Do Independent and Parallel Processing Physicians Influence Each Other's Performance? Evidence from the Emergency Department

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Problem definition: Understanding potential channels through which physicians impact each other's performance can yield new insights into better management of hospitals' operations. For example, various studies of hospital operations model physicians as parallel servers (e.g., within a queueing system) and assume that they have independent speed and/or quality. In settings where physicians have to work on the same patients or tasks, it is clear that this assumption might be violated as the speed and/or quality of one physician often depends on that of the other. However, it is largely unknown whether and how this interdependency between physicians' performance might exist in settings where physicians do not work together.

Methodology/results: We make use of data on more than 110,000 visits made to our partner hospital's Emergency Department (ED) and investigate whether and how ED physicians who are known to serve their own patients without much interactions with each other affect each other's performance. We find strong empirical evidence that, despite working independently and in parallel, ED physicians (a) affect each other's both speed and quality, and (b) they do so through their shared utilization of resources such as test services or those required for admitting ED patients to the hospital. Thus, we establish evidence of an important *resource spillover effect* in EDs. Furthermore, we find that this resource spillover effect has an impact which is in the opposite direction to settings in which servers work together. Specifically, we find that a faster peer decreases a focal physician's average speed while a slower peer increases it. Similarly, a higher-quality peer decreases a focal physician's average quality while a lower-quality peer increases it. We further show that during high-volume shifts (i.e., when the shared resources are most constrained), the magnitude of these effects increases.

Managerial implications: Our results indicate that better pairing of ED physicians who work during the same shifts should be viewed as an important lever that can allow hospital administrators to improve their operations without additional investments.

Key words: Physician Performance; Physician Diversity; Emergency Department Operations

1. Introduction

Decisions regarding how to schedule physicians during the same shifts are made everyday in hospitals. Making such decisions, however, without considering the potential effects of physicians on each other's performance could have significant implications. In this study, we examine how physicians' shared utilization of resources affect physician speed and quality in the context of an Emergency Department (ED) setting. EDs provide an interesting study setting where physicians aim to optimize speed (to sustain a reasonable flow in the interest of those patients waiting) while maintaining quality for the patient being seen in a shared-resource environment (Emergency Department Cases 2015). In addition, ED physicians each work on serving their own patients, and cases where joint work among them is needed to serve the same patient is very rare. Thus, understanding whether and how ED physicians affect each other's speed and quality can generate important insights into physician pairing and scheduling methods that can ultimately lead to more effective and efficient care delivery mechanisms.

To gain such an understanding, we utilize a large dataset that we have collected from the ED of our partner hospital, which is one of the leading hospitals in the U.S[1]. Our data include 115,350 patient visits associated with 32 ED physicians who have served patients in our partner hospital. An automated rotational patient assignment algorithm (Traub et al. 2016) randomly assigns all arriving patients to physicians in our partner hospital's ED. This randomization process mitigates the concern of physicians' selection of patients (e.g., potential cherry-picking behaviors) that can influence physician performance and cause endogeneity issues in our study. All visits from July 12, 2012, to July 31, 2016 that were associated with patients who were identified in the Electronic Medical Record (EMR) as having been seen by an ED physician were included in our analysis. Our dataset comprises detailed patient-specific information including demographic (age, gender, race), encounter-level information such as the number of ordered diagnostic tests, chief complaint, and Emergency Severity Index (ESI) level (a five-level triage scale with 1 indicating the most urgent and 5 denoting the least urgent case) as well as important timestamps capturing patients' movement through the ED from registration to discharge. A summary statistics of the main variables used in our analysis is presented in Table 1. We excluded 2,914 patient visits from our analysis, because they had missing values. In addition, we removed all observations associated with 4 physicians who had fewer than 200 patient visits over our 4-year study period. This left us with a final dataset with a total of 110,325 patient visits.

[1] One of the authors of this paper is the chairman of the ED at our partner hospital, and has significantly contributed to our understanding of the issues related to this study in their practice.

Table 1 Summary Statistics - Patient and Physician Characteristics

Variable	Mean	SD	Min	Max
Patient Characteristics				
Patient Age	58.64	20.89	1	105
Female (%)	53	1.83	48	58
White (%)	91	1.54	87	95
ESI Level	2.98	0.57	1	5
Physician Characteristics				
IV Order Count per Patient Visit	3.13	2.12	0	32
Ultrasound Order Count per Patient Visit	1.28	0.50	0	5
Radiology Order Count per Patient Visit	1.20	0.59	0	11
MRI Order Count per Patient Visit	1.69	0.91	0	6
CT Order Count per Patient Visit	0.32	0.57	0	8
Lab Order Count per Patient Visit	11.74	6.53	0	136
Experience (Years)	22.16	7.49	6	39
Job Tenure (Years)	8.38	6.01	0	18
Admission Rate (%)	0.11	0.03	0.05	0.20
LOS (Minutes)	235.02	26.84	180.64	297.81
72-hr Rate of Return (%)	0.03	0.01	0.01	0.06
Contact-to-Disposition Time (Minutes)	144.13	24.37	87.55	215.39

Note: N = 110,325. Observations are at the patient-visit level.

Our analysis of this data resulted in new findings that have important implications for both researchers and hospital administrators. Specifically, our findings establish statistically significant evidence that physicians impact each other's performance through their utilization of shared resources. Furthermore, we find that this indirect effect of physicians on one another, which we term the *resource spillover effect*, is in the opposite direction to what both the conventional wisdom and research on the influence of peers suggest. In particular, we observe that on average a faster peer has a negative effect on a focal physician's speed. Our results also document a slower peer's positive effect on the focal physician's average speed. In addition, we show that, on average, a higher-quality peer negatively impacts a focal physician's quality, but a lower-quality peer positively affects the focal physician's quality.

We further explore the causal mechanism behind these resource spillover effects by conducting mediation analyses. Specifically, we examine the influence of peers on a focal physician's performance through two potential mediators: the physician's average test order count and admission rate. Our results show that a faster peer has an increasing effect on the focal physician's test orders per patient visit, which in turn has a negative effect on a focal physician's speed. This is due to the fact that, on average, faster physicians have a lower test order rate: issuing less tests per patient allows them to be faster, since tests delay the service process. Hence, working alongside a faster peer (who has a less rate of using tests) allows the focal physician to utilize the test services more (i.e., order more tests) by making them less congested and more available. This, in turn, results in a reduced speed for the focal physician, again since ordering more tests reduces speed. Our results further suggest that a slower peer has a statistically significant decreasing effect on a focal physician's average test order count and, in turn, a positive effect on a focal physician's speed. Specifically, a slower peer blocks the focal physician from using the test services in a timely manner. This roadblocking behavior reduces the average number of tests ordered by the focal physician, making him/her faster.

With regards to peer influence on quality, we find that higher-quality peers have a negative effect and lower-quality peers have a positive effect on a focal physician's admission rate which, in turn, negatively and positively influence a focal physician's quality, respectively. Specifically, we observe that higher quality ED physicians have a higher admission rate on average, especially when metrics such as 72-hour readmission rate is used to gauge quality. Thus, in the presence of a higher-quality peer (who has a higher admission rate), a focal physician may not have access to the resources needed in order to admit his/her patients. As such, his/her admission rate and, in turn, quality decreases on average. Similarly, working alongside a lower-quality peer (who has a lower admission rate) results in an increase in the focal physician's admission rate, and hence, improved quality (e.g., a lower 72-hour readmission rate).

To check the robustness of these findings, we perform various tests which allow us to address potential concerns regarding physicians' selection into peer groups, endogeneity, and/or spurious correlations with omitted variables. For example, we use the nearest-neighbor propensity score matching method without replacement to construct matched samples of physicians that achieve balance across a set of observable covariates related to patient and ED characteristics, including patient age, gender, race, ESI, and ED volume. We re-run our analysis on these matched samples of physicians that achieve balance on all observable covariates, and find that our main inferences remain the same.

The insights we generate into the existence, magnitude, and directional impact of the resource spillover effect have critical implications in a variety of services in which workers utilize shared scarce resources. In particular, our findings shed light on an interesting interplay between constrained capacity and influence of workers on each other's performance. Within the hospital operations literature, given the large body of studies documenting the adverse effects of workload on physicians' performance (KC and Terwiesch 2009, Powell et al. 2012, Berry Jaeker and Tucker 2017, Batt and Terwiesch 2017), our study offers a potential way for alleviating the negative impact of high workload. Specifically, our findings suggest that scheduling physicians alongside diverse peers with whom they utilize shared resources more efficiently would have a positive effect on the operations of hospitals. Furthermore, our results have significant financial implications for hospitals. Given the mounting pressure on hospitals to reduce costs (e.g., payment reforms), healthcare providers aim to reduce Length of Stay (LOS) and increase the number of patients they serve per bed per unit of time. In particular, considering that in an ED, a 15-minute decrease in LOS could result in \$1.4 million of additional revenue for a hospital (The Becker's Hospital Review 2016), our findings could lead to substantial savings for hospital EDs while maintaining a good level of care quality.

In addition to these practice-related implications, our study has also some important theoretical contributions. Past studies on service systems, and in particular EDs, have modeled physicians as parallel servers (see, e.g., Saghafian et al. 2015 and the references therein for a review of queueing studies of ED operations). The underlying assumption in these studies is that servers have *exogenous* average performances (e.g., an exogenous service rate). Our work shows that this assumption is largely questionable. In particular, we provide evidence that the performance of a particular server/physician (in terms of speed and quality) depends on those of the other servers that are working in the same shift with him/her. Performance rates of servers, hence, are to a great extent *endogenous*. This finding would not be surprising if the physicians were treating patients as a team. Instead, the ED physicians in our setting work on different patients in parallel and independent of each other. Yet, we find that their performance (measured in terms of speed and/or quality) is not fully exogenous. Our paper attributes this finding to shared utilization of constrained resources (e.g., labs or admission services). That is, use of such shared resources leads to nuanced inter-dependencies among physicians' performance. Furthermore, we show that these nuanced inter-dependencies create opposite-directional effects among physicians.

2. Related Studies

Our study is mainly related to three streams of literature: queueing studies of service systems, the behavioral operations management literature surrounding physicians' speed and quality, and physician scheduling.

Queueing Studies of Service Systems: A central assumption in studies that make use of queuing models to examine service systems is that parameters related to speed and/or quality of a server is exogenous. In a verity of queuing models of EDs, for example, physicians are modeled as parallel processing servers with exogenous service rates (see, e.g., Saghafian et al. 2015 for a review). A number of studies have relaxed this assumption to incorporate the fact that servers might change their performance based on the congestion in the system. For example, Dong et al. (2015) examine the effect of congestion on system performance and find that when a queueing system is congested, a slowdown phenomenon emerges. Delasay et al. (2016) find that employees adjust their service rate by speeding up or slowing down according to system load (i.e., the number of users in the system) and overwork, respectively.

Shunko et al. (2017) use behavioral experiments to show that workers process items at a slower rate in single-queue (SQ) systems than in multi-server parallel-queues (PQ) systems. The authors attribute the slowdown effect in the SQ system to social loafing in a shared workload environment. Using field data, Wang and Zhou (2018) compare cashiers' service time in a supermarket setting with a SQ structure of two servers, to a PQ structure. The authors document a 10.7% decrease in cashiers' service time. Gopalakrishnan et al. (2014) study the optimal tradeoffs between the cost of exerting effort and the value of having idle time in an M/M/N queueing system. Our study contributes to this literature by showing that servers' characteristics are endogenous, in that they depend on parameters of the other servers. This endogeneity in our setting, however, is not related to social loafing or strategic response of servers to spiked workloads that the above-mentioned studies document. Instead, we find that a server's parameters depend on which other server is working in parallel to him/her: a focal server's performance is affected by that of his/her peer, because of a resource spillover.

Behavioral Operations Management: Our study is also related to the behavioral operations management literature surrounding worker speed and quality. A large body of literature has documented how employees adjust their service behavior in response to certain situations by either speeding up or slowing down (Powell and Schultz 2004, Do et al. 2018). For example, Schultz et al. (1998) find that workers speed up when they are the cause of disruptions (blocking and starving) in the flow of work. Several studies have studied the behavioral effects of workload on physician performance. KC and Terwiesch (2009) show that hospital employees speed up as load level increases. KC and Terwiesch (2012) provide evidence for a negative association between the occupancy level of a cardiac intensive care unit and patient LOS due to early discharge of patients from the hospital. Armony et al. (2015) find evidence for both ED slow-down and speed-up and propose plausible explanations such as fatigue, medical staff and/or equipment overload for the slowdown effect. In addition to these effects on speed, the effects of workload on physician quality have also been documented in the literature. Kuntz et al. (2015) show a nonlinear relationship between hospital workload and mortality rates. Powell et al. (2012) found that high workload results in a reduction in physician diligence over paperwork which, in turn, yields less revenue per patient. Saghafian et al. (2018) study the trade-offs in speed and quality in the ED, but unlike our study, they focus on the effect of using telemedical physicians.

Our work builds upon the above-mentioned studies by demonstrating how physicians affect each other's speed and/or quality through shared utilization of resources, and highlights the need to consider such peer influence in staffing and planning models. In addition, our findings suggest that during high-volume shifts when resources are more constrained, the influence of peers increases in magnitude. Given that high congestion levels are linked to both longer patient LOS (Kuntz et al. 2011) and higher readmission rates (Anderson et al. 2012), our insights offer hospital administrators a potential strategy to alleviate these negative consequences: a better pairing of physicians that work during the same shifts.

Physician Scheduling. There is a large body of analytical literature on staffing/scheduling decisions. Most classical models developed in the operations management literature assume that workers are similar and independent of each other. Recent studies including Wallace and Whitt (2005), Ata and Van Mieghem (2009), and Ward and Armony (2013) have relaxed this assumption by incorporating worker heterogeneity in scheduling and planning models. Similarly, Arlotto et al. (2014) consider both worker heterogeneity and learning for staffing decisions.

A related stream of literature has focused on scheduling and appointment systems in healthcare settings (see, e.g., Cayirli and Veral 2009, Gupta and Denton 2008). A number of these studies are based on the assumption that patients are homogeneous (Begen and Queyranne 2011, Cayirli et al. 2012). Other studies have used variability in service duration to account for the heterogeneity in patient characteristics. For example, higher variance in treatment duration of patients has been shown to create higher variability in the system. As such, several studies have suggested sequencing patients based on their variance of service duration (Robinson and Chen 2003, and Cayirli et al. 2008). For example, Wang (1999) argues that larger variability will lead to longer waiting times, so sequencing patients with smaller service duration variance first can reduce waiting times for subsequent patients.

More closely related to ED operations, Sinreich et al. (2012) use two heuristic algorithms for staffing physicians, nurses and technicians. The authors show that the work schedules developed by these two algorithms result in a 20% to 64% decrease in patient waiting time and a 7% to 29% reduction in LOS. Yankovic and Green (2011) develop a variable finite-source queuing model representing the nursing system to approximate the actual interdependent dynamics of bed occupancy levels and demands for nursing. Patel and Vinson (2005) propose organizing ED staff members into teams consisting of one physician, two nurses, and one technician in a single suburban ED setting and report decreases in patient wait time and the Left Without Being Seen (LWBS) rate. None of these studies, however, consider the potential impact of physicians on each other's performance, and how it might be used to improve scheduling and staffing decisions.

3. Methodology

We exploit longitudinal data on ED physicians to examine whether and how independent and parallel processing physicians affect each other's performance. We identify a focal physician's peers in our setting as those physicians who are scheduled to work alongside the focal physician during the same shifts. We measure physician performance in terms of speed and quality using the LOS and 72-hour return metrics, respectively. A patient's LOS captures the time from when the patient checks into the ED to the time when s/he leaves. A shorter LOS implies that more patients can be moved through the ED per unit time. Therefore, LOS serves as a valid proxy for an ED physician's speed. The 72-hour return metric indicates patients' return to the ED within 72 hours of their initial discharge. When patients return to the ED, it is possible that during their first visit not all their medical issues were sufficiently addressed. Although controversial, this metric has been proposed and used as a measure of quality in the Emergency Medicine literature (Abualenain et al. 2013, Pham et al. 2011, Klasco et al. 2015). Nevertheless, we also re-run our analyses using two other quality metrics that measure how often a physician overcalls and undercalls his/her patients' illness severity. We observe similar results to those obtained by using the 72-hour rate of return as the main measure of quality.

To examine whether and how physicians influence each other in our setting, we model how a focal physician's performance, measured in terms of speed and quality, is affected by the presence of his/her peers. Specifically, our unit of analysis is focal physician i who works alongside his/her peer physician j while treating patient k at time t. The outcomes of interest which capture physician i's speed and quality at time t are the LOS and the 72-hour return of patient k, respectively. We define a focal physician's peer group at time t as all other physicians who are scheduled to work in the ED during the same time. Our dataset provides us with the identity of the main physician associated with each patient visit. Using this information, we are able to infer the identities of physician peers corresponding to each patient k's visit by identifying all physicians for whom there exists at least one assigned patient in our dataset whose contact-to-disposition time (the time from initial physician contact to the time when a disposition decision is issued) overlaps with that of patient k. We then construct a dataset comprising of all possible combinations of focal-peer physician pairs. This leaves us with 304,877 observations. We examine the effect of peer physician j's characteristics on focal physician i's performance by introducing treatment variables coded as 1 if peer physician j has a higher speed, higher quality, a different medical degree, or is of the opposite gender compared to focal physician i. In addition to differences in speed and quality, we included differences in variables such as medical degree and gender to examine if they also play a role in how physicians influence each other's performance.

Since our goal is to derive insights that could be useful in the area of physician scheduling (improving performance by making use of suitable pairs during shifts), we have chosen the one-to-one peer analysis approach for easier interpretation of our results. We use the quartiles of physician speed and quality measures to compare physicians along these dimensions. Figures 1 and

2 illustrate the distribution of the average speed and quality measures of the physicians in our dataset, respectively. In order to account for possible variations in physicians' performance over our study period, we measure a physician's performance at time t with respect to his/her patient visits prior to time t.

We control for patient k's characteristics including age, gender, race, and ESI level as well as focal physician i's characteristics with respect to patient k's visit at time t such as hospital admission (binary variable indicating whether the patient was admitted to the hospital after the ED visit) and the number of tests ordered. In addition, we control for familiarity between the focal and peer physicians. Similar to Huckman et al. (2009), we define physician familiarity at time t as the number of minutes a focal physician has spent working alongside his/her peer prior to time t. For the initial calculation of the physician familiarity metric, we use all observations associated with the first year of our sample study and exclude these observations from our final sample. This leaves us with 276,007 observations.

In addition to controlling for patient- and physician-level characteristics, we control for ED volume at time t. We include hour, day, month, and year fixed effects to control for any unobserved time-varying effects as well as physician fixed effects that absorb all observed and unobserved time-invariant physician characteristics. We cluster the error terms at the focal physician level to account for autocorrelation in the data.

We estimate the influence of peers in our setting using the following regression model:

$$Y_{ijkt} = \beta_1 T_{ijt} + \beta_2 P_{ikt} + \beta_3 R_{ikt} + \beta_4 E_{it} + \beta_5 Q_{ijt} + \gamma_t + \sigma_i + \epsilon_{ijkt}, \tag{1}$$

where Y_{ijkt} represents focal physician i's outcome of interest with respect to patient k's visit at time t while working alongside peer physician j. T_{ijt} denotes treatment variables corresponding to physicians i and j's relative characteristics at time t. P_{ikt} and R_{ikt} refer to vectors of physician i and patient k's characteristics at time t, respectively. E_{it} represents ED volume and Q_{ijt} refers to familiarity between physicians i and j at time t. γ_t refers to time fixed effects and σ_i denotes physician fixed effects. ϵ_{ijkt} is a statistical noise. We use OLS and logistic regression models to estimate the influence of peers on a focal physician's speed and quality, respectively.

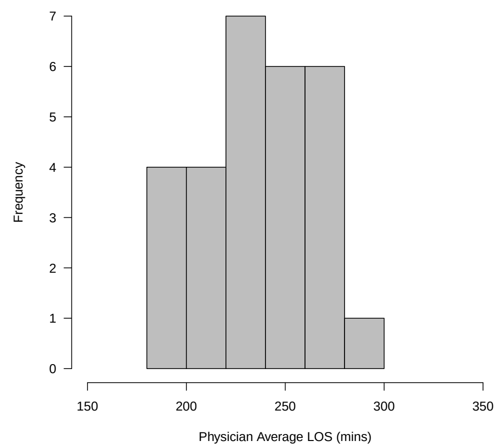

Figure 1 **Distribution of Physicians' Average LOS (in Minutes)**

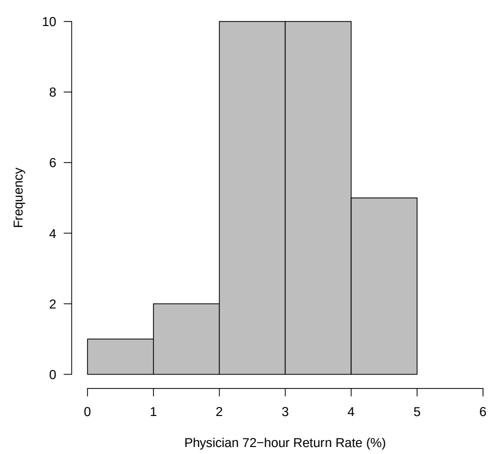

Figure 2 **Distribution of Physicians' 72-hr Rate of Return (in Percentage)**

4. Results and Discussion

Table 2 presents the effect estimates of faster and slower peers on a focal physician's speed and quality[2]. The statistically significant ($p < 0.001$) effect estimates of faster and slower peers on the focal physician's average patient LOS is positive and negative, respectively. Our results demonstrate that, in the presence of a faster peer, a focal physician's patient LOS increases by 5.2 minutes. Similarly, we observe that the focal physician's speed decreases by 5.1 minutes on average while working with a slower peer. As shown in Table 2, we do not find statistically significant evidence for the effects of faster and slower peers on a focal physician's average quality.

[2] Complete regression results are presented in Appendix A.

Table 2 Speed Effect Estimates

	LOS	Rate of Return
Faster Peer	5.2402***	0.0004
	(0.6709)	(0.0267)
Slower Peer	-5.1070***	0.0170
	(0.6293)	(0.0263)
Same-Speed Peer	-0.5166***	-0.0283
	(0.4324)	(0.0312)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3 presents the effect estimates of higher- and lower-quality peers on a focal physician's average speed and quality. We document a statistically significant negative effect of a higher-quality peer and positive effect of a lower-quality peer on a focal physician's average quality.

We do not, however, find statistically significant evidence for the influence of higher- and lower-quality peers on a focal physician's average speed. To ensure that our insights are not due to the measure of quality we use (the 72-hour rate of return), in Section 8 we derive the effect estimates of higher- and lower-quality peers using two alternative quality measures. Our findings reveal that the insights into how higher- and lower-quality physicians influence each other are not sensitive to how a physician's quality is measured.

To illustrate a more clear picture of the implications of these effects, in Table 2 we determine the effect estimates of a same-speed peer as a point of comparison. We find that the marginal effect of working alongside a faster (slower) peer is a 1.9-minute increase (4.6-minute decrease) in the focal physician's average patient LOS compared to working with a same-speed peer. Similarly, the effect estimate of a higher- (lower-) quality peer on a physician's average quality represents a marginal effect of 6% increase (20% decrease) in the odds for the return of the physician's patients within 72 hours of discharge.

In Appendix B, we present the effect estimates of a peer physician's medical degree and gender on a focal physician's performance. We do not observe any statistically significant effect on a focal physician's performance when using these variables. The lack of statistical significance, however, might be attributed to the lack of variations in these variables in our data (thus, a low power). For example, the number of female physicians in our data is fairly limited. Therefore, we leave it to future research to further explore the potential impact of these variables.

Table 3 Quality Effect Estimates

	LOS	Rate of Return
Higher-Quality Peer	-0.7553	0.0850*
	(0.6697)	(0.0459)
Lower-Quality Peer	0.6836	-0.2036***
	(0.8513)	(0.0533)
Same-Quality Peer	0.0667	0.6836***
	(0.5936)	(0.0424)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

5. Endogeneity in Physician Shift Assignment

As noted in Section 1, patients arriving to our partner hospital's ED are randomly assigned to physicians via an automated randomized algorithm. This removes potential endogeneity concerns that could bias our results, had the physicians self-selected their patients or if specific patients were seen by specific physicians. Estimation of peer influence in our setting, however, is still complicated because of the non-random assignment of physicians to shifts, which allows for the possibility of unobserved characteristics to confound the relationship between the treatment and the outcome. Although the unsystematic nature of physician assignment to shifts in our setting largely mitigates this concern, we conduct formal robustness tests to gain full confidence.

In the first test, we address physicians' potential self-selection in peer groups by constructing a sub-sample of observations in which shift assignments are as close as possible to random. Specifically, we construct a sub-sample of physicians' atypical patient visits with respect to their peers at the time of these visits. Atypical observations associated with each physician are identified as those which break out of a physician's scheduling pattern, and hence, could be viewed as a result of an exogenous shock (e.g., late change of schedule, physician calling in sick, etc.) to the physician assignment system. We identify these atypical observations as the least number of interactions (less than 8% of total patient visits) between each focal physician and his/her peers across the sample period. Specifically, for each physician in our dataset, we identify those peers with whom the physician has had the least number of interactions (less than 8% of the physician's total patient visits across the 4-year sample period). We then include all observations associated with the physician and those identified peer physicians in the subsample. We re-run our analysis on this sub-sample and find the results (presented in Tables 4 and 5) to be consistent with our main findings. This suggests that our results are unlikely to be driven by physicians' self-selection into peer groups.

Table 4 Atypical Subsample - Speed Effect Estimates

	LOS	Rate of Return
Faster Peer	6.3821***	0.0853
	(1.6332)	(0.1080)
Slower Peer	-3.9734*	0.0574
	(2.2060)	(0.0826)
Observations	27,248	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5 Atypical Subsample - Quality Effect Estimates

	LOS	Rate of Return
Higher-Quality Peer	-0.0703	0.2769**
	(0.5571)	(0.1096)
Lower-Quality Peer	0.6872	-0.2187*
	(0.9795)	(0.1228)
Observations	27,248	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

In the second test, we study the relationship between the number of high-performing physicians and ED volume. Specifically, for each patient k's visit at time t, we examine whether physician i's performance relative to his/her peers is correlated with ED volume at time t. Hence, a positive correlation between ED volume and the number of high-performing physicians might indicate that high-performing physicians are assigned to high-volume shifts. To test this, we make use of the following model:

$$E_{ikt} = \beta_1 T_{it} + \beta_2 P_{ikt} + \beta_3 R_{ikt} + \gamma_t + \epsilon_{ikt}, \tag{2}$$

where E_{ikt} denotes ED volume[3] at time t of patient k's visit, and T_{it} is an indicator variable coded as 1 if physician i is a higher-than-average performer in terms of speed and/or quality relative to his/her peers. P_{ikt} in model (2) represents patient k's characteristics at time t including age, race, gender, and ESI level, and R_{ikt} refers to physician i's characteristics with regards to treating

[3] As described earlier, ED volume at time t indicates the number of patients being seen by all physicians other than physician i.

patient k at time t including the number of tests ordered and the contact-to-disposition time in minutes. Lastly, γ_t in model (2) denotes time fixed effects and ϵ_{ikt} is a statistical noise.

It should be noted that we run model (2) two times; once where T_{it} denotes a higher-than-average physician with respect to speed and once where T_{it} indicates a high-performing physician with respect to quality. According to the results presented in Tables 6 and 7, we find no statistically significant relationship between ED volume and the number of high-performing physicians. The results of both tests address the concern of physicians' potential selection into peer groups and confirm that endogeneity issues are plausibly mitigated in our setting.

6. Robustness Checks

In this section, we present robustness checks to test the validity of our main findings and the approaches that establish them.

6.1. Propensity Score Matching

In order to ensure that physician pairs in our sample have similar distributions on all observable covariates related to patient and ED characteristics, we use matching to construct well-matched samples of physician pairs. Specifically, we use the nearest-neighbor propensity score matching without replacement within a specified caliper width[4]. Furthermore, we match observations using all patient- and ED-related covariates in our data, including patient age, gender, race, ESI level, and ED volume. The results of re-running model (1) on the matched samples of physician pairs are presented in Tables 8 and 9, and show that our main findings discussed in the previous sections remain fairly unchanged. To test whether this is due to the fact that our matching technique fails to improve the balance between the covariates, we compare the covariates across treatment and control groups before and after matching. Tables 1-6 in Appendix C present the mean baseline values of all covariates prior to matching across the treatment and control groups (stratified by different peer characteristics). We find that, without matching, the distribution of ED volume and some of the covariates related to patient characteristics including age and ESI level are relatively unbalanced across the treated and control groups. Tables 7-12 in Appendix C illustrate how matching improves the balance in the means of these covariates across the treatment and control samples.

[4] We use a caliper width of 0.1 times the pooled standard deviation of the logit of the propensity score (Rosenbaum and Rubin 1985).

Table 6 Effect Estimates - High-Performing Physicians (Speed)

	ED Volume
Faster Physician	0.2485
	(0.3076)
Observations	276,007
Time Fixed Effects	Yes
Controls	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7 Effect Estimates - High-Performing Physicians (Quality)

	ED Volume
Higher-Quality Physician	-0.0968
	(0.2735)
Observations	276,007
Time Fixed Effects	Yes
Controls	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8 Speed Effect Estimates - Matched Sample

	LOS	Rate of Return
Faster Peer	1.3717***	0.0073
	(0.4804)	(0.0229)
Slower Peer	-5.1593***	0.0387
	(0.5864)	(0.0324)
Observations	121,564	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 9 Quality Effect Estimates - Matched Sample

	LOS	Rate of Return
Higher-Quality Peer	-0.7553	0.0850*
	(0.6697)	(0.0459)
Lower-Quality Peer	0.6836	-0.2036***
	(0.8513)	(0.0533)
Observations	200,922	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Furthermore, we tested the overlap assumption to ensure that there is sufficient overlap in the distributions of covariates between the matched treated and control groups. For example, Figures 1-6 in Appendix D plot the kernel density of a few of the matching covariates for the faster peer effect analysis, and show that, the estimated densities of the treated and control groups have most of their respective masses in regions in which they overlap each other. We observed the same level of overlap for all other peer characteristics as well.

Finally, in order to ensure that our analysis is not sensitive to the choice of our matching technique, we also used alternative matching approaches including one-to-one matching with and without replacement and coarsened exact matching. In each case, our main inferences remained unchanged.

6.2. Alternative Model Specification

To ensure robustness of our results to different model specifications, we re-run our analysis using an alternative specification to model (1). Specifically, given the evidence provided in the related literature on the impact of ED congestion on performance (e.g., KC and Terwiesch 2009, Kuntz et al. 2015), we include both linear and quadratic forms of ED volume in our model. Specifically, we make use of the following model:

$$Y_{ijkt} = \beta_1 T_{ijt} + \beta_2 P_{ikt} + \beta_3 R_{ikt} + \beta_4 E_{it} + \beta_5 E_{it}^2 + \beta_6 Q_{ijt} + \gamma_t + \sigma_i + \epsilon_{ijkt}. \tag{3}$$

The regression results presented in Tables 10 and 11 confirm our main findings. Specifically, we observe statistically significant evidence for opposite-direction effects with respect to physicians' relative speed and quality.

7. Potential Mechanisms

The results discussed in the previous section show that both slower and lower-quality physicians have positive effects on a focal physician's average performance, while faster and higher-quality physicians negatively impact the performance of their peers. In this section, we explore two potential mechanisms which may drive these observed effects: resource spillover and social influence.

7.1. Resource Spillover

A setting such as an ED where shared (and limited) resources are often utilized to serve patients resembles a queuing system in which a server can potentially be impacted by spillover from other servers. For example, if a server is faster to use resources (e.g., issue tests), s/he can hinder the ability of the other server to use the same resources in a timely manner (for multi-stage ED queueing models with limited resources, see, e.g., Saghafian et al. (2012), Huang et al. (2015), and the

Table 10 Speed Effect Estimates - Alternative Model Specification

	LOS	Rate of Return
Faster Peer	3.8208***	-0.0022
	(0.8223)	(0.0279)
Slower Peer	-3.4183***	0.0215
	(0.7998)	(0.0302)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 11 Quality Effect Estimates - Alternative Model Specification

	LOS	Rate of Return
Higher-Quality Peer	-0.5782	0.1204***
	(0.8749)	(0.0437)
Lower-Quality Peer	1.0472	-0.1761***
	(1.3315)	(0.0512)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

references therein). Thus, a high-performing peer's negative effect on a focal physician's performance could be a result of a resource spillover effect. Furthermore, such resources are typically more binding during busy times when the ED volume is high. Hence, this spillover mechanism is expected to be more pronounced during busy periods. Therefore, to first gain an understanding of whether or not resource spillover could be the mechanism underlying our findings, we compare the magnitude of our findings among two sub-samples of focal-peer observations: one pertaining to shifts with higher-than-average patient volume (i.e., when resources are more constrained), and one comprising of shifts with lower-than-average volume (i.e., when resources are less constrained).

From the results presented in Tables 12 and 13, we observe that the effects corresponding to high-volume shifts are indeed larger in magnitude compared to those associated with low-volume shifts. This suggests that resource spillover is likely to be the driving force behind our results. However, to gain a deeper understanding, we next perform mediation analyses to more formally investigate the causal pathways that might explain our findings.

Table 12 Effect Estimates - Below Average ED Volume

	LOS	Rate of Return
Faster Peer	2.0990***	0.0422
	(0.6046)	(0.0371)
Slower Peer	-2.3293***	-0.0107
	(0.4333)	(0.0397)
Higher-Quality Peer	-1.2995	0.0881*
	(0.3658)	(0.0509)
Lower-Quality Peer	0.5966	-0.1339*
	(0.5485)	(0.0726)
Observations	138,003	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 13 Effect Estimates - Above Average ED Volume

	LOS	Rate of Return
Faster Peer	4.3900***	-0.0035
	(0.8955)	(0.0323)
Slower Peer	-4.2014***	0.0813
	(0.7952)	(0.0368)
Higher-Quality Peer	0.3032	0.1399***
	(0.9338)	(0.0478)
Lower-Quality Peer	0.9142	-0.2231***
	(1.0909)	(0.0678)
Observations	138,004	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

7.1.1. Mediation Analysis Our analysis thus far suggests that physicians' utilization of shared ED resources is likely to be the driving force behind our results. To further explore this potential driving force, we now make use of mediation analyses. In particular, we estimate the effect of peers' relative performance on a focal physician's performance via two potential mediators: physician test order count and admission rate. To this end, we use a bootstrapping approach (Hayes 2009) and employ linear and logistic regression models to estimate the direct and indirect influence of peers on a focal physician's speed and quality, respectively.

The results of our bootstrapping (with 10,000 iterations) approach are presented in Tables 14 and 15. With regards to peer influence on speed, our results (presented in Table 14) provide statistically significant evidence for the mediating effect of physician test order count. Specifically, we find that

Table 14 Mediation Effect Estimates - Physicians' Relative Speed

Mediation Analysis	Test Order Count	Avg Length of Stay
Faster Peer Influence	0.5466***	
	(0.0327)	
Test Order Count Effect		4.1645***
		(0.0301)
Faster Peer Direct Effect		13.971***
		(0.6753)
Faster Peer Indirect Effect		2.261***
		(0.1372)
Faster Peer Influence 95% Bias-Corrected Confidence Interval		[0.126, 0.16]
Slower Peer Influence	-0.7734***	
	(0.0331)	
Slower Peer Direct Effect		-14.889***
		(0.6594)
Slower Peer Indirect Effect		-3.189***
		(0.1526)
Slower Peer Influence 95% Bias-Corrected Confidence Interval		[0.163, 0.19]

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15 Mediation Effect Estimates - Physicians' Relative Quality

Mediation Analysis	Admission Rate	Avg Rate of Return
Higher-Quality Peer Influence	0.0019	
	(0.0013)	
Admission Rate Effect		-0.0070***
		(0.0009)
Higher-Quality Peer Direct Effect		0.00525
		(0.0002)
Higher-Quality Peer Indirect Effect		-0.00013
		(0.000007)
Higher-Quality Peer Influence 95% Bias-Corrected Confidence Interval		[-0.0376, 0.05]
Lower-Quality Peer Influence	-0.0009	
	(0.0013)	
Lower-Quality Peer Direct Effect		-0.0062
		(0.0002)
Lower-Quality Peer Indirect Effect		-0.000006
		(0.0001)
Lower-Quality Peer Influence 95% Bias-Corrected Confidence Interval		[-0.0214, 0.03]

Note: *p<0.1; **p<0.05; ***p<0.01

a peer's relative speed has a statistically significant effect on a focal physician's test order count (p <0.001), which in turn, negatively affects his/her speed (p <0.001). This is further supported by the 95% bias-corrected confidence interval for the size of the effect which excludes zero, suggesting significant mediation. We find no statistically significant evidence for the mediating effect of physician test order count on a focal physician's quality.

With regards to the second mediator, physician admission rate, our results (presented in Table 15) provide statistically significant evidence for the effect of a peer physician's admission rate on a focal physician's average quality (p <0.001). We find no statistically significant evidence for the effect of a peer's relative quality on the focal physician's admission rate. The 95% bias-corrected confidence intervals for the size of the effects do not exclude zero, suggesting the lack of significant mediation effect of physician admission rate.

Table 16 presents the correlation of variables corresponding to physician and patient average characteristics. We observe a negative correlation between physicians' average speed and test order count. This and our other tests imply that, on average, a faster peer utilizes less test orders compared to a focal physician. Intuitively, via ordering less tests, a physician can improve his/her speed. Furthermore, working alongside such a physician (i.e., a faster peer who is not using test services as much) makes the test services more available to the focal physician, which increases the likelihood of ordering more tests by the focal physician. Ordering more tests by the focal physician, in turn, translates to a reduction in his/her speed. Similarly, a slower peer hinders the ability of the focal physician from utilizing the test services, because a slower peer orders more tests on average, making test services less available to the focal physician. Therefore, the focal physician tends to decrease his/her test order count, resulting in an increase in his/her speed.

From Table 16, we observe that a physician's admission rate is negatively correlated with his/her 72-hour rate of return, and in turn, is positively correlated with the physician's quality. Hence, a higher-quality peer has a higher patient admission rate on average. Intuitively, by admitting more patients to the hospital post ED service, a physician can reduce the likelihood of his/her patients returning to the ED in the next few days. Admitting more patients to the hospital also implies more use of the resources that are needed for admitting patients. These mean that working alongside a higher-quality physician hinders a focal physician from utilizing such resources as needed. This results in a decrease in the focal physician's admission rate and, accordingly, his/her average quality. The same line of reasoning applies to a lower-quality peer with a lower admission rate, working alongside whom would allow the focal physician to admit more patients. This results in an increase in the focal physician's admission rate, and hence, an increase in his/her average quality.

Collectively, the results of our mediation analyses provide strong evidence for the mediating effect of physician test order count on a focal physician's speed. This provides further support for the resource spillover mechanism and underscores the influence of peers' utilization of shared resources (such as test services) on a focal physician's performance. However, we believe a carefully designed experiment (e.g., a randomized controlled trial) is needed to fully confirm these findings. We leave it to future research to conduct such an experiment and further clarify the important role of resource spillover as a main driving force behind how physicians influence each other.

Table 16 Correlation Matrix of Patient and Physician Average Characteristics

	Avg LOS	Avg Rate of Return	Admission Rate	Female (%)	Avg Age	Avg ESI	White (%)	Avg Test Count
Avg LOS	1.00	-0.23	0.10	0.39	0.30	-0.11	-0.16	0.36
Avg Rate of Return	-0.23	1.00	-0.19	0.06	-0.53	0.02	0.52	0.10
Admission Rate	0.10	-0.19	1.00	-0.30	0.46	-0.06	0.12	0.23
Female (%)	0.39	0.06	-0.30	1.00	0.05	-0.35	0.33	0.04
Avg Age	0.30	-0.53	0.46	0.05	1.00	0.07	0.02	-0.09
Avg ESI	-0.11	0.02	-0.06	-0.35	0.07	1.00	-0.24	0.08
White (%)	-0.16	0.52	0.12	0.33	0.02	-0.24	1.00	-0.15
Avg Test Count	0.36	0.10	0.23	0.04	-0.09	0.08	-0.15	1.00

Note: Observations are at a patient-visit level.

7.2. Social Influence

Peers can influence individuals through a number of social mechanisms including peer pressure, higher aspirations, and social norms. The relevant literature suggests that peers exert their influence through these channels when they serve as a commitment device imposing some social cost on a person whom they observe (Buechel et al. 2018). They can have a "pulling up" effect on individuals performing poorly or can have a "chocking" effect leading to under-performance. To examine whether social influence is the main driver of our findings, we examine whether the magnitude of the documented effects depends on the frequency of interactions between focal-peer physician pairs. If two physicians are rarely scheduled during the same shift, it is less likely they would work alongside each other in the future. Hence, it is unlikely that they would be responsive to some social cost they might impose on each other (Mas and Moretti 2009). To test this hypothesis, we divide our data into two sub-samples according to the physician familiarity metric. That is, we construct two sub-samples of patient visits: one associated with focal-peer physician pairs who scored higher than average on the familiarity metric, and one pertaining to the pairs who scored lower than average on this metric. We conduct the same matching and regression analyses on both sub-samples. Comparing the magnitude of the observed effects across the two sub-samples (presented in Tables 17 and 18) provides no statistically significant evidence that social influence is the driving force behind our results.

Put together, our results provide strong support for the resource spillover effect as the main driving force behind our findings, while indicating that social influence is not likely to play a significant role.

8. Alternative Quality Measures

In our main analysis, we made use of the 72-hour return rate to measure physician quality. As noted earlier, this is a widely used measure of quality of ED physicians, though not the only one. To gain further confidence about the validity of our results, and to ensure that our results are not merely due to the specific measure of quality we use, we now estimate the effects of higher- and lower-quality peers using alternative quality metrics. Specifically, we repeat our matching and regression analyses using two alternative quality metrics: one capturing how often a physician

Table 17 Effect Estimates - Below Average Familiarity

	LOS	Rate of Return
Faster Peer	0.8542*	-0.0098
	(0.4698)	(0.0329)
Slower Peer	-2.9700***	0.0641
	(1.1083)	(0.0292)
Higher-Quality Peer	-1.3397	0.1603***
	(0.9491)	(0.0530)
Lower-Quality Peer	0.4147	-0.2763***
	(1.1249)	(0.0743)
Observations	138,003	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 18 Effect Estimates - Above Average Familiarity

	LOS	Rate of Return
Faster Peer	1.5088*	0.0124
	(0.7987)	(0.0341)
Slower Peer	-2.0560***	0.0398
	(0.6804)	(0.0490)
Higher-Quality Peer	-0.3429	0.0503
	(1.1021)	(0.0526)
Lower-Quality Peer	0.5544	-0.0117
	(1.0734)	(0.0561)
Observations	138,004	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

overcalls his/her patients' illness severity and one related to how frequently a physician undercalls the severity of his/her patients' illness. Contrary to the 72-hour return metric which evaluates a physician's quality with regards to his/her discharged patients, these overcall and undercall metrics capture a physician's quality with respect to his/her admitted patients[5]. We define the overcall metric as the percentage of a physician's patients who are admitted to the hospital (after their ED service) by him/her but are then discharged within 12 hours of their admission. Similarly, the undercall metric measures the percentage of a physician's patients who are admitted to the hospital by him/her but are then upgraded from a floor bed to a more intensive area of care within 24 hours of their admission. Thus, these measures capture how well a physician makes the correct call about

[5] Both admitted and discharged status refer to decisions made by the physician post ED service.

the needs and illness severity of his/her patients.[6] Tables 19 and 20 present the effect estimates of higher- and lower-quality peers using these overcall and undercall measures, respectively.

In both cases, our inferences are similar to those made in the previous sections using the 72-hour rate of return as the measure of quality. Specifically, the statistically significant effect estimates of higher- and lower-quality peers with respect to the undercalling rate (presented in Table 19), are positive and negative, respectively. Furthermore, the results presented in Table 20 show effect estimates of higher- and lower-quality peers with respect to the overcalling rate on a focal physician's average quality, respectively. The effects presented in Table 20 are, however, not statistically significant, which is most likely due to a lack of power in our analyses of the overcalling metric (unlike 72-hour readmission cases, the number of patients with an overcall is fairly limited in our sample). Nonetheless, in terms of direction of the effects, our results show consistency with our main findings: higher-quality peers negatively affect a focal physician's average quality while lower-quality peers have a positive effect on the average quality of the focal physician.

9. Managerial Implications

We now summarize some of the main implications of our results. First, our findings allow hospital/ED administrators to better match/pair physicians working in the same shifts. Specifically, our study sheds light on ways to improve the performance of ED physicians by pairing them with the "right" peers. Our findings show that scheduling physicians alongside peers with whom they utilize shared resources more efficiently could have a positive effect on the overall performance. Importantly, unlike many other process or quality improvement interventions, our findings allow hospitals to improve performance without substantial investments and by only changing how physicians are paired.

Second, the insights generated from our results could assist hospital administrators in the area of physician training. While scheduling high-performing physicians (in terms of both speed and quality) with lower-than-average performers could be beneficial to the overall operations of an ED, it could also create learning opportunities for the low-performing physicians. More broadly, since most training programs require individuals to work alongside another physician, our findings can be helpful in designing more effective training programs.

[6] Of note, the 12- and 24-hour thresholds used for defining these metrics are based on inputs from our ED physician collaborators. However, we also perform sensitivity analyses on these thresholds and observe that our main results hold.

Table 19 Undercall Effect Estimates

	LOS	24-Hour Upgrade
Higher-Quality Peer	-1.3584	0.6956***
	(1.0719)	(0.1630)
Lower-Quality Peer	0.7552	-0.5078***
	(1.1258)	(0.1361)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 20 Overcall Effect Estimates

	LOS	12-Hour Discharge
Higher-Quality Peer	-1.8123	0.0193
	(1.0624)	(0.1065)
Lower-Quality Peer	1.8464	-0.0273
	(1.1749)	(0.0890)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Finally, it is important to consider the financial implications of our findings for hospitals. We find the marginal effects of working alongside peers with opposite characteristics to be greater than those of the baseline case of working with homogeneous peers. As illustrated in Figures 3 and 4, our results suggest that matching a physician with a slower peer results in a 10% improvement in the focal physician's average LOS. Similarly, pairing a focal physician with a lower-quality peer leads to a 6% improvement in the focal physician's readmission rate. These 10% and 6% improvements in LOS and readmissions suggested by our findings can translate to substantial financial gains for hospitals based on the estimates provided in the literature. For example, the literature suggests that a 15-minute decrease in LOS in the ED could result in $1.4 million of additional revenue for a hospital (The Becker's Hospital Review 2016). Similarly, the cost of hospital readmissions is estimated to be close to $26 billion annually (Wilson et al. 2019). Given these, we hope that future research can make use of our results and offer hospital administrators superior ways of "pairing" physicians. If our estimates are accurate, hospital administrators should find enough financial incentives to follow such superior ways, and accordingly, implement changes in their physician scheduling practices.

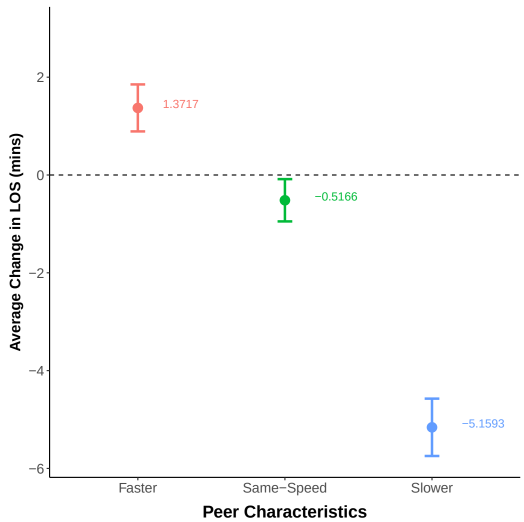

Figure 3 **Effect Estimates - Speed**

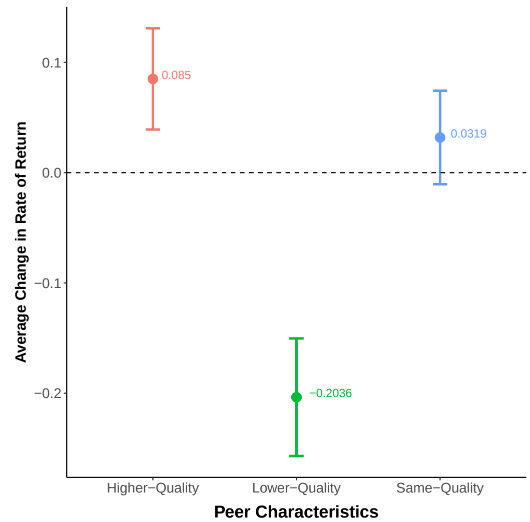

Figure 4 **Effect Estimates - Quality**

10. Limitations

It is important to note the limitations of our study. First, while we control for various observed factors that affect physician performance and provide strong evidence to ensure that our results are not attributable to confounding effects, there might still be factors affecting physician performance that are unobservable in our dataset. Second, our analysis does not consider how learning among physicians might shape the long-term effects of peers on physician performance. Prior research has shown that an individual's long-term performance improves over time as a result of learning from peers (Chan et al. 2014, Edmondson et al. 2001). Our focus in this study has been on shorter-term (i.e., operational level) effects. However we note that future research can focus on the longer-term effects, and thereby generate important insights into potential learning effects that might be induced by physician peers. Finally, while we use simple measures of physician performance to gauge physicians' speed and quality, it should be noted that there are various other metrics, both qualitative and quantitative, that can be used. Future research can extend our analyses by using such measures and by removing some of the limitations of our study. Given the importance of gaining a better understanding of how physicians influence each other's performance, we expect to see more studies in this vein in the near future.

11. Conclusion

In this study, we examine how physicians who work in parallel to one another affect each other's performance. In particular, our results demonstrate that a faster peer has a negative effect and a slower peer has a positive average effect on a focal physician's speed. Similarly, a higher-quality peer is found to negatively impact a focal physician's average quality while a lower-quality peer is shown to positively affect the average quality of the focal physician. We find that these opposite-direction effects are due to the utilization of shared resources among physicians. Notably, our findings show that physicians influence each other's speed and quality through affecting each other's test ordering behavior and admission rate, respectively.

Our findings have important practical implications for improving the performance of physicians by highlighting the need to consider physician shared utilization of resources as an important component of effective physician staffing strategies. In particular, our findings can be used by hospital administrators when designing (a) staffing and shift schedules, and (b) training programs. In both of these, understanding how physicians influence each other can have a significant impact on the overall performance of hospitals. Given the importance of gaining such an understanding, we hope to see further studies that quantify ways through which physicians impact their peers.

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Appendix A: Regression Results - Main Effect Estimates

Table 1 Regression Results - Faster Peer

	(1) LOS	(2) 72-hour Rate of Return
Patient Age	0.0936***	0.0011
	(0.0222)	(0.0017)
Patient Gender	2.0878***	-0.0590
	(0.7093)	(0.0578)
Patient Race	-0.1318	0.1774
	(1.0056)	(0.1094)
Patient ESI	-1.3682	-0.1356***
	(1.0936)	(0.0518)
Patient Admission	19.8987***	-0.5681***
	(1.6904)	(0.0907)
ED Volume	9.9204***	-0.0021
	(0.5318)	(0.0035)
US Order Count	11.7711***	-0.1320
	(1.0573)	(0.1005)
MRI Order Count	32.7309***	0.0054
	(2.5395)	(0.1770)
Radiology Order Count	8.7060***	-0.3119***
	(0.9788)	(0.0494)
IV Med Fluid Order Count	9.0816***	0.0299
	(0.6090)	(0.0182)
Lab Order Count	1.9591***	-0.0239***
	(0.1219)	(0.0078)
CT Order Count	15.9243***	-0.1779**
	(0.9580)	(0.0664)
Faster Peer	5.2402***	0.0004
	(0.6709)	(0.0267)
Constant	127.782***	-2.1981***
	(8.4191)	(0.5344)
Observations	276,007	276,007
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2 Regression Results - Slower Peer

	(1) LOS	(2) 72-hour Rate of Return
Patient Age	0.0940***	0.0001
	(0.0204)	(0.0009)
Patient Gender	2.4324**	-0.0920*
	(1.1615)	(0.0478)
Patient Race	-1.3517	0.1357
	(0.9245)	(0.1020)
Patient ESI	-0.8567	-0.0914**
	(1.4441)	(0.0432)
Patient Admission	18.7836***	-0.4328***
	(3.3336)	(0.0888)
ED Volume	11.4024***	-0.0054
	(1.0729)	(0.0036)
US Order Count	10.3093***	-0.0928
	(1.5695)	(0.0613)
MRI Order Count	25.6152***	0.0013
	(4.2991)	(0.1497)
Radiology Order Count	6.7595***	-0.2866***
	(1.3282)	(0.0434)
IV Med Fluid Order Count	7.7752***	0.0174
	(0.8247)	(0.0163)
Lab Order Count	1.7228***	-0.0328***
	(0.2751)	(0.0059)
CT Order Count	13.1314***	-0.0656
	(1.8237)	(0.0585)
Slower Peer	-5.1070***	0.0170
	(0.6293)	(0.0263)
Constant	131.6160***	-2.0948***
	(6.4960)	(0.3138)
Observations	276,007	276,007
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3 Regression Results - Higher-Quality Peer

	(1) LOS	(2) 72-hour Rate of Return
Patient Age	0.1413***	-0.0011
	(0.0157)	(0.0011)
Patient Gender	2.1213***	-0.0653
	(0.5222)	(0.0481)
Patient Race	-2.0426*	0.1687**
	(0.9208)	(0.0729)
Patient ESI	1.1299	-0.0635*
	(0.8837)	(0.0380)
Patient Admission	20.6569***	-0.4326***
	(1.6434)	(0.0641)
ED Volume	10.2164***	-0.0045
	(0.4919)	(0.0036)
US Order Count	11.9380***	-0.1570**
	(1.0656)	(0.0734)
MRI Order Count	31.1662***	0.0300
	(2.2902)	(0.1374)
Radiology Order Count	8.3117***	-0.2646***
	(0.8279)	(0.0296)
IV Med Fluid Order Count	8.9931***	0.0130
	(0.5144)	(0.0128)
Lab Order Count	1.8106***	-0.0309***
	(0.1309)	(0.0062)
CT Order Count	15.1579***	-0.0643
	(1.1683)	(0.0457)
Higher-Quality Peer	-0.7553	0.0850*
	(0.6697)	(0.0459)
Constant	132.9968***	-2.3875***
	(7.9453)	(0.3245)
Observations	276,007	276,007
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4 Regression Results - Lower-Quality Peer

	(1) LOS	(2) 72-hour Rate of Return
Patient Age	0.1145***	-0.0012
	(0.0190)	(0.0011)
Patient Gender	2.4443***	-0.0657**
	(0.7368)	(0.0335)
Patient Race	-1.4484**	0.1795**
	(0.7145)	(0.0794)
Patient ESI	0.9877	-0.0622
	(0.8922)	(0.0468)
Patient Admission	18.7906***	-0.3885***
	(2.5009)	(0.0571)
ED Volume	10.9392***	-0.0039
	(0.8478)	(0.0028)
US Order Count	11.2892***	-0.1262*
	(1.5698)	(0.0696)
MRI Order Count	27.5377***	0.0415
	(3.1634)	(0.1477)
Radiology Order Count	7.5608***	-0.2630***
	(1.1230)	(0.0488)
IV Med Fluid Order Count	8.2593***	0.0185
	(0.7901)	(0.0153)
Lab Order Count	1.7048***	-0.0306***
	(0.2115)	(0.0052)
CT Order Count	14.1751***	-0.0737*
	(1.6722)	(0.0419)
Lower-Quality Peer	0.6836	-0.2036***
	(0.8513)	(0.0533)
Constant	132.5669***	-2.1545***
	(7.4841)	(0.3136)
Observations	276,007	276,007
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix B: Degree and Gender Effect Estimates

Table 1 Degree Effect Estimates

	LOS	Rate of Return
Different-Degree Peer	1.6196	0.0044
	(1.0182)	(0.0448)
Same-Degree Peer	4.6037	-0.0514
	(3.6240)	(0.0018)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2 Gender Effect Estimates

	LOS	Rate of Return
Opposite-Gender Peer	0.6650	0.0116
	(0.7033)	(0.0222)
Same-Gender Peer	-2.2945	-0.0090
	(0.9967)	(0.0345)
Observations	276,007	
Time Fixed Effects	Yes	
Physician Fixed Effects	Yes	
Controls	Yes	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix C: Covariate Balance Tables

Table 1 Pre-Matching Covariate Balance Stratified by Faster Peer

	0	1	p	test SMD
Number of Observations	169547	106460		
ED Volume (mean (sd))	27.24 (14.96)	28.41 (13.07)	<0.001	0.084
Patient Age (mean (sd))	59.31 (20.64)	59.61 (20.53)	<0.001	0.014
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.926	<0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.017	0.009
Patient ESI (mean (sd))	2.96 (0.55)	2.96 (0.54)	0.441	0.003

Table 2 Pre-Matching Covariate Balance Stratified by Slower Peer

	0	1	p	test SMD
Number of Observations	170617	105390		
ED Volume (mean (sd))	28.16 (13.35)	26.94 (15.63)	<0.001	0.084
Patient Age (mean (sd))	59.53 (20.56)	59.26 (20.65)	0.001	0.013
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.752	0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.179	0.005
Patient ESI (mean (sd))	2.96 (0.54)	2.96 (0.55)	0.473	0.003

Table 3 Pre-Matching Covariate Balance Stratified by Higher-Quality Peer

	0	1	p	test SMD
Number of Observations	175511	100496		
ED Volume (mean (sd))	27.78 (14.87)	27.54 (13.16)	<0.001	0.017
Patient Age (mean (sd))	59.46 (20.60)	59.37 (20.60)	0.244	0.005
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.759	0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.517	0.003
Patient ESI (mean (sd))	2.96 (0.54)	2.96 (0.54)	0.760	0.001

Table 4 Pre-Matching Covariate Balance Stratified by Lower-Quality Peer

	0	1	p	test SMD
Number of Observations	177739	98268		
ED Volume (mean (sd))	27.57 (13.66)	27.91 (15.32)	<0.001	0.023
Patient Age (mean (sd))	59.38 (20.61)	59.51 (20.57)	0.102	0.007
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.407	0.003
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.480	0.003
Patient ESI (mean (sd))	2.96 (0.54)	2.96 (0.54)	0.949	<0.001

Table 5 Pre-Matching Covariate Balance Stratified by Different-Degree Peer

	0	1	p	test SMD
Number of Observations	230190	45817		
ED Volume (mean (sd))	27.80 (14.44)	27.11 (13.41)	<0.001	0.050
Patient Age (mean (sd))	59.34 (20.60)	59.87 (20.55)	<0.001	0.026
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.295	0.005
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.352	0.005
Patient ESI (mean (sd))	2.96 (0.54)	2.95 (0.55)	0.087	0.009

Table 6 Pre-Matching Covariate Balance Stratified by Opposite-Gender Peer

	0	1	p	test SMD
Number of Observations	213040	62967		
ED Volume (mean (sd))	27.77 (14.54)	27.40 (13.33)	<0.001	0.027
Patient Age (mean (sd))	59.41 (20.62)	59.49 (20.51)	0.394	0.004
Female Patient (mean (sd))	0.54 (0.50)	0.53 (0.50)	0.001	0.015
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.130	0.007
Patient ESI (mean (sd))	2.96 (0.54)	2.96 (0.54)	0.899	0.001

Table 7 Post-Matching Covariate Balance Stratified by Faster Peer

	0	1	p	test SMD
Number of Observations	60782	60782		
ED Volume (mean (sd))	27.61 (12.62)	27.62 (12.63)	0.973	<0.001
Patient Age (mean (sd))	59.32 (20.57)	59.31 (20.57)	0.991	<0.001
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	1.000	<0.001
White Patient (mean (sd))	0.92 (0.27)	0.92 (0.27)	1.000	<0.001
Patient ESI (mean (sd))	3.01 (0.54)	3.01 (0.54)	1.000	<0.001

Table 8 Post-Matching Covariate Balance Stratified by Slower Peer

	0	1	p	test SMD
Number of Observations	105390	105390		
ED Volume (mean (sd))	26.90 (13.09)	26.94 (15.63)	0.590	0.002
Patient Age (mean (sd))	59.29 (20.40)	59.26 (20.65)	0.805	0.001
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.910	<0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.907	0.001
Patient ESI (mean (sd))	2.96 (0.55)	2.96 (0.55)	0.682	0.002

Table 9 Post-Matching Covariate Balance Stratified by Higher-Quality Peer

	0	1	p	test SMD
Number of Observations	100461	100461		
ED Volume (mean (sd))	27.54 (13.01)	27.51 (12.89)	0.621	0.002
Patient Age (mean (sd))	59.45 (20.59)	59.37 (20.59)	0.356	0.004
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.907	0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.937	<0.001
Patient ESI (mean (sd))	2.96 (0.54)	2.96 (0.54)	0.155	0.006

Table 10 Post-Matching Covariate Balance Stratified by Lower-Quality Peer

	0	1	p	test SMD
Number of Observations	98217	98217		
ED Volume (mean (sd))	27.73 (13.78)	27.83 (14.01)	0.113	0.007
Patient Age (mean (sd))	59.44 (20.57)	59.51 (20.57)	0.468	0.003
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.860	0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.949	<0.001
Patient ESI (mean (sd))	2.96 (0.55)	2.96 (0.54)	0.346	0.004

Table 11 Post-Matching Covariate Balance Stratified by Different-Degree Peer

	0	1	p	test SMD
Number of Observations	45809	45809		
ED Volume (mean (sd))	27.11 (12.80)	27.07 (12.91)	0.643	0.003
Patient Age (mean (sd))	59.97 (20.43)	59.87 (20.56)	0.445	0.005
Female Patient (mean (sd))	0.54 (0.50)	0.54 (0.50)	0.853	0.001
White Patient (mean (sd))	0.91 (0.28)	0.91 (0.28)	0.630	0.003
Patient ESI (mean (sd))	2.95 (0.54)	2.95 (0.55)	0.288	0.007

Table 12 Post-Matching Covariate Balance Stratified by Opposite-Gender Peer

	0	1	p	test SMD
Number of Observations	61601	61601		
ED Volume (mean (sd))	27.14 (12.56)	27.13 (12.79)	0.957	<0.001
Patient Age (mean (sd))	59.49 (20.31)	59.47 (20.51)	0.839	0.001
Female Patient (mean (sd))	0.53 (0.50)	0.53 (0.50)	1.000	<0.001
White Patient (mean (sd))	0.92 (0.28)	0.92 (0.28)	1.000	<0.001
Patient ESI (mean (sd))	2.96 (0.54)	2.96 (0.54)	1.000	<0.001

Appendix D: Kernel Density Plots - Faster Peer Effect

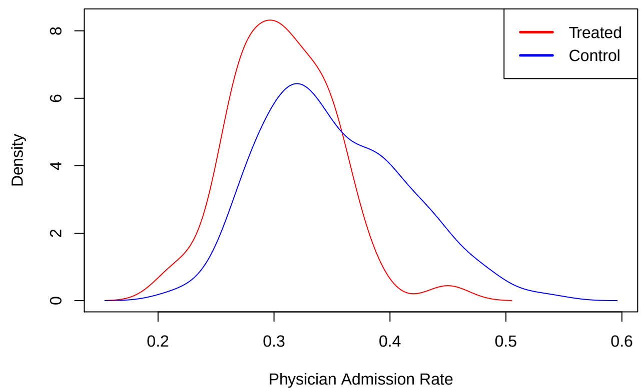

Figure 1 Kernel Density Graph - Admission Rate

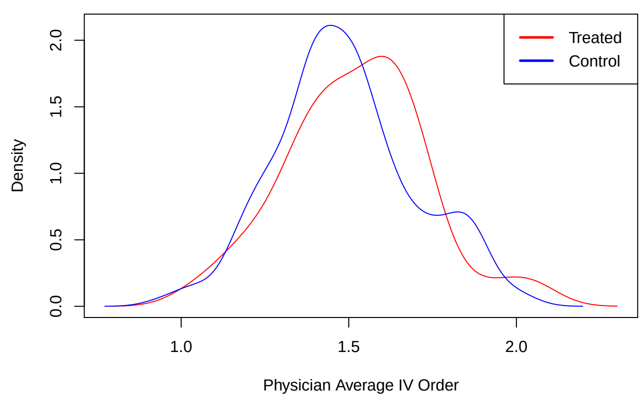

Figure 2 Kernel Density Graph - Average IV Order

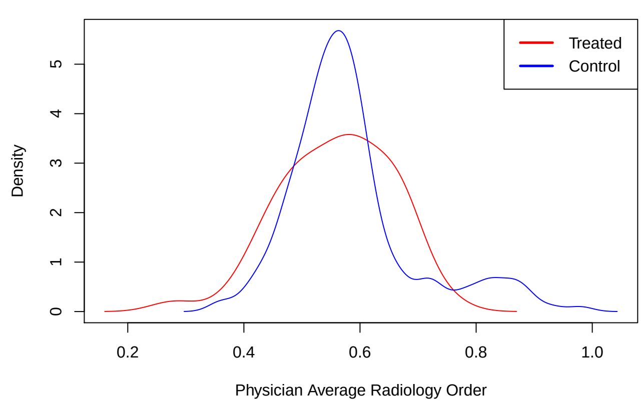

Figure 3 Kernel Density Graph - Average Radiology Order

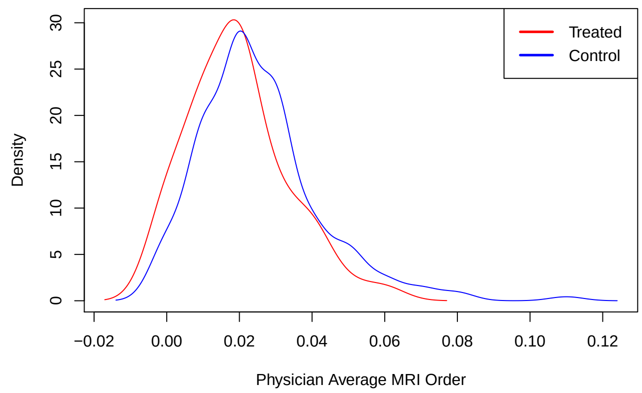

Figure 4 Kernel Density Graph - Average MRI Order

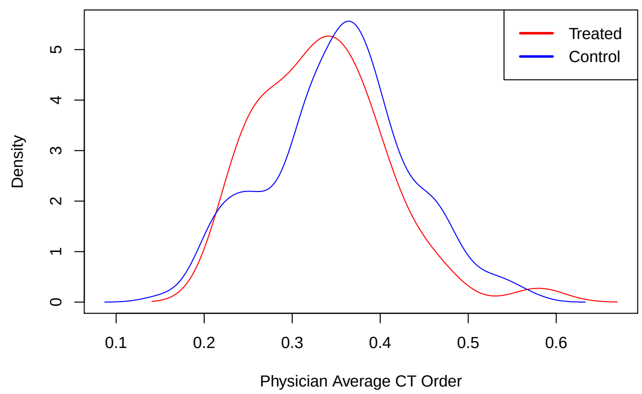

Figure 5 Kernel Density Graph - Average CT Order

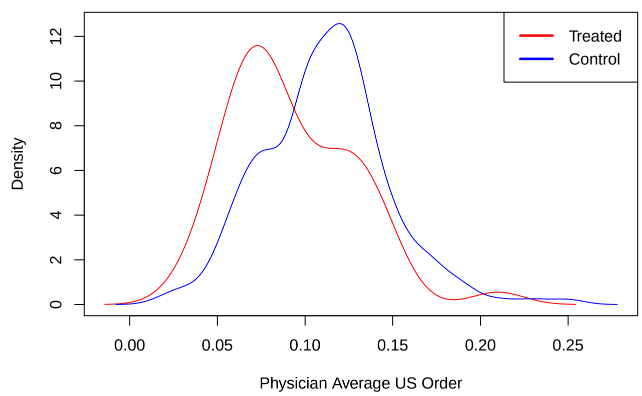

Figure 6 Kernel Density Graph - Average US Order