by a surgeon in a day to two different days leads to a reduction of 2.06 (resp. 2.82) days in total expected ICU time (resp. post-LOS).

Finally, we examine the impact of workload on three binary patient outcomes, reoperation, readmission, and mortality, which are estimated using full information MLE[8]. First, we find that higher daily workload increases the likelihood of reoperation. Specifically, adding one more case leads to a three percentage points increase in the reoperation probability for each case performed by the surgeon on the same day. The magnitude of such an increase seems large at first, as the original reoperation probability is about 7% (see Table 4). We note that the median surgeon daily workload is two cases; thus adding one more case is equivalent to a 50% increase in daily workload. Such large impact of workload on medical outcomes is also observed in the literature. For example, Kc and Terwiesch (2009) finds that a 10% increase in overwork increases the morality rate by 2.2 percentage points, which is a 32% relative change in their setting.

Similar negative effect of higher daily workload is also observed for the likelihood of hospital readmission. Specifically, adding one more case increases the readmission probability by 6.5 percentage points when estimated from the full sample. For 30-day mortality, however, the effect of daily workload is not significant. The insignificant effect for mortality seems surprising at first, given the negative impact of daily workload on other outcomes. One possible reason for such difference is that surgeons tend to pay greater attention to the patients with high risk of death, thus the mortality rate is less impacted by surgeon daily workload. In addition, the lack of significance may be because there is not enough variation in this outcome for the IV analysis to be statistically significant. Interestingly, we see that without the IV, using OLS, the coefficient is positive and statistically significant at the 5% level. This may be because if a patient is at high risk of death, they are more likely to be operated on even when the OR schedule is full, resulting in an increased risk of death for patients on high workload days on average. Thus, the endogeneity bias may go in the opposite direction for mortality compared to the other outcomes: Surgeons may nominally be able to operate on more low-risk patients in a given day, resulting in low-risk patients being more likely to be operated on during high workload days. However, when a patient with very high risk of death comes along, this patient can also be squeezed into the high workload days.

4.2. Heterogeneous Effects of surgeon daily workload: Elective and Non-elective Patients

In the previous section, we see that increased daily workload leads to longer incision time and worse patient outcomes on average. In this section, we further investigate the impacts of daily workload for elective and non-elective cases separately. The non-elective cases include urgent, emergent, and salvage cases, and account for more than half (53%) of the full sample. The separate analyses allow us to investigate the potential heterogeneity in the impact of daily workload for different types of patients. In particular, we estimate the econometric models (1) and (2) using the subsamples of elective and non-elective cases separately.

We first show that the relevance of the two IVs in the estimation for the two subsamples. Table 9 reports the estimated η_1 and η_2 in (5) using the elective and non-elective cases, respectively. We see the two IVs still

[8] The sample size varies for the three binary outcomes. This is because some levels of categorical variables (e.g., specific procedure types) lead to perfect predictions of the binary outcome, thus the corresponding observations are dropped from the estimation.

impact the surgeon daily workload with expected signs in the two subsamples. Moreover, the magnitudes are similar in the two subsamples as in the full sample. These results support the validity of the two IVs for the subsamples of elective and non-elective cases.

Table 9 Impact of IVs on Daily Workload (Elective and Non-elective Sample)

	Elective Sample		Non-elective Sample	
IV	$NumCases_i$	$SumInc_i$	$NumCases_i$	$SumInc_i$
$TotOther_i$	-0.065^{***}	-0.338^{***}	-0.081^{***}	-0.392^{***}
	(0.008)	(0.039)	(0.008)	(0.040)
$GapNext_i$	0.006	0.053^{*}	0.005	0.043^{*}
	(0.005)	(0.026)	(0.004)	(0.021)
Num Obs.	2474	2474	2871	2871
Adj R^2	0.122	0.142	0.160	0.171

Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. Coefficients and standard errors of two IVs in (5) for elective and non-elective samples.

Table 10 shows the estimated effects of surgeon daily workload (number of other cases) for the elective (Panel A) and non-elective samples (Panel B), respectively. As in Table 8, we report the estimated coefficients for the three continuous dependent variables (incision time, post-LOS, and total ICU time), and the AMEs for the three binary dependent variables (reoperation, readmission, and mortality). The coefficient γ in (2) for the three binary dependent variables, when estimated by the elective and non-elective samples, are given in Table 23 of Appendix D. The results when we measure surgeon' daily workload by $SumInc_i$ (total incision time of other cases) are qualitatively similar, and are summarized in Table 21 of Appendix D for elective and non-elective cases.

Table 10 Estimated Effects of Daily Workload (Number of Other Cases) on Surgery Duration and Patient Outcomes: Elective and Non-elective Sample

	Continuous y_i: Coefficients			Binary y_i: AME		
	Incision time	Post-LOS	Total ICU time	Reoperation	Readmission	Mortality
Panel A: Elec	0.378^{**}	-0.288	0.121	0.017	0.029	0.060
	(0.140)	(1.015)	(0.729)	(0.039)	(0.066)	(0.050)
Num Obs.	2474	2474	2454	2394	2398	1897
Panel B: Non-elec	0.486	3.004^{*}	$1.906^{\dagger}$	0.049^{*}	0.082^{*}	-0.004
	(0.341)	(1.501)	(1.054)	(0.021)	(0.039)	(0.012)
Num Obs.	2871	2870	2865	2871	2697	2769

The estimated effects of surgeon daily workload (number of other cases) on surgery duration and patient outcomes for the elective and non-elective sample. We report the estimated coefficients in (1) for the three continuous dependent variables, and the AME from (2) for the three binary dependent variables. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

We find substantial heterogeneity in the effects of surgeon daily workload for elective and non-elective cases. The effect of daily workload on incision time is statistically significant (at 1% level) for elective cases (Panel A), but insignificant for non-elective cases (Panel B). The magnitude of the impact for elective cases is similar to that for the full sample. In particular, performing one more case increases the incision time of each elective case by 23 minutes, which is equivalent to an 8% increase on average. The heterogeneity in the impact on incision time may be due to the fact that non-elective cases (urgent and emergent cases) are generally more urgent and time sensitive than elective cases, so their incision time is less impacted by surgeon daily workload.

However, such heterogeneity appears in the opposite direction when we examine the impact of surgeon daily workload on patient outcomes. Specifically, we find that increased surgeon daily workload significantly impacts the surgery outcomes of non-elective patients, but not for elective ones. For example, for the post-LOS, we see that the coefficient of $NumCases_i$ is statistically significant for the non-elective cases, but insignificant for the elective ones ("Post-LOS" column). Moreover, the magnitude of the effect is larger for the non-elective cases than that for the full sample: Adding one more case leads to 3.04 more days in the post-LOS of non-elective patients, which is more than twice as that for the full sample (1.45 days). Similar heterogeneity is also seen in the total ICU time ("Total ICU time" column). The estimated coefficient of $NumCases_i$ is 1.91 days for the total ICU time of non-elective cases, which is much larger than that for the full sample (1.03 days). On the other hand, the daily workload does not significantly impact the total ICU time of elective cases. Finally, we find that the surgeon daily workload significantly increases the likelihood of reoperation and readmission for non-elective patients, but is insignificant for elective patients. Adding one more case increases the probabilities of reoperation and readmission by 4.9 and 8.2 percentage points for the non-elective cases. Both effects are larger than that for the full sample (3.0 and 6.5 percentage points for reoperation and readmission respectively). These consistent results show that the surgery outcomes of non-elective patients are more negatively affected by surgeon daily workload.

One potential explanation for the heterogeneous effect for patient outcomes is that non-elective cases are generally more urgent and complicated than elective ones, with more severe patients. Thus, the outcomes of non-elective cases may be more sensitive to surgeon fatigue or operational constraints due to high daily workload. On the other hand, the elective patients are on average less severe, and they recover more quickly after the operation. This can be seen by the summary statistics of the patient outcomes in Table 4: the non-elective patients have longer post-LOS and total ICU time, and higher likelihood of reoperation and readmission on average. The standard deviations of total ICU time and post-LOS are also much larger for the non-elective patients, implying there is more variation in their surgical outcomes than the elective patients.

Our results demonstrate the consistent negative impact of surgeon daily workload on multiple patient outcomes. Such effects are particularly significant for non-elective patients, who are generally more severe.

Our results provide new empirical evidence for the link between high workload level and worse patient outcomes (see, e.g., Kc and Terwiesch (2009) and Kuntz et al. (2015)). From the managerial perspective, it suggests that when hospitals design their surgery schedules, they should take into account the effects of surgeon daily workload in order to improve patient flow and patient outcomes. We explore this direction in Section 5.

4.3. Robustness Checks

We conduct similar regression analyses under alternative specifications to examine the robustness of our main findings. We briefly discuss the results below. First, as shown in Section 3.1, the $GapNext_i$ (expected gap to next block) is a less powerful IV than $TotOther_i$ (number of cases by other surgeons) in explaining the variation in surgeon daily workload. In addition, imputation is needed to construct $GapNext_i$ for the period without block schedule information. Thus, we run the regressions (1) and (2) using only $TotOther_i$ as the IV. This allows us to keep the entire sample and without using any imputation. The results are very similar to that in our main specifications. We still find high daily workload is associated with longer surgery duration and worse patient outcomes. The heterogeneity in the estimated effects between elective and non-elective cases also holds.

In our main specification, we winsorize the three continuous outcomes (incision time, post-LOS, and total ICU time) at their 97.5th percentile, respectively. For robustness checks, we also experiment the winsorization levels of 95th and 99th percentiles. We find the results are largely similar, although the magnitudes of the effects vary. Specifically, for winsorization level of 95th, 97.5th, and 99th percentile, the impact of $NumCases_i$ on total ICU time is 0.569, 1.031, and 1.565 days, respectively. The increase in the magnitude can be explained as follows. The distribution of total ICU time (as well as post-LOS) has a long tail on the right. Thus, different winsorization levels can lead to substantial change of the upper bound of the final sample. For example, the 95th, 97.5th, and 99th percentile of total ICU time is 19.1, 29.7, and 48.5 days respectively.

In addition, we perform the regressions on the subsample with complete block schedule. As we mentioned, this will substantially decrease the sample size as the block schedule is missing for more than a half of the horizon. The results are still consistent, although some of them become insignificant. We still observe the negative impact of daily workload on incision time and likelihood of reoperation, as well as on post-LOS and total ICU time for non-elective patients. Finally, we estimate using the sample consisting of eight standard procedures, which consists of 65% of all cases. For these standard procedures, we add their predicted mortality scores as a severity indicator to the exogenous variables X_i. The predicted mortality score measures the patient's likelihood of operative mortality. It is trained and validated on a national database (O'Brien et al. 2018), thus does not hinge on the outcomes of the sample we use. This risk score is only available for the standard procedures. The results for the standard procedure sample are qualitatively

consistent. We find higher daily workload of the attending surgeon is associated with longer incision time and total ICU time.

We summarize the estimated effects of $NumCases_i$ under alternative specifications in Tables 24 and 25 of Appendix D. Due to the smaller sample sizes of the block and standard case samples, we do not estimate the heterogeneous effects on binary outcomes (i.e., by elective and non-elective cases separately) using those samples. Recall the rates of adverse outcomes are generally low in our sample, especially for standard procedures; thus, we do not have a large enough sample size for these regressions to converge. The results of $SumInc_i$ as the daily workload measure are qualitatively similar, and are available upon request.

Finally, we perform an additional robustness check for the post-LOS. Unlike the total ICU time which is measured in hours, the post-LOS can only be computed on a daily basis as we do not have the exact discharge time in the STS data. This may introduce a bias in the total recovery time of patients. For example, consider two patients who complete surgery on the same day and who have the same day-of-discharge from the hospital. Under our post-LOS measure, these patients have the same exact post-LOS. However, if one of the patients exited the OR at 6PM, the recovery time will be six hours shorter than the patient who exited the OR at 12PM, if they are both discharged from the hospital at the same time. To account for patients' actual recovery time, we use several more conservative measures of post-LOS by adjusting the original measure using the OR entry or exit time of each case. We find that our estimation results by TSLS are very similar when using these more conservative measures. The definitions of these alternative measures are summarized in Appendix D. Their estimation results are provided in Table 26.

5. A Surgery Scheduling Model with Impact from Daily Workload

Our empirical analyses show that increased surgeon daily workload can lead to longer surgery duration and worse patient outcomes. In this section, we propose a surgical scheduling model that incorporates such effects. While there is a rich literature on surgery scheduling, most of it assumes exogenous distributions for the surgery duration and patient outcomes (e.g., post-LOS). That is, the impact of surgeon workload is largely ignored. However, as shown in our results, high daily workload of surgeons is associated with multiple negative outcomes. Thus, our model aims to quantify the potential benefits we can obtain by incorporating these effects into surgical scheduling.

Our model considers a relatively small change to the current schedule used by our partner hospital. In particular, we consider the reassignment of the operations in our sample to different days. By changing the surgery dates, we aim to capture the potential benefit of smoothing surgeon daily workload. As we discussed in Section 4, this can decrease surgery duration and improve patient outcomes. On the other hand, we keep the ORs open in each day and the surgeon assigned to each patient unchanged. This allows us to isolate the impacts of optimizing the surgery dates, and thus highlight the benefit of incorporating the effects of surgeon daily workload in surgical scheduling. In addition, it provides an easily implementable potential

solution to improve the scheduling in the hospital. We expect the benefit to be larger if we introduce other types of decisions in our model, e.g., the number of ORs open in each day.

5.1. Notations and Decision Variables

We solve the scheduling model for each calendar week (Sunday to Saturday) in the four year horizon of our sample. We now introduce the notations and decision variables. For a given week, we index each case by $i \in C$, where C is the set of all cases performed on the weekdays in the given week.[9] According to the surgery status, the set C can be divided into three exclusive subsets C_{el}, C_{ug}, and C_{es}, which represent the elective, urgent, as well as emergent and salvage cases respectively. For each case i, we denote its surgeon by $\tilde{s}(i)$ and original surgery date by $\tilde{t}(i)$.

We index the day in the week by $t \in T$ and the surgeon by $s \in S$, with T and S being the sets of surgery dates and surgeons for cases $i \in C$. We use A_s to denote the set of cases performed by surgeon s. Our optimization model considers which cases to assign to each day. Thus, our decision variables are $x_{i,t}$ for $i \in C$ and $t \in T$. Each $x_{i,t}$ is a binary variable; it takes value one if case i is assigned to day t, and zero otherwise.

5.2. Feasibility Constraints

In this section, we formulate the set of constraints to ensure the feasibility of the resulting schedule. First, every case should be assigned one and only one date in the final schedule. This translates to

$$\sum_{t \in T} x_{i,t} = 1, \forall i \in C. \tag{6}$$

For each case, we specify its feasible set of surgery dates according to its status. For elective cases, we allow them to be assigned to any day of the week of the original date. This is because elective patients are generally stable, thus each surgeon has high flexibility in scheduling their operations. On the other hand, we impose that urgent cases can only be scheduled on the original date or the adjacent days, while the emergent and salvage cases can only be scheduled on the original date. These constraints reflect the reality that urgent cases are more time sensitive than elective ones as their patients are more severe. In addition, the hospital has little control over the arrival time of emergent and salvage patients. We formulate these constraints as

$$x_{i,t} = 0, \text{ if } i \in C_{ug} \text{ and } |t - \tilde{t}(i)| > 1, \tag{7}$$

and

$$x_{i,t} = 0, \text{ if } i \in C_{es} \text{ and } t \neq \tilde{t}(i). \tag{8}$$

We also require that the total number of operations performed on each day to be the same as in the original schedule. We impose this constraint so the cardiac department does not need to adjust its resource

[9] We exclude the operations on the weekends (2.8% of sample) in our optimization model, as their times are generally hard to change.

allocation across days or change the schedule of the ORs allocated to the cardiac department versus other surgical departments. This constraint can be formulated as

$$\sum_{i \in C} x_{i,t} = \sum_{s \in S} n_{s,t}^{(c)}, \ \forall t \in T, \tag{9}$$

where $n_{s,t}^{(c)}$ denotes the number of cases performed by surgeon s on day t in the original schedule. Thus, the summation $\sum_{s \in S} n_{s,t}^{(c)}$ is the total number of cases performed on day t by all surgeons.

Next, we impose an upper bound on surgeon daily workload, i.e., the number of cases performed by each surgeon in a day, to reflect a physical limit on how much time a surgeon can spend operating. On average, a surgery takes 7.11 hours to complete, with a minimum of 2.15 hours and a median of 6.8 hours. Thus, while surgeons can work overtime and parallelize part of some operations, a reasonable upper bound on the number of cases per day is 2 or 3. As we keep the surgeon assigned to each case unchanged, the number of cases by surgeon s on day t in the new schedule can be expressed as,

$$\tilde{n}_{s,t} = \sum_{i \in A_s} x_{i,t}. \tag{10}$$

The summation on the right-hand side includes all the cases by surgeon s. Then, the constraint on surgeon daily workload can be formulated as

$$\tilde{n}_{s,t} \leq \max\{\bar{n}^{(c)}, n_{s,t}^{(c)}\}, \ \forall t \in T \text{ and } \forall s \in S, \tag{11}$$

where $\bar{n}^{(c)}$ is a model parameter to be specified. It denotes the maximum daily workload of a surgeon in the new schedule, unless the surgeon already performs more cases in the original schedule.

Finally, we set an upper bound on the number of days worked by each surgeon in a week. Although asking the surgeons to work for more days naturally smooth their daily workload, it would be difficult to implement in reality given their other responsibilities such as seeing patients in the office, teaching, attending conferences, etc. Note that the surgeon s works on day t in the new schedule if at least one case is performed, i.e., $\tilde{n}_{s,t} > 0$. Thus, we can formulate the constraint as

$$\sum_{t \in T} \mathbf{1}\{\tilde{n}_{s,t} > 0\} \leq \max\{\bar{n}^{(d)}, n_s^{(d)}\}, \ \forall s \in S. \tag{12}$$

where $n_s^{(d)}$ is the number of working days by surgeon s in the original schedule; $\bar{n}^d$ is the model parameter denoting the maximum number of days worked by a surgeon, unless the surgeon works for more days in the original schedule.

The constraint (12) is inconvenient to implement as the indicator function is non-linear. We circumvent this difficulty by proposing the following linear formulation. Let the binary variable $z_{s,t}$ denote whether surgeon s works on day t in the new schedule. We bound it by

$$z_{s,t} \leq M \cdot \tilde{n}_{s,t} \text{ and } z_{s,t} \geq m \cdot \tilde{n}_{s,t}, \tag{13}$$

where M (resp. m) is a sufficiently large (resp. small) constant. In our study, we can set them as $M = 100$ and $m = 0.01$. It is easy to verify by (13) that $z_{s,t}$ takes value one if $\tilde{n}_{s,t} > 0$ and zero if $\tilde{n}_{s,t} = 0$. Thus, it always equals to the indicator function $\mathbf{1}\{\tilde{n}_{s,t} > 0\}$. Then, we can rewrite the constraint (12) in the following linear form as

$$\sum_{t \in T} z_{s,t} \leq \max\{\bar{n}^d, n_s^{(d)}\}, \ \forall s \in S. \tag{14}$$

In summary, our model includes the constraints (6), (7) – (8), (9), (11), and (13) – (14), all of which are formulated in linear form.

5.3. Objective Functions and MIQP Formulation

We now introduce the objective function for our model and show how to formulate the surgical scheduling model as a Mixed-Integer Quadratic Program (MIQP). We consider three alternative objective functions: minimizing the total expected incision time, post-LOS, or total ICU time. Following our econometric model (1), the expected value of the three variables can be expressed as

$$\hat{y}_i = X_i\beta + \gamma NumCases_i. \tag{15}$$

Here we use the number of other cases as the surgeon daily workload measure. The variable $\hat{y}_i$ is specified as incision time, post-LOS, and total ICU time, respectively. The coefficients β and γ are reported in Section 4 for each dependent variable. We also allow for the heterogeneity in the impacts of daily workload for elective and non-elective cases.

By (15), the expected value $\hat{y}_i$ can be decomposed to two parts

$$l_i = X_i\beta \text{ and } d_i = \gamma NumCases_i.$$

To focus on the impact of daily workload, we assume the first part l_i, which primarily depends on the patient's risk and operative factors, remains unchanged in the new schedule. However, the second part d_i will be affected by the surgeon's workload in the new schedule. Our objective is to minimize the total expected value $\hat{y}_i$, i.e., $\min \sum_{i \in C} \hat{y}_i$. As we assume l_i does not change, this is equivalent to minimizing the sum of the d_i, which is

$$\min \sum_{i \in C} d_i.$$

We now explicitly express the objective $\min \sum_{i \in C} d_i$ under the new schedule. The total daily workload term for surgeon s on day t is

$$d'_{s,t} = \sum_{i \in A_s} d_i x_{i,t}.$$

It is straightforward to see the summation over all cases in C is equal to that over all surgeons and days:

$$\sum_{i \in C} d_i = \sum_{s \in S} \sum_{t \in T} d'_{s,t}. \tag{16}$$

As such, it is sufficient to write out the objective function as a function of $d'_{s,t}$ instead of d_i.

The number of cases performed by surgeon s on day t is given by $\tilde{n}_{s,t}$ in (10). To account for the heterogeneous effects as discussed in Section 4.2, we need to further obtain the number of elective and non-elective cases. Similar to (10), they are given by

$$\tilde{n}^{(el)}_{s,t} = \sum_{i \in A_s} x_{i,t} \mathbf{1}\{i \in C_{el}\} \text{ and } \tilde{n}^{(ne)}_{s,t} = \sum_{i \in A_s} x_{i,t} \mathbf{1}\{i \notin C_{el}\}.$$

Then, the total impact from daily workload for surgeon s on day t can be expressed as

$$d'_{s,t} = (\tilde{n}_{s,t} - 1) \cdot \left(\gamma^{(el)} \tilde{n}^{(el)}_{s,t} + \gamma^{(ne)} \tilde{n}^{(ne)}_{s,t}\right).$$

Here $\gamma^{(el)}$ and $\gamma^{(ne)}$ are the estimated coefficient γ for the daily workload effect on incision time, post-LOS, or total ICU time – depending on which one we are to minimize – for the elective and non-elective cases respectively, which are reported in Table 10 of Section 4.1. We set the coefficient to be zero if it is not statistically significant at the 10% level. When we ignore the heterogeneity in the impacts of daily workload, we use the average treatment effects in Table 8 with $\gamma^{(el)} = \gamma^{(ne)} = \gamma^{(avg)}$. Plugging $d'_{s,t}$ into (16), the objective function is given by

$$\min \sum_{s \in S} \sum_{t \in T} (\tilde{n}_{s,t} - 1) \cdot \left(\gamma^{(el)} \tilde{n}^{(el)}_{s,t} + \gamma^{(ne)} \tilde{n}^{(ne)}_{s,t}\right),$$

which can be explicitly expressed as

$$\min \left\{ \sum_{s \in S} \sum_{t \in T} \tilde{n}_{s,t} \cdot \left(\gamma^{(el)} \tilde{n}^{(el)}_{s,t} + \gamma^{(ne)} \tilde{n}^{(ne)}_{s,t}\right) - \gamma^{(el)} \sum_{t \in T} \sum_{s \in S} \tilde{n}^{(el)}_{s,t} - \gamma^{(ne)} \sum_{t \in T} \sum_{s \in S} \tilde{n}^{(ne)}_{s,t} \right\}.$$

The summations in the last two terms, $\sum_{t \in T, s \in S} \tilde{n}^{(el)}_{s,t}$ and $\sum_{t \in T, s \in S} \tilde{n}^{(ne)}_{s,t}$, represent the total numbers of elective and non-elective cases from all surgeons in the week. As they remain unchanged in the new schedule, we can drop the last two terms in the objective function and simplify it as

$$\min \sum_{s \in S} \sum_{t \in T} \tilde{n}_{s,t} \cdot \left(\gamma^{(el)} \tilde{n}^{(el)}_{s,t} + \gamma^{(ne)} \tilde{n}^{(ne)}_{s,t}\right). \tag{17}$$

It is easy to verify that the objective function is quadratic in the decision variables $x_{i,t}$. Thus, our model is formulated as a MIQP with quadratic objective (17) and linear constraints (6), (7) – (8), (9), (11), and (13) – (14). The decision variables are $x_{i,t}$ for $i \in C$ and $t \in T$, as well as $z_{s,t}$ for $s \in S$ and $t \in T$ as introduced in (13). All the decision variables are binary. A complete formulation of the MIQP is given in Appendix C.

5.4. Results

In this section, we summarize the results from our scheduling model, which demonstrate the benefit of incorporating the effects of surgeon daily workload in surgical scheduling. For our main numerical results, we set $\bar{n}^{(c)} = 2$ and $\bar{n}^{(d)} = 3$ in (11) and (12), respectively. This means that the surgeon's maximum daily workload is two cases and the maximum number of working days is three days, unless the corresponding quantity is larger in the original schedule. We emphasize that these are relatively strict constraints, and we expect the benefit from our surgical scheduling model to be larger if we relax them.

We show our main results in Table 11. The first two columns show the variable we are optimizing ("Objective") and the estimated effects ("Effect") we use in our objective function (17), with which we solve the surgical scheduling model. The third and fourth columns ("Obj orig" and "Obj new") report the objective values (17) under the original and new schedules, respectively. The fifth column ("ΔObj") reports the absolute reduction in the objective function, which demonstrates the benefit of applying our surgical scheduling model. The next column ("Number of reduced week") reports the number of weeks (out of the 209 weeks in our sample) that we can achieve reduction in the objective function under the new schedule. Finally, the last column ("Rel. ΔTotal") shows the relative reduction in the sum of the corresponding variable we are optimizing over, i.e.,

$$\text{Rel. } \Delta\text{Total} = \Delta\text{Obj}/\text{Sum}(y),$$

where $\text{Sum}(y) = \sum_{i=1}^{N} y_i$ with N being the total number of cases and y_i denoting the observed value from the STS data[10]. Thus, Rel. ΔTotal represents the relative reduction in total incision time, post-LOS, or ICU time. It provides an alternative measure for the benefit from the new surgical schedule.

Table 11 Results of the Surgical Scheduling Model

Objective	Effect	Obj orig	Obj new	ΔObj	Number of reduced weeks	Rel. ΔTotal (in % points)
Incision time (in hours)	Avg	3897.95	3573.73	324.22	180	1.28
	Het	1637.87	1360.42	277.45	197	1.09
Post-LOS (in days)	Avg	12763.52	11701.89	1061.63	180	1.76
	Het	14214.93	12085.09	2129.84	196	3.54
Total ICU time (in days)	Avg	9346.02	8568.64	777.37	180	3.03
	Het	9274.72	7885.08	1389.64	196	5.42

Note that when we use the average effect of daily workload for elective and non-elective cases, i.e., $\gamma^{(el)} = \gamma^{(ne)} = \gamma^{(avg)}$, the optimal schedules from the model are the same for the three variables. To see why this is the case, by (17), the objective with average effect can be expressed as

$$\min \gamma^{(avg)} \cdot \sum_{s \in S} \sum_{t \in T} \left(\tilde{n}_{s,t}\right)^2 . \tag{18}$$

[10] As in our estimations, we winsorize the corresponding variables to their 97.5th percentile.

Thus, the coefficient $\gamma^{(avg)}$ does not impact the solution (although it affects the objective value). Similarly, we obtain the same optimal schedule for post-LOS and ICU time when we use the heterogeneous effect of daily workload. In this case, the objective function can be written as

$$\min \gamma^{(ne)} \cdot \sum_{s \in S} \sum_{t \in T} \tilde{n}_{s,t} \tilde{n}_{s,t}^{(ne)}. \tag{19}$$

This is because we have $\gamma^{(el)} = 0$ for post-LOS and ICU time, i.e., surgeon daily workload does not impact the two outcomes of elective cases.

We now analyze the results of our surgical scheduling model. In Table 11, we see that our new schedule leads to substantial improvement for all three outcomes using both average and heterogeneous effects of daily workload. For total incision time, the new schedule with average (resp. heterogeneous) effect leads to a 324 (resp. 277) hours decrease in the four-year horizon, which is equivalent to a 1.28% (resp. 1.09%) relative reduction. The OR is an extremely expensive resource with cost up to $37 per minute (Childers and Maggard-Gibbons 2018). Thus, the reduction in the incision time can save the hospital up to $18,000 each year. On the other hand, given the average incision time is 4.8 hours in our sample, the hospital may be able to add 17 new cases each year due to the reduction in OR time from the new schedule. With some cardiac operation netting margins of over $21,000 per case on average (Robinson 2011), this has the potential to translate to an additional $357,000 in profit for this service. In addition, we find that the new schedule leads to improvement for most (180) of the 209 weeks in our sample. This shows that the benefit of our scheduling model is not limited to a small number of weeks, and the original schedule can be substantially improved.

Our scheduling model also substantially reduces the total expected post-LOS and ICU time when optimized to do so. Recall that when considering the average treatment effect, the resulting schedules are identical, so all three metrics are improved. When considering the heterogeneous treatment effect, the reported savings are for when the schedule is optimized to minimize the particular outcome; the other outcomes will also be improved, but perhaps to a lesser amount than when we specifically optimized for it. Using the average effect, the new schedule decreases the total post-LOS by 1062 days and the total ICU time by 777 days, which translate to a 1.76% and 3.03% relative drop respectively. The benefit is even larger with heterogeneous effect, as the relative reduction for post-LOS (resp.ICU time) increases to 3.54% (resp. 5.42%). The bigger benefit under heterogeneous effect can be explained as follows. First, as shown in Table 10, the surgeon daily workload does not negatively impact the post-LOS and ICU time of elective cases. This gives us more flexibility in adjusting the schedule. Second, the impact of surgeon daily workload on the non-elective cases is much larger than that estimated from the full sample (3.00 vs 1.41 for post-LOS and 1.91 vs 1.03 for ICU time). This leads to the greater benefit from the new schedule when using the heterogeneous effect.

The benefits for post-LOS and ICU time from our new schedule are economically important. To see this, we convert the reduction in the downstream resource to the number of more patients the hospital

can accommodate each year, assuming the downstream resource is the only bottleneck. Over the four year horizon in our data set, this can be computed as:

$$\Delta\text{Pat} = \frac{\Delta\text{Obj}}{4 \text{ years} \times \text{Avg}(y)},$$

where $\text{Avg}(y) = \sum_{i=1}^{N} y_i/N$ denotes the average post-LOS or ICU time. Taking the results with heterogeneous effects as an example, the reduction in the total post-LOS and ICU time translates to 44 and 64 more patients admitted each year, respectively. In addition, we find similar reduction in the average occupancy level in the downstream unit and ICU from the new schedule. With the heterogeneous effect, the average census in the downstream unit and ICU decreases by 3.50% and 4.45% respectively. The above results highlight the potential benefits of our surgical scheduling model in reducing downstream congestion, which can be a bottleneck in the perioperative environment.

5.5. Analysis of the New Schedules

We have shown that our surgical scheduling model can improve the incision time, post-LOS, and ICU time. We now take a closer look at the new schedule to investigate the mechanisms that lead to the improvement. This provides important managerial insights on how hospitals should account for the impact of surgeon daily workload in surgical scheduling.

We consider two schedules from our model. The first is the one using the average effect with the objective given in (18). As mentioned before, the resulting schedule is the same for the three outcomes (incision time, post-LOS, and ICU time). The second is the one using the heterogeneous effect for post-LOS and ICU time, where the surgeon daily workload impacts the non-elective cases but not the elective ones. The corresponding objective is given in (19). In Table 12, we provide some summary statistics of the two schedules (first two rows) as well as the original one (last row). The columns $\tilde{n}_{s,t} = i$ for $i = 1, 2, 3, 4$ report the number of surgeon-day pairs for which the surgeon performs i cases in a day. The last column shows the average number of days worked by a surgeon in a week, given the surgeon appears at least once in the schedule. Table 13 provides the summary statistics of the three schedules that are related to non-elective cases. The columns $\tilde{n}_{s,t}^{(ne)} = i$ for $i = 1, 2, 3, 4$ report the number of surgeon-day pairs that a surgeon performs i non-elective cases a day. The last column in Table 13 shows the average number of elective cases performed by a surgeon in a day, given the surgeon performs at least one non-elective case in that day. It thus measures the co-occurrence of elective and non-elective cases in the schedule.

We first consider the schedule under the average effect. To minimize the objective function (18), the new schedule should smooth surgeon workload across days, i.e., reducing the number of days with multiple cases. In Table 12, we see that this is indeed achieved by our model as the new schedule significantly reduces the number of days with high workload. Specifically, the number of surgeon-day pairs with $\tilde{n}_{s,t} = 3$, i.e., the surgeon performs three cases in the day, decreases from 177 in the original schedule to 67 in the new

Table 12 Summary Statistics of Schedules

Effect	$\tilde{n}_{s,t}=1$	$\tilde{n}_{s,t}=2$	$\tilde{n}_{s,t}=3$	$\tilde{n}_{s,t}=4$	Avg n_{day}
Average	2620	1256	67	4	3.02
Heterogeneous	2425	1292	104	7	2.93
Original	2268	1249	177	13	2.83

Table 13 Summary Statistics of Schedules: Non-elective Cases

Effect	$\tilde{n}^{(ne)}_{s,t}=1$	$\tilde{n}^{(ne)}_{s,t}=2$	$\tilde{n}^{(ne)}_{s,t}=3$	$\tilde{n}^{(ne)}_{s,t}=4$	$\mathsf{E}(\tilde{n}^{(el)}_{s,t}\vert\tilde{n}^{(ne)}_{s,t}>0)$
Average	1985	409	23	0	0.21
Heterogeneous	2148	341	14	0	0.14
Original	1872	424	48	2	0.27

schedule. Similar reduction is also observed for the surgeon-day pairs with $\tilde{n}_{s,t}=4$ (from 13 to 4). The reduction in these high workload days is mostly made up by the surgeon-day pairs with a single case (i.e., $\tilde{n}_{s,t}=1$), which increases from 2,268 to 2,620 in the new schedule. While each surgeon's total workload in terms of the number of cases is unchanged for each week, the number of days each surgeon works is increased slightly, from 2.83 to 3.02 days on average. This result shows that the new schedule effectively smooths surgeon workload across days.

Next, we examine the new schedule obtained with heterogeneous effect for post-LOS and ICU time. Since $\tilde{n}_{s,t}=\tilde{n}^{(el)}_{s,t}+\tilde{n}^{(ne)}_{s,t}$, the objective function (19) can be written as

$$\min \gamma^{(ne)} \sum_{s\in S}\sum_{t\in T}\left[\left(\tilde{n}^{(ne)}_{s,t}\right)^2+\tilde{n}^{(el)}_{s,t}\tilde{n}^{(ne)}_{s,t}\right].$$

Thus, the minimization of the objective includes two parts: smoothing surgeon's non-elective workload across days, as well as reducing the *co-occurrence* of elective and non-elective cases. Both of the two aspects are reflected in the new schedule according to Table 13. First, the new schedule significantly reduces the number of surgeon-day pairs with multiple non-elective cases: the number of pairs with $\tilde{n}^{(ne)}_{s,t}=2$ (resp. $\tilde{n}^{(ne)}_{s,t}=3$) decreases from 424 to 341 (resp. 48 to 14) in the new schedule. In addition, the new schedule decreases the co-occurrence of elective and non-elective cases: given the surgeon performs at least one non-elective case, the average number of elective cases in that day drops from 0.27 in the original schedule to 0.14 in the new schedule.

While the solution to our scheduling model leads to substantial improvements, it is important to check the change in the number of working days of surgeons in each week. Although asking a surgeon to work for more days naturally smooths the workload, it might be difficult to implement in practice if the change is substantial. We address such concern as follows. First, in our model, we set the surgeon's maximum working days in a week as three days ($\bar{n}^{(d)}=3$), unless the surgeon works for more days in the original schedule. This choice is close to the the average level in the original schedule (2.83 days per week). In

addition, as shown the last column in Table 12, the average number of working days in each week only slightly increases in the new schedule (3.02 under the average effect and 2.93 under the heterogeneous effect). We also examine the number of working days for each surgeon-week combination and find that 80% of them remain unchanged in the new schedule. Thus, our surgical scheduling model can achieve substantial improvement in the surgery outcomes without significantly increasing the number of working days of surgeons.

As a further robustness check, we solve the surgical scheduling model with $\bar{n}^{(c)} = 3$ and $\bar{n}^{(d)} = 1$. That is, we increase the maximum daily workload of surgeons to three cases a day, but do not allow surgeons to work for more days in the week than in the original schedule. We still find improvements from the resulting schedules, although the benefits becomes smaller when using the average effects of daily workload. Specifically, the corresponding new schedules reduce the total incision time, post-LOS, and ICU time by 0.41%, 0.57%, and 0.98%, respectively when we use the average effects. The reductions increase to 0.81%, 2.81%, and 4.31% when we use heterogeneous effects.

6. Conclusion and Discussion

In many human-run service systems, service time and quality can be endogenously affected by the level of workload. In this work, we focus on the relationship between workload and performance in the context of cardiac surgery. Specifically, we study how surgery duration and patient outcomes are impacted by surgeon daily workload, i.e., the number of cases performed by a surgeon in a day. Using a detailed data set of cardiac surgery, we find that higher surgeon daily workload leads to longer surgery duration and worse patient outcomes including longer post-surgery LOS in the ICU and in the hospital, as well as higher likelihoods of reoperation and readmission. Our study provides new evidence for the negative impact of surgeon fatigue or operational constraints due to high daily workload. It suggests that hospitals may be able to improve surgery performance if surgeon workload can be smoothed across days. Based on our findings, we develop a surgery scheduling model that incorporates the effect of surgeon workload and show that both surgery duration and patient outcomes can be substantially improved under our proposed new schedule.

When identifying the effect of surgeon daily workload, it is crucial to address the endogeneity problem that arises from unobserved patient risk factors. To handle this challenge, we develop two novel IVs using the operational factors in the cardiac department. In particular, we leverage a data set about the surgeons' block schedules assigned by the department to construct one of the IVs. We find surgeons tend to schedule more operations if their next scheduled block is far away. This introduces exogenous variation in surgeon daily workload, which is essential for constructing proper IVs. We also find that there is substantial heterogeneity in the effects of daily workload for different types of patients: the impact on incision time is more significant for elective patients, while the surgery outcomes of non-elective patients are more affected by surgeon daily workload.

While our results provide strong evidence of the impact of workload on cardiac surgery outcomes, our study has a number of limitations. First, we only have block schedules from part of our data set and we had to impute the rest of the schedule. While our imputation seems to be reasonable, it would be ideal to have the full schedule available. Second, our data comes from a single hospital. Though we are able to estimate the effects across eight surgeons at our partner hospital, other hospitals may have different scheduling procedures which may make the IVs more or less appropriate. Third, as we have conducted an IV analysis, our results only provide insight into cases that *comply* with the IVs. There are some operations that must happen, regardless of shared resources of block schedule, so our analysis does not provide insights into the effect of surgeon workload on these cases. Finally, as noted earlier, because post-surgery LOS is measured in days (rather than hours), we have a potential censoring issue which we address with a conservative adjustment to the post-LOS outcome measure.

Our scheduling model demonstrates the potential improvements in patient flow in the OR (via incision time) and post-surgery (via post-surgery LOS and total ICU time) by accounting for the impact of surgeon workload on these metrics when scheduling surgery. We find that by simply reshuffling operations within a week, with substantial restrictions on how much non-elective operations can be moved, substantial improvements could be achieved. With even more flexibility in how/when to schedule surgery, it is possible even larger gains can be achieved. As such, our results suggest that it is important for hospital managers and surgeons to consider the impact of surgeon workload when managing their ORs.

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Appendix A: Description and Summary Statistics of Independent Variables in (1) and (2)

To control for the effects of patient's characteristics and severity levels, we include a comprehensive list of demographic, risk, operative, and operational factors as independent variables in our estimation models. Some of these factors are already discussed in Section 3. We now provide the description and summary statistics for other independent variables included in X_i for our models (1) and (2).

In Table 14, we document the descriptions, types, and summary statistics of the independent variables. We also provide their locations in the STS data collection form. We handle missing values in the binary and categorical variables as follows: if the number of missing observations is smaller than 100 (1.8% of the sample), we impute their values using the majority from the cases in the same New York Heart Association (NYHA) class. Otherwise, we add a new category "Unknown" to represent the missing values. Summary statistics of the categorical variables are reported in Table 15. Note that the NYHA classification is not available (N/A) if the patient has not experienced heart failure. The Pulmonary Artery (PA) pressure is coded as "High" if it is higher than 55mg, and "Low" otherwise.

We classify the cases to different surgery types to control for the procedures performed by the surgeons. First, we have eight standard surgery types from the STS data. For the cases that do not fall into the standard types, we classify their surgery types by the following heuristic rule. We collect from the STS data which of the following four procedures are performed in the operation: coronary artery bypass, valve, other cardiac procedure, and other non-cardiac procedure. If only one of the four procedures is performed, we classify the case as a non-standard isolated type, e.g., "non-standard isolated valve" if only the valve procedure is conducted. If more than one of the procedures are performed, we classify the case as the "non-standard multiple" type. Finally, if none of the four procedures is performed, we classify it as "not identified." In total, we have six types for the non-standard procedures, i.e., four non-standard isolated ones, non-standard multiple, and not identified. The numbers of cases of each type (both standard and non-standard ones) are summarized in Table 16.

In summary, the independent variable X_i in (1) and (2) includes the factors in Table 14, patient's gender and age, surgery status, patient's admission type, surgery type in Table 16, surgeon's identifier, patient's pre-LOS, block schedule status, and dummies for weekday, month, and year of the operation.

Appendix B: Definition of Independent Variables in the Schedule Imputation Model (3)

In this section, we document the independent variables included in $X'_{s,t}$ for the logistic regression model (3). To impute whether the surgeon is assigned a block schedule on a given day, we include multiple operational factors related to the workload of the focal and other surgeons. As we mentioned in the main body, future information can be included in $X'_{s,t}$ as we are imputing the block schedule instead of making any prediction.

Table 17 summarizes the variables included in $X'_{s,t}$ (plus a constant term) for the logistic model (3). In particular, $ORTime_{s,t}$ denotes the sum of OR time of the cases by surgeon s on day t, ignoring overlapping due to surgery parallel. $StartHour_{s,t}$ and $EndHour_{s,t}$ are calculated using the OR entry and exit time of the cases by surgeon s on day t; $StartHour_{s,t}$ (resp. $EndHour_{s,t}$) corresponds to the OR entry (resp. OR exit) time of the earliest (resp. latest) case, rounded to the nearest hour. $PatRemain_{s,t}$ is the number of patients remaining in the hospital for surgeon s. This refers to the patients that (1) already admitted to the hospital by day $t-1$, (2) operations have not been performed by day $t-1$, and (3) operations are eventually performed by surgeon s. $WDElecRatio_{s,t}$ is the proportion of elective cases by surgeon s in $[t-180, t+180]$ that fall on the same weekday as t. This variable is included as surgeons' blocks

Table 14 Description and Summary Statistics of Other Independent Variables in Models (1) and (2)

Variable	Description	Section in STS	Type	Mean
Race	Patient's race	Demographics	Categorical	-
Endocard	Endocarditis	Risk factor	Binary	0.053
PeriAD	Peripheral arterial disease	Risk factor	Binary	0.088
Lung	Lung disease with severity $\geq$ mild	Risk factor	Binary	0.192
Hypertension	Hypertension	Risk factor	Binary	0.777
CaroStenosis	Carotid Stenosis	Risk factor	Binary	0.054
Syncope	Syncope	Risk factor	Binary	0.031
Dialysis	Dialysis for renal failure	Risk factor	Binary	0.030
Diabetes	Insulin control for diabetes	Risk factor	Binary	0.111
Liver	Liver disease	Risk factor	Binary	0.022
Cancer	Cancer within five years	Risk factor	Binary	0.062
Thoracic	Thoracic aorta disease	Risk factor	Binary	0.094
DrugUse	Recent or remote drug use	Risk factor	Binary	0.088
Smoke	Smoke status of patient	Risk factor	Categorical	-
PrevCI	Previous cardiac intervention	Previous Intervention	Binary	0.431
CardShock	Cardiogenic shock	Preoperative	Binary	0.076
MI	Prior MI	Preoperative	Binary	0.120
NYHA	NYHA classification	Preoperative	Categorical	-
Aorta	Aorta procedure performed	Operative	Binary	0.123
Incidence	Non-initial cardiovascular surgery	Operative	Binary	0.188
PA_Pressure	PA systolic pressure	Hemodynamics	Categorical	-
TotCABG	Number of arteries bypassed	Coronary Bypass	Continuous	1.36

Table 15 Summary Statistics of Categorical Variables in Table 14

Variable	Category	Num Obs.	Ratio
NYHA	N/A	1933	0.361
	I	516	0.096
	II	998	0.186
	III	991	0.185
	IV	663	0.124
	Unknown	251	0.047
Race	White	4273	0.798
	Asian	590	0.110
	Black	274	0.051
	Other	215	0.040
Smoke	FALSE	2694	0.503
	TRUE	2429	0.454
	Unknown	229	0.043
PA Pressure	High	376	0.070
	Low	2247	0.420
	Unknown	2729	0.510

Table 16 Numbers of Cases by Surgery Types

Surgery Type	Number of Cases	Ratio
CABG	1718	0.321
AVR	683	0.128
MVR	225	0.042
MVr	254	0.047
CABG + AVR	318	0.059
CABG + MVR	57	0.011
CABG + MVr	58	0.011
AVR + MVR	107	0.020
Non-standard isolated Valve	574	0.107
Non-standard isolated CAB	28	0.005
Non-standard isolated cardiac	369	0.069
Non-standard isolated non-cardiac	15	0.003
Non-standard multiple	690	0.129
Not identified	256	0.048

tend to fall on specific weekdays to reduce the variation in surgeons' schedule. Most elective cases are performed in their surgeons' block. We have in total 23 independent variables (plus a constant term) in the logistic model (3) for imputing the block schedule.

Table 17 Definition of Independent Variables in the Schedule Imputation Model (3)

Variable	Definition
$Surg_s$	Dummy variable for surgeon identifier
$WeekDay_t$	Dummy variable for weekday of t
$ElecCur_{s,t}$, $UrgCur_{s,t}$, $EmergCur_{s,t}$	Number of elective/urgent/emergent cases by surgeon s on day t
$ElecOth_{s,t}$, $UrgOth_{s,t}$, $EmergOth_{s,t}$	Number of elective/urgent/emergent cases by other surgeons on day t
$ORTime_{s,t}$	Total OR time of cases by surgeon s on day t
$StartHour_{s,t}$, $EndHour_{s,t}$	Start and end of the cases by surgeon s on day t
$StartLate_{s,t}$, $EndEarly_{s,t}$	Indicators for $StartHour_{s,t} \geq$ 8AM and $EndHour_{s,t} \leq$ 3PM
$AdmCur_{s,t}$	Numbers of patients admitted by surgeon s on day t
$PatRemain_{s,t}$	Numbers of patients remaining in the hospital for surgeon s
$NumPreDay_{s,t}$, $NumPostDay_{s,t}$	Numbers of cases by surgeon s in the previous and next weekday
$WorkPreDay_{s,t}$, $WorkNextDay$	Indicators for $NumPreDay_{s,t} \geq 1$ and $NumPostDay_{s,t} \geq 1$
$NumCurWeek_{s,t}$	Numbers of days worked by surgeon s in current calendar week
$DistLast_{s,t}$, $DistNext_{s,t}$	Number of days from the previous and next working day of surgeon s
$WDElecRatio_{s,t}$	Proportion of elective cases by surgeon s in $[t-180, t+180]$ that are performed on the same weekday as t

Appendix C: Surgical Scheduling MIQP Formulation

The final MIQP formulation to minimize total incision time is given below.

$$\min_{x_{i,j}} \sum_{s \in S} \sum_{t \in T} \tilde{n}_{s,t} \cdot \left(\gamma^{(el)} \tilde{n}_{s,t}^{(el)} + \gamma^{(ne)} \tilde{n}_{s,t}^{(ne)}\right)$$

such that

$$\tilde{n}_{s,t} = \sum_{i \in A_s} x_{i,t},$$

$$\tilde{n}_{s,t}^{(el)} = \sum_{i \in A_s} x_{i,t} \mathbf{1}\{i \in C_{el}\},$$
$$\tilde{n}_{s,t}^{(ne)} = \sum_{i \in A_s} x_{i,t} \mathbf{1}\{i \notin C_{el}\},$$
$$\sum_{t \in T} x_{i,t} = 1, \forall i \in C,$$
$$x_{i,t} = 0, \text{ if } i \in C_{ug} \text{ and } |t - \tilde{t}(i)| > 1,$$
$$x_{i,t} = 0, \text{ if } i \in C_{es} \text{ and } t \neq \tilde{t}(i),$$
$$\sum_{i \in C} x_{i,t} = \sum_{s \in S} n_{s,t}^{(c)}, \ \forall t \in T,$$
$$\tilde{n}_{s,t} \leq \max\{\bar{n}^{(c)}, n_{s,t}^{(c)}\}, \ \forall t \in T \text{ and } \forall s \in S,$$
$$z_{s,t} \leq M \cdot \tilde{n}_{s,t},$$
$$z_{s,t} \geq m \cdot \tilde{n}_{s,t},$$
$$\sum_{t \in T} z_{s,t} \leq \max\{\bar{n}^{d}, n_{s}^{(d)}\},$$
$$x_{i,j}, z_{s,t} \in \{0, 1\}.$$

Appendix D: Supplementary Tables

This section includes the supplementary tables. Table 18 summarizes the correlation between the two IVs and 21 observable severity factors of patients. Table 19 show the coefficients of the two IVs in (5) when we estimate (2) and (5) by full MLE for binary outcomes. Tables 20 and 21 report the estimated effects on surgery duration and patient outcomes when we use total incision time of other cases ($SumInc_i$) as the surgeon daily workload measure. Tables 22 and 23 show the estimated coefficient γ for the two workload measures in (2) for the three binary outcomes. The robustness check results under different specifications are summarized in Tables 24 and 25.

In addition, as a robustness check for the estimation results of post-LOS, we use several more conservative measures of post-LOS by adjusting the original measure using the OR entry or exit time of each case. The estimated coefficients of $NumCases_i$ by TSLS are given in Table 26. The first column shows the original results in Tables 8 and 10, in which we compute the post-LOS as the number of days between the surgery and discharge dates. In the second column ("Entry $\geq$ 3PM"), we subtract a day from the post-LOS if the OR entry time of the case is later than 3PM as there is some evidence that late surgery start times are associated with an increase of LOS by 1 day (Cifarelli et al. 2021). In the third column ("Overnight"), we subtract a day from the post-LOS if the case is performed overnight, i.e., the patient exits the OR on the day after its surgery date. In the fourth column ("Overnight and Exit Hour"), we first subtract a day from the post-LOS if the case is performed overnight and then, for all cases, subtract the hours elapsed before OR exit on the day of OR exit. In the last two columns, we first adjust for the overnight concern as described before and then further subtract a day from the post-LOS if the patient leaves the OR after 12PM and 4PM, respectively. We see from Table 26 that our estimated effects for post-LOS remain similar in all these conservative measures. This shows the robustness of our results.

Table 18 Correlation between IVs and Observable Severity Factors

Factor	$TotOther_i$	$GapNext_i$
Gender: Male	−0.019	0.003
Status: non-electives	−0.096	0.084
Age	0.054	−0.042
NYHA: III or IV	0.002	0.059
Endocarditis	−0.017	0.035
Previous intervention	−0.031	0.045
Peripheral arterial disease	0.002	0.040
Incidence	−0.030	0.055
Lung disease	0.023	0.038
Hypertension	0.034	−0.025
Drug use	−0.017	0.022
Cancer	0.008	0.009
Carotid stenosis	0.027	0.016
Cardiogenic shock	−0.052	0.097
Syncope	0.001	−0.010
MI	−0.007	0.014
Dialysis	−0.013	0.041
Diabetes	0.005	0.005
Systolic pressure: high	0.009	0.040
Liver disease	0.020	0.035
Thoracic aorta disease	−0.020	−0.049
Smokes	−0.006	0.029

Table 19 Estimated Coefficients of IVs by Full MLE of (5) and (2) (Full Sample)

	Reoperation		Readmission		Mortality	
IV	$NumCases_i$	$SumInc_i$	$NumCases_i$	$SumInc_i$	$NumCases_i$	$SumInc_i$
$TotOther_i$	-0.074^{***}	-0.369^{***}	-0.072^{***}	-0.359^{***}	-0.075^{***}	-0.373^{***}
	(0.008)	(0.051)	(0.008)	(0.052)	(0.008)	(0.051)
$GapNext_i$	0.005	$0.043^{\dagger}$	$0.007^{\dagger}$	0.053^{*}	$0.006^{\dagger}$	0.047^{*}
	(0.004)	(0.022)	(0.004)	(0.026)	(0.004)	(0.022)
Num Obs.	5345	5345	5116	5116	5081	5081

Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. Coefficients and standard errors of two IVs in (5) when we estimate (2) and (5) jointly by full MLE for reoperation, readmission, and mortality.

Table 20 Estimated Effects of Daily Workload (Total Incision Time of Other Cases) on Surgery Duration and Patient Outcomes: Full Sample

	Continuous y_i: Coefficients			Binary y_i: AME		
	Incision time	Post-LOS	Total ICU time	Reoperation	Readmission	Mortality
Panel A: Full	0.083^{*}	0.269^{**}	0.194^{*}	0.005^{*}	$0.013^{\dagger}$	0.002
	(0.038)	(0.100)	(0.088)	(0.002)	(0.008)	(0.002)
Num Obs.	5345	5344	5319	5345	5116	5081
Panel B: Full (w/o IV)	-0.016	0.015	0.009	-0.000	-0.000	$0.002^{\dagger}$
	(0.010)	(0.034)	(0.016)	(0.001)	(0.001)	(0.001)
Num Obs.	5345	5344	5319	5345	5116	5081

The estimated effects of surgeon daily workload (total incision time of other cases) on surgery duration and patient outcomes for the full sample. We report the estimated coefficients in (1) for the three continuous dependent variables, and the AME from (2) for the three binary dependent variables. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 21 Estimated Effects of Daily Workload (Total Incision Time of Other Cases) on Surgery Duration and Patient Outcomes: Elective and Non-elective Sample

	Continuous y_i: Coefficients			Binary y_i: AME		
	Incision time	Post-LOS	Total ICU time	Reoperation	Readmission	Mortality
Panel A: Elec	0.072^{**}	-0.063	0.005	0.002	0.004	0.012
	(0.025)	(0.182)	(0.135)	(0.007)	(0.012)	(0.009)
Num Obs.	2474	2474	2454	2394	2398	1897
Panel B: Non-elec	0.098	0.606^{*}	0.384^{*}	0.010^{*}	0.018^{*}	-0.001
	(0.064)	(0.264)	(0.192)	(0.004)	(0.008)	(0.002)
Num Obs.	2871	2870	2865	2871	2697	2769

The estimated effects of surgeon daily workload (total incision time of other cases) on surgery duration and patient outcomes for the elective and non-elective sample. We report the estimated coefficients in (1) for the three continuous dependent variables, and the AME from (2) for the three binary dependent variables. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 22 Estimated Coefficients of Daily Workload in (2) for Binary Outcomes: Full Sample

	Reoperation		Readmission		Mortality	
	$NumCases$	$SumInc_i$	$NumCases$	$SumInc_i$	$NumCases$	$SumInc_i$
Panel A: Full	0.268^{**}	0.049^{*}	$0.371^{\dagger}$	$0.075^{\dagger}$	0.197	0.039
	(0.089)	(0.021)	(0.203)	(0.041)	(0.213)	(0.039)
Num Obs.	5345	5345	5116	5116	5081	5081
Panel B: Full (w/o IV)	-0.019	-0.004	-0.002	-0.002	0.190^{*}	$0.034^{\dagger}$
	(0.038)	(0.006)	(0.050)	(0.008)	(0.083)	(0.018)
Num Obs.	5345	5345	5116	5116	5081	5081

Estimated coefficient γ in (2) for the full sample. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 23 Estimated Coefficients of Daily Workload in (2) for Binary Outcomes: Elective and Non-elective Sample

	Reoperation		Readmission		Mortality	
	$NumCases$	$SumInc_i$	$NumCases$	$SumInc_i$	$NumCases$	$SumInc_i$
Panel A: Elec	0.273	0.040	0.183	0.024	1.035*	0.202*
	(0.524)	(0.096)	(0.411)	(0.077)	(0.422)	(0.082)
Num Obs.	2394	2394	2398	2398	1897	1897
Panel B: Non-elec	0.329*	0.065*	0.452*	0.098*	-0.060	-0.010
	(0.131)	(0.028)	(0.186)	(0.040)	(0.197)	(0.038)
Num Obs.	2871	2871	2697	2697	2769	2769

Estimated coefficient γ in (2) for the elective and non-elective samples. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 24 Estimated Effects of Daily Workload (Number of Other Cases) on Surgery Duration and Patient Outcomes: Different Specifications

	Incision time			post-LOS			Total ICU time		
Specification	All	Elective	Non-elec	All	Elective	Non-elec	All	Elective	Non-elec
One IV	0.443*	0.369*	0.499	1.488*	-0.211	3.077†	1.127*	0.294	1.975†
	(0.219)	(0.160)	(0.345)	(0.596)	(1.104)	(1.618)	(0.492)	(0.779)	(1.098)
Winsorize: 95th pct	0.403*	0.381***	0.442	1.029**	0.312	1.956*	0.569†	0.323	0.962†
	(0.197)	(0.101)	(0.317)	(0.338)	(0.845)	(0.847)	(0.292)	(0.545)	(0.535)
Winsorize: 99th pct	0.476*	0.428*	0.531	2.260*	-0.311	4.442†	1.565†	0.003	2.936
	(0.234)	(0.174)	(0.364)	(0.978)	(1.138)	(2.352)	(0.813)	(1.033)	(1.809)
Num Obs.	5345	2474	2871	5347	2476	2871	5321	2455	2866
Block Sample	0.534†	0.249	0.808	1.067	0.655	3.782**	1.103	0.824	2.447*
	(0.273)	(0.181)	(0.504)	(1.204)	(1.121)	(1.404)	(0.749)	(0.962)	(1.065)
Num Obs.	2489	1182	1307	2489	1182	1307	2482	1177	1305
Standard Types	0.291†	0.523***	0.137	0.668	0.339	1.146	0.591*	0.822	0.634
	(0.175)	(0.084)	(0.286)	(0.699)	(0.958)	(1.282)	(0.283)	(0.658)	(0.576)
Num Obs.	3416	1717	1699	3416	1717	1699	3407	1709	1698

Estimated coefficient γ in (1) for three continuous dependent variables under different specifications. Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 25 Estimated Effects of Daily Workload (Number of Other Cases) on Binary Outcomes: Different Specifications

	Reoperation	Readmission	Mortality
One IV	0.035^{**}	0.062	0.009
	(0.011)	(0.038)	(0.011)
Num Obs.	5345	5116	5081
Block Sample	$0.062^{\dagger}$	0.013	-0.002
	(0.032)	(0.057)	(0.026)
Num Obs.	2487	2354	2267
Standard Types	0.018	0.006	0.005
	(0.016)	(0.019)	(0.012)
Num Obs.	3413	3333	3112

Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 26 Estimated Effects of Daily Workload (Number of Other Cases) on Post-LOS with Different Adjustments

Original	Entry $\geq$ 3PM	Overnight	Overnight and Exit Hour	Overnight and Exit $\geq$ 12PM	Overnight and Exit $\geq$ 4PM
Panel A: Full sample					
1.408^{*}	1.710^{**}	1.464^{**}	1.516^{**}	1.405^{*}	1.631^{**}
(0.565)	(0.578)	(0.566)	(0.556)	(0.561)	(0.516)
Panel B: Non-elective sample					
3.004^{*}	3.364^{*}	3.069^{*}	3.124^{*}	2.994^{*}	3.226^{*}
(1.501)	(1.521)	(1.485)	(1.487)	(1.495)	(1.446)

Robust standard error is reported in parenthesis; $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.