Do Physicians Influence Each Other's Performance? Evidence from the Emergency Department

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Understanding potential channels through which physicians impact each other's performance can yield new insights into better management of hospitals' operations. We use evidence from Emergency Medicine to study whether and how physicians who work alongside each other during the same shifts affect each other's performance. We find strong empirical evidence that physicians affect each other's speed and quality in our setting. Specifically, our results show that a faster peer decreases while a slower peer increases the average speed of a focal physician. Similarly, we find that a higher-quality peer decreases a focal physician's average quality while a lower-quality peer increases the average quality of the focal physician. We identify resource spillover from peers' utilization of shared resources as the main driver of the observed effects and show that during high-volume shifts (i.e., when the shared resources are most constrained), the magnitude of the effects increases. We provide further evidence for the resource spillover mechanism by showing that physicians influence their peers' speed and quality through affecting their test order count and admission rate, respectively. While some of these observed effects tend to be long-lived, we find that their magnitudes are fairly heterogeneous among physicians. In particular, our results show that newly-hired and/or high-performing physicians are typically more sensitive to the influence of their peers. Finally, we draw conclusions from our results and discuss how they can be utilized by hospital administrators to improve the overall performance of physicians via better scheduling patterns that require specific physicians to work during the same shifts.

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

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1. Introduction

Decisions regarding how to schedule physicians during the same shifts are made everyday in hospitals. Making such decisions, however, without considering whether and how physicians who work alongside each other affect each other's performance could have significant implications. In this study, we examine how physicians who work during the same shifts influence each other's 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). Thus, understanding whether and how physicians influence each other's speed and quality in EDs can generate insights into physician pairing and scheduling methods that can ultimately lead to more effective and efficient care delivery mechanisms.

In order to identify and quantify the potential influence of peers, we exploit longitudinal data on ED physicians and estimate peer influence on a focal physician's performance. We address the question of whether peer physicians' characteristics including relative performance (measured in terms of speed and quality), type of medical degree (M.D. vs. D.O.), and gender affect a focal physician's performance. While prior research has identified peer networks using physical proximity (Manchanda et al. 2008) and social networks (Trusov et al. 2010), we define 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 Length of Stay (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, since 72-hour rate of return might not be a perfect measure of quality, 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, and observe similar results to those obtained by using the 72-hour rate of return metric.

Our results establish statistically significant evidence for peer physician influence. Specifically, we find 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, a higher-quality peer is shown to negatively impact a focal physician's quality, and a lower-quality peer is found to positively affect the focal physician's quality on average.

We explore two potential mechanisms that might be driving our results: social influence and resource spillover. Our findings indicate that spillover from physicians' utilization of shared ED resources is the main driver of the effects we observe. In particular, we find that the magnitude of the documented effects increases during high-volume shifts (i.e., when resources are more constrained), suggesting that the existence of limited shared resources in the ED plays an important role in how physicians affect each other's speed and quality. This insight has potential implications in a variety of services in which workers utilize shared scarce resources, and sheds light on an interesting connection between constrained capacity and influence of workers on each other's performance.

We further explore the resource spillover mechanism by examining the effect of peers on a focal physician's average test order count. Our results show that a faster peer increases the focal physician's test orders per patient visit on average by allowing the focal physician to utilize the test ordering services as needed. Ordering more tests, in turn, results in a reduced speed for the focal physician. A slower peer, however, blocks the focal physician from using the test ordering services in a timely manner. This 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. Given the positive relationship between a physician's admission rate and quality in our dataset, we infer that 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, quality on average.

We further examine whether our observed opposite-directional effects are short-lived or persistent over time. Specifically, we examine the existence and magnitude of the documented effects among a sub-sample of physicians who worked consistently throughout our study period. Our findings present strong evidence for peer influence on a focal physician's average speed throughout our study period, indicating that the influence of peers on a focal physician's speed is persistent over time. In contrast, the effects with respect to physicians' relative quality appear to be short-lived. These findings suggest that while peer influence on speed is orthogonal to shift composition, the influence of peers on quality seems to be dependent on time-variable factors that are unobservable in our study.

We also investigate the heterogeneity in peer influence with regards to physicians' job tenure and relative performance by comparing the magnitude of the documented effects among heterogeneous sub-samples of physicians. We find that newly-hired physicians are more sensitive to the influence of their slower and lower-quality peers compared to physicians with more years of tenure. This is consistent with the notion that as physicians gain more experience in their work environment, they become less responsive to the impact of their peers. In addition, our results show that the magnitude of the observed effects is greater among higher-than-average performers. The directions and magnitude of the heterogeneous effects that we observe among physicians are consistent with our overall finding that scheduling diverse physicians during the same shift would improve the overall performance of a hospital's ED.

Our findings have important practice-related implications for improving the operations of EDs. Given the large body of literature 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 by making use of our results on how physicians affect each other's performance. 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 EDs.

Finally, we note that to correctly estimate the impact that physicians have on each other's speed and quality, one must consider potential sources of endogeneity and confounding. For example, although there exists no systematic scheduling scheme in our setting, physicians' preferences in shift assignments might still cause endogeneity problems. We conduct various robustness tests to address physicians' selection into peer groups and mitigate the concern of spurious correlations with omitted variables. Moreover, to make sure that our comparisons are made using comparable observations, we use the nearest-neighbor propensity score matching without replacement to construct a matched sample of physicians that achieve balance across a set of observable covariates related to physician, patient, and ED characteristics including hospital admission (binary variable), number of test orders per patient visit, patient age, gender, race, Emergency Severity Index (ESI) level (a five-level triage scale with 1 indicating the most urgent and 5 denoting the least urgent case), and ED volume[1]. We re-run our analysis on this matched sample of focal-peer physician pairs that achieve balance on all observable covariates, and observe that our inferences remain the same. We also perform a variety of other robustness checks that involve using alternative variable definitions and model specifications. Overall, our various tests give us confidence that our findings are fairly robust and not sensitive to endogeneity or other misspecification issues that can make our results biased. Furthermore, our results could have significant financial implications for hospitals. Given the mounting pressure on hospitals to reduce costs (e.g., payment reforms), healthcare providers aim to reduce LOS and increase the number of patients they serve per bed per unit of time. Our insights into ways physicians impact each other's speed and quality could aid providers in achieving this goal without sacrificing quality. 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.

Our findings also have a few essential theoretical implications. First, to the best of our knowledge, our work is among the first to shed light on opposite-direction effects in how co-workers influence

[1] For the purposes of this study, we define ED volume as the total number of patients being seen by all physicians other than the focal physician.

each other's performance (working alongside a faster and/or higher quality peer degrades a focal worker's speed and/or quality, respectively). This is partially due to the fact that we study an environment that is different in various dimensions than those considered in the previous literature. For example, the literature on peer effects (see, e.g., Mas and Moretti 2009, Chan et al. 2014, Steinbach et al. 2016) has generally focused on settings where peers work in teams towards a common goal. The setting of our study, a hospital's ED, comprises physicians who are individually responsible for serving their patients. Similarly, prior studies in the literature have mainly examined peer effects in settings where (a) workers can monitor each other's actions and outcomes (e.g., slowing down by a cashier in a supermarket can be immediately observed by another cashier), and (b) less-than-desirable performance by a worker has negative externalities on his/her co-workers (e.g., when a cashier slows down, customers move to the queue of another cashier, increasing his/her workload). In our research setting, actions and outcomes that we study are not immediately observable by co-workers, since patients are almost always served in private rooms by individual physicians assigned to them, and measuring outcomes such as LOS or readmission rates requires data analysis and appropriate patient risk adjustments. Furthermore, unlike the extant literature, there are no significant immediate negative externalities in our research setting, because patients are "pushed" to the physicians using a randomized rotational assignment algorithm that ensures fairness; see Traub et al. 2016. Thus, for example, slowing down in serving patients by a physician does not increase the workload of another physician. Second, while the above-mentioned literature establishes mechanisms such as "social influence" or "free-riding" as main driving forces, we shed light on "resource spillover" and related roadblocking behaviors (e.g., a physician who is slow because of ordering too many tests hinders the ability of another physician to make use of test services in a timely manner) as the main mechanism behind our findings.

2. Related Studies

Our study is mainly related to two streams of literature: studies on how workers influence each other's performance, and operations management literature surrounding physicians' speed and quality. Within the first stream, Sacerdote (2001) utilizes random assignment of freshman year roommates and dormmates at Dartmouth College to document the effect of peers on grade point average and fraternity membership. Using a controlled field experiment, Falk and Ichino (2006) find that students asked to stuff letters into envelopes perform faster when they work in pairs than when they work alone. The authors further show that low-productivity workers are the most sensitive to the behavior of peers. Mas and Moretti (2009) study peer effects among cashiers in a supermarket chain and attribute the positive effect of productive peers on a worker's productivity to increased social pressure. Jackson et al. (2009) and Azoulay et al. (2010) offer evidence for peer effects in the workplace that are induced by knowledge spillover. Negative effects of peers have also been documented in the literature, though rarely and also in studies that differ from ours in research goals and setting, among others. For example, Steinbach et al. (2016) compare the performance of workers in a group production process working alone and in the presence of peers and identify free-riding as the main channel through which negative effects among workers emerge (see also Cornelissen et al. 2017).

Peer effects among physicians have been studied in prior research using exogenous sources of variation in peer characteristics. For example, Iyengar et al. (2015) examine peer effects in the context of prescription choices of physicians and find that peer influence among physicians can affect both the trial and repeat prescription orders of a risky new drug. In a different setting, Huesch (2011) examines intra- and inter-group practice spillovers among a group of cardiologists by observing their use of a new medical device, and presents strong evidence for intra-group peer influence. While our study is related to how peers influence each other's performance, the focus of this paper is not to estimate peer effects. Rather, we examine whether and how physicians who work alongside each other during the same shifts influence each other's performance by conducting pair-wise comparisons of physicians with different characteristics working during the same shifts.

Our study is also related to the behavioral operations management literature surrounding worker speed and quality. A number of studies in the literature have established the effects of learning among peers. For example, Diwas et. al (2013) study individual learning among a group of cardio-thoracic surgeons and find that individuals learn more from their own successes than from their own failures, but they learn more from the failures of others than from others' successes. Aksin et. al (2015) find a positive association between diversity of partnership experience and efficiency at the London Ambulance Service. While these studies find positive effects of peers derived through learning, our study finds opposite-directional effects of peers. Specifically, our findings show that physicians' use of shared ED resources affect their performance while working together during the same shift. Our study contributes to this literature by showing a different channel, not explored by the extant literature, through which physicians adjust their speed and quality in response to their peers. 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. The authors also demonstrate a positive association between overwork and risk of mortality. 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, shared resources being overstrained, medical staff and equipment overload for the slowdown effect. The effects of workload on physician quality have also been documented in the literature. Kuntz et al. (2014) 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 and 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 these studies by demonstrating how physicians affect each other's speed and/or quality, and highlights the need to consider peer influence in staffing and planning models. In addition, we provide empirical evidence for physician influencing each other's performance through affecting each other's test ordering behavior. 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 rate (Anderson et al. 2012), our insights offer hospital administrators with a potential strategy to alleviate these negative consequences by making use of peer influence.

3. Empirical Setting and Data

We utilize a large dataset collected from the ED of our partner hospital, which is one of the leading hospitals in the U.S. 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 and related potential cherry-picking behaviors that can influence physician performance. All visits from July 12, 2012, to July 31, 2016 that were associated with patients who were identified in the Electronic Medical Record as having been seen by an ED physician were included in our analysis. Our dataset comprises patient-specific information including demographic (age, gender, race), encounter-level information such as the number of ordered diagnostic tests, chief complaint, and ESI as well as detailed timestamps capturing patients' movement through the ED from registration to discharge. A summary statistics of the variables used in our analysis are presented in Table 1. We excluded 2,914 patient visits with missing values from our analysis. In addition, we removed all observations associated with 4 physicians who had fewer than 200 patient visits over the 4-year study period. This leaves us with a final dataset comprising 110,325 patient visits. On average there exist 4,492 observations per physician in our dataset. At a shift-level, we observe on average 5 physicians working alongside each other during the same shift.

Table 1 Summary Statistics - Patient Visit-Level

Variable	Mean	SD	Min	Max
Patient Age	58.64	20.89	1	105
Female Patient (%)	53	2	50	58
White Patient (%)	91	1	88	94
Patient ESI	2.98	0.57	1	5
IV Order Count	3.13	2.12	0	32
Ultrasound Order Count	1.28	0.50	0	5
Radiology Order Count	1.20	0.59	0	11
MRI Order Count	1.69	0.91	0	6
CT Order Count	0.32	0.57	0	8
Lab Order Count	11.74	6.53	0	136
Contact-to-Disposition Time (minutes)	141.76	127.28	0	12953

Note: N = 110,325

4. Methodology

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. Hence, our treatment group consists of all physician pairs such that the peer physician has any of the aforementioned characteristics relative to focal physician i and the control group comprises all other physician pairs. We use the quartiles of physician speed and quality measures to compare physicians along these dimensions. We use binary variables to indicate physicians relative performance characteristics (e.g., faster, higher quality, etc.) for easier interpretation of our results and generating clear insights that can be utilized in practice in areas such as physician scheduling. To ensure that our results were not dependent on our choice of binary variables, we re-run our analysis using continuous measures of physician speed and quality. We find the results (presented in Appendix D) to be consistent with our main findings. Furthermore, to ensure robustness of our findings, we re-run our analysis at the shift level such that we estimate the effect of peers' average performance on a focal physician's performance. The results, presented in Appendix E, confirm our opposite-directional findings with respect to physicians' relative speed and quality.

We evaluate physicians' relative speed and quality using their average patient LOS and 72-hour return rate, respectively.[2] Figures 1 and 2 illustrate the distribution of the average speed and quality measures of the physicians in our dataset, respectively.

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. Controlling for these factors allows us to provide fair comparisons. It is especially important to control for these factors because, as is indicated in the previous literature (see, e.g., Saghafian et al 2014 and the references therein), there is a high level of variation in terms of patient complexity in EDs (i.e., the amount of work each patient brings). 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 253,922 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

[2] In Section 11, as a robustness check, we re-run our analyses by considering different measures of quality.

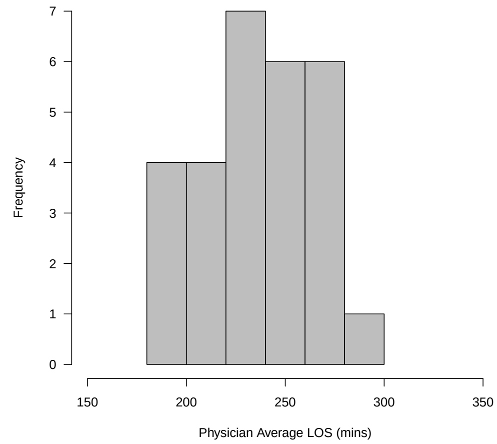

Figure 1 **Distribution of Physicians' Average LOS (in Minutes)**

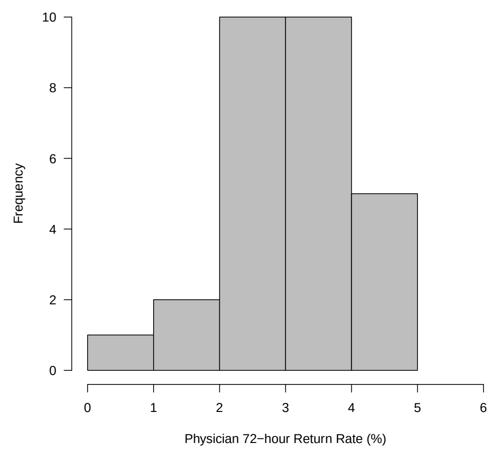

Figure 2 **Distribution of Physicians' 72-hr Rate of Return (in Percentage)**

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 which control for common shocks affecting all physicians. σ_i denotes physician fixed effects and 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.

5. Results and Discussion

Table 2 presents the effect estimates of faster and slower peers on a focal physician's speed and quality[3]. The statistically significant (p <0.001) coefficient estimate of faster and slower peer effects

[3] The full regression results are presented in Appendix I.

Table 2 Speed Effect Estimates

	Faster Peer	Slower Peer
LOS	5.2402***	-5.1070***
	(0.6709)	(0.6293)
Rate of Return	0.0004	0.0170
	(0.0267)	(0.0263)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

on the focal physician's average patient LOS is positive and negative, respectively. In particular, our results demonstrate that in the presence of a faster peer, a focal physician's patient LOS increases by 5.2 minutes compared to the presence of a peer with slower or equal speed. Similarly, we observe that the focal physician's speed decreases by 5.1 minutes on average while working with a slower peer in comparison to working with a faster or equal-speed 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.

Table 3 presents the effect estimates of a 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 these insights are not due to the measure of quality we use (the 72-hour rate of return), in Section 11 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.

In Table 4, we present the effect estimates of a different- and same-degree peers (M.D. vs. D.O.) on a focal physician's performance. We do not observe any statistically significant effects on a focal physician's performance. With regards to a peer's gender, our results (presented in Table 5) do not provide statistically significant evidence of peer influence on a focal physician's speed nor his/her quality in either direction. The lack of statistical significance, however, might be attributed to the limited number of female physicians (thus, a low power) in our dataset. We discuss the important implications of our results in Section 12.

Table 3 Quality Effect Estimates

	Higher-Quality Peer	Lower-Quality Peer
LOS	-0.7553	0.6836
	(0.6697)	(0.8513)
Rate of Return	0.0850*	-0.2036***
	(0.0459)	(0.0533)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 4 Degree Effect Estimates

	Different-Degree Peer	Same-Degree Peer
LOS	1.6196	4.6037
	(1.0182)	(3.6240)
Rate of Return	0.0044	-0.0514
	(0.0448)	(0.0018)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5 Gender Effect Estimates

	Opposite-Gender Peer	Same-Gender Peer
LOS	0.6650	-2.2945
	(0.7033)	(0.9967)
Rate of Return	0.0116	-0.0090
	(0.0222)	(0.0345)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

6. Endogeneity in Physician Shift Assignment

Estimation of peer influence in our setting is complicated by 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 mitigates the potential endogeneity issue, we conduct robustness tests to address this concern.

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 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 (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 6-9) to be consistent with our main findings. This suggests that our results are unlikely to be driven by physicians' self-selection into peer groups.

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. We do so because 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 at time t of patient k's visit (as described earlier, ED volume at time t indicates the number of patients being seen by all physicians other than physician i), 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 (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 patient k at time t including the number of tests ordered and the contact-to-disposition time in minutes. Lastly, γ_t in (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 10 and 11, we find no statistically significant relationship between ED volume and the number of high-performing physicians. The

Table 6 Atypical Subsample - Speed Effect Estimates

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

Table 7 Atypical Subsample - Quality Effect Estimates

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

Table 8 Atypical Subsample - Gender Effect Estimates

	Opposite-Gender Peer	Same-Gender Peer
LOS	6.1811	-2.1703
	(5.8639)	(2.9488)
Rate of Return	-0.0281	-0.0612
	(-0.0111)	(0.0412)
Observations	27,248	27,248
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 9 Atypical Subsample - Degree Effect Estimates

	Different-Degree Peer	Same-Degree Peer
LOS	-1.4180	-0.3933
	(2.3507)	(1.9619)
Rate of Return	0.0856	0.0130
	(0.0976)	(0.0764)
Observations	27,248	27,248
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 10 High-Performing Physicians (Speed) and ED Volume

	ED Volume
Faster Physician	0.2485
	(0.3076)
Observations	110,325
Time Fixed Effects	Yes
Controls	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 11 High-Performing Physicians (Quality) and ED Volume

	ED Volume
Higher-Quality Physician	-0.0968
	(0.2735)
Observations	110,325
Time Fixed Effects	Yes
Controls	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

results of both tests address the issue of physicians' selection into peer groups and confirm that endogeneity concerns are plausibly mitigated in our setting. Finally, as noted earlier, arriving patients in our setting are randomly assigned to physicians through an automated rotational patient assignment algorithm (Traub et al. 2016). Thus, concerns related to assignment of patients to physicians are also largely mitigated in our setting.

7. Robustness Checks

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

7.1. 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]. We have chosen to match on all patient- and ED-related observable covariates in our data including patient age, gender, race, ESI level, and ED volume. Tables 1-6 in Appendix A present the mean baseline values of all covariates across the treatment and control groups stratified by each aforementioned peer characteristic as well as the standardized mean difference between the treatment and control groups. We find that the

[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).

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 A illustrate how matching improves the balance in the means of the covariates across the treatment and control samples. In order to ensure that our results were not sensitive to the choice of the matching technique used, we have re-done our analysis using alternative matching approaches including exact matching (binary variables) and greedy one-to-one matching with and without replacement (categorical variables). A caliper width of 0.1 times the pooled standard deviation of the logit of the propensity score was chosen for all alternative matching techniques. The results presented in Appendix B show that, in each case, our inferences remain unchanged.

We tested the overlap assumption to ensure that there is sufficient overlap in the distributions of covariates between the matched treated and control groups. In all cases, the estimated densities of the treated and control groups have most of their respective masses in regions in which they overlap each other. Figures 1-6 in Appendix C plot the kernel density of a few of the matching covariates for the faster peer effect analysis. We observe the same level of overlap for all other peer characteristics as well. We re-run model (1) on matched samples of physician pairs. The results presented in Tables 12 and 13 show that our main findings remain unchanged.

7.2. 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:

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

The regression results presented in Tables 14 and 15 confirm our main findings. Specifically, we observe statistically significant evidence for opposite-direction effects with respect to physicians' relative speed and quality. Overall, this and our other tests mentioned earlier gives us confidence that our results are fairly robust and not sensitive to our main assumptions or empirical setups.

8. Mechanisms

The results discussed in the previous sections show that both slower and lower-quality physicians have positive effects on a focal physician's average performance while faster and higher-quality

Table 12 Speed Effect Estimates - Matched Sample

	Faster Peer	Slower Peer
LOS	1.5143***	-4.12832***
	(0.3412)	(0.4521)
Rate of Return	0.0064	0.0532
	(0.0342)	(0.0754)
Observations	121,564	210,780
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 13 Quality Effect Estimates - Matched Sample

	Higher-Quality Peer	Lower-Quality Peer
LOS	-0.2342	0.6542
	(0.5432)	(0.7754)
Rate of Return	0.0656*	-0.3423***
	(0.0543)	(0.0735)
Observations	200,922	196,434
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 14 Speed Effect Estimates - Alternative Model Specification

	Faster Peer	Slower Peer
LOS	3.8208***	-3.4183***
	(0.8223)	(0.7998)
Rate of Return	-0.0022	0.0215
	(0.0279)	(0.0302)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 15 Quality Effect Estimates - Alternative Model Specification

	Higher-Quality Peer	Lower-Quality Peer
LOS	-0.5782	1.0472
	(0.8749)	(1.3315)
Rate of Return	0.1204***	-0.1761***
	(0.0437)	(0.0512)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

physicians negatively impact the performance of their peers. In this section, we explore two main mechanisms which may drive these observed effects: social influence and resource spillover.

8.1. 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 16 and 17) provides no statistically significant evidence that social influence is the driving force behind our results. Furthermore, as we noted in Section 1, social influence typically exists in settings where direct negative externalities (e.g., increase in a worker's workload due to a slowdown behavior by the peer) are significant, actions and performance outcomes are observable, and the work environment resembles a teamwork setting (in which workers pursue a common goal and are compensated similarly and as a team; see, e.g., Mas and Moretti 2009). Since our setting does not involve any of these aspects, it is unlikely that social influence can play a major role in driving our results.

8.2. Resource Spillover

Our findings might be attributed to physicians' utilization of shared resources such as laboratory services, nurses, and hallways. A setting such as an ED where shared (and limited) resources are often utilized resembles a queuing system in which a server can be impacted by spillover from other servers (Gerla and Kleinrock 1980, Batt and Terwiesch 2017). For example, if a server utilizes resources (e.g., issues more tests) more often, 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,

Table 16 Effect Estimates - Below Average Familiarity

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	0.8542*	-2.9700***	-1.3397	0.4147
	(0.4698)	(1.1083)	(0.9491)	(1.1249)
Rate of Return	-0.0098	0.0641	0.1603***	-0.2763***
	(0.0329)	(0.0292)	(0.0530)	(0.0743)
Observations	59,320	58,888	116,778	109,866
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 17 Effect Estimates - Above Average Familiarity

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	1.5088*	-2.0560***	-0.3429	0.5544
	(0.7987)	(0.6804)	(1.1021)	(1.0734)
Rate of Return	0.0124	0.0398	0.0503	-0.0117
	(0.0341)	(0.0490)	(0.0526)	(0.0561)
Observations	46,500	43,314	84,154	86,602
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

see, e.g., Saghafian et al. (2012), Huang et al. (2015), and the 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 test 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, and one comprising of shifts with lower-than-average volume. From the results presented in Tables 18 and 19, we observe that the effects corresponding to high-volume shifts are indeed larger in magnitude compared to those associated with low-volume shifts.[5]

This suggests that resource spillover is more likely to be the driving force behind our opposite-direction effects than other mechanisms such as social influence. However, to gain further confidence, we also perform some more direct tests, which we discuss next.

[5] In order to ensure that our results were not sensitive to the choice of sub-sampling in our dataset, we re-run our analysis using interaction terms. The results (presented in Appendix G) show that our findings remain unchanged.

Table 18 Effect Estimates - Below Average ED Volume

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	2.0990***	-2.3293***	-1.1892	0.5966
	(0.6046)	(0.4333)	(0.7321)	(0.5485)
Rate of Return	0.0422	-0.0107	0.0881*	-0.1339*
	(0.0371)	(0.0397)	(0.0509)	(0.0726)
Observations	101,006	111,282	101,392	97,520
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 19 Effect Estimates - Above Average ED Volume

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	4.3900***	-4.2014***	0.3032	0.9142
	(0.8955)	(0.7952)	(0.9338)	(1.0909)
Rate of Return	-0.0035	0.0813	0.1399***	-0.2231***
	(0.0323)	(0.0368)	(0.0478)	(0.0678)
Observations	111,914	99,498	99,600	99,016
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

8.2.1. Peer Influence on Test Order Count To further investigate the resource spillover mechanism, we examine whether physicians affect each other's performance through influencing each other's test ordering behavior. To this end, we make use of the following regression model:

$$Q_{ijkt} = \beta_1 T_{ijt} + \beta_2 R_{ikt} + \beta_3 E_{it} + \beta_4 Q_{ijt} + \gamma_t + \sigma_i + \epsilon_{ijkt}, \qquad (4)$$

where Q_{ijkt} represents focal physician i's test order count for patient k's visit at time t while working alongside peer physician j.

The results presented in Table 20 provide evidence that physicians influence each other's speed through affecting each other's test ordering behavior. Specifically, our results indicate that working alongside a faster peer increases a focal physician's test orders by 0.19 tests per patient on average. Similarly, our results show that working with a slower peer results in an on average decrease of 0.18 tests per patient. However, as illustrated in Table 20, we find no statistically significant evidence that physicians influence each other's quality by affecting each other's test ordering behavior. Table 21 presents the correlation of variables corresponding to physician and patient average characteristics. We observe a negative correlation between a physician's average speed and test order count per patient visit. Hence, it is likely that a faster peer utilizes less test orders on average compared

Table 20 Effect Estimates on Test Order Count

	Test Order Count
Faster Peer	0.1928***
	(0.0742)
Slower Peer	-0.1793***
	(0.0665)
Higher-Quality Peer	0.0346
	(0.0448)
Lower-Quality Peer	0.0129
	(0.0597)
Observations	253,921
Time Fixed Effects	Yes
Physician Fixed Effects	Yes
Controls	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 21 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

to a focal physician. As a result, s/he allows the focal physician to make use of the test services in a timely manner. This, in turn, results in an increase in the focal physician's average test orders and a decrease in the physician's average speed. Similarly, a slower peer hinders the ability of the focal physician from utilizing the test services by ordering more tests relative to the focal physician. Therefore, a focal physician's test order count decreases, resulting in an increase in the speed of the focal physician. This gives us further confidence about the role of the resource spillover mechanism.

8.2.2. Peer Influence on Admission Rate Our results presented earlier provide no statistically significant evidence that physicians influence each other's quality through affecting peers' test order count. Given that the effect estimates of higher- and lower-quality peers increase in magnitude during high-volume shifts (as presented in Table 19), we consider other potential channels through which the resource spillover effect might emerge. From Table 21, 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. As such, s/he would utilize more of the resources that are needed for admitting patients (e.g., inpatient beds) and hinder the 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 an increase in his/her average quality. To test this hypothesis, we use the following logistic regression model:

$$A_{ijkt} = \beta_1 T_{ijt} + \beta_2 R_{ikt} + \beta_3 E_{it} + \beta_4 Q_{ijt} + \gamma_t + \sigma_i + \epsilon_{ijkt}, \tag{5}$$

where A_{ijkt} denotes the log odds of focal physician i's admission of patient k, while working alongside peer physician j at time t. Table 22 presents the effect estimates of higher- and lower-quality peers on a focal physician's admission rate. The coefficient estimates of higher- and lower-quality peers, although not statistically significant, are negative and positive, respectively. The results indicate that a higher-quality peer negatively affects a focal physician's admission rate while a lower-quality peer has a positive effect on the admission rate of the focal physician. These findings provide further evidence for the resource spillover mechanism and show that physicians influence each other's quality through affecting each other's admission rate. However, we believe a carefully designed experiment (e.g., a randomized controlled trial) is needed to fully confirm the role of resource spillover as the main driver of our findings.

9. Peer Influence Over Time

Whether peers' influence on a focal physician's performance is short-lived or persists after an extended period of time has important implications for physician scheduling as well as designing appropriate physician training programs. The longitudinal nature of our data and the low turn-over rate (6.2%) of the physicians in our study allow us to examine the persistence of peer influence over time.

To this end, we start by dividing our dataset into two sub-samples each corresponding to observations in the first and second half of our study period. To gain insights, we include in our analysis only those physicians who worked continuously and consistently throughout the study period. We then employ the same matching strategy for these sub-samples and run model (1) to derive the effect estimates separately for each sub-sample. Tables 23-26 present the results. Tables 23 and 24 show statistically significant evidence for the faster and slower peers' influence on a focal physician's speed in both sub-samples. Moreover, we observe that the effect estimates of both faster and slower peers increase in magnitude over time. Hence, our findings suggest that the effects of peers with respect to relative speed are long-lived, and might get stronger the longer physicians work alongside each other. However, our effect estimates of higher- and lower-quality physicians on a focal physician's quality (presented in Tables 25 and 26) are statistically significant only in the

Table 22 Effect Estimates on Admission Rate

	Admission Rate
Higher-Quality Peer	-0.0084
	(0.0165)
Lower-Quality Peer	0.0230
	(0.0160)
Observations	253,921
Time Fixed Effects	Yes
Physician Fixed Effects	Yes
Controls	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 23 Faster Peer Influence Over Time Estimates

	First Half	Second Half
LOS	2.0761***	6.6150***
	(0.6464)	(1.2030)
Rate of Return	0.0524	-0.0455
	(0.0486)	(0.0476)
Observations	102,252	94,620
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 24 Slower Peer Influence Over Time Estimates

	First Half	Second Half
LOS	-4.7735***	-5.7488***
	(1.2487)	(1.1402)
Rate of Return	-0.0104	0.0059
	(0.0503)	(0.0410)
Observations	90,654	100,216
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 25 Higher-Quality Peer Influence Over Time Estimates

	First Half	Second Half
LOS	0.4517	-0.6776
	(0.8451)	(1.0553)
Rate of Return	0.1238***	0.0048
	(0.0361)	(0.0376)
Observations	88,502	95,630
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 26 Lower-Quality Peer Influence Over Time Estimates

	First Half	Second Half
LOS	-0.0293	0.8858
	(1.3771)	(1.1597)
Rate of Return	-0.2152***	0.0078
	(0.0668)	(0.0538)
Observations	90,552	89,656
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

first half of our study period. This suggests that peer influence on quality is short-lived. As a robustness check, we have re-run our analysis using interaction terms. The results (presented in Appendix F) show that our findings hold.

10. Heterogeneity in Peer Influence

Our analysis thus far does not account for heterogeneity in physician peer influence. In this section, we examine the magnitude of the documented effects across heterogeneous groups of physicians. To this end, we construct sub-samples of physicians using (a) their job tenure (a measure indicating how recently they joined), and (b) their relative performance compared to their peers.

Job Tenure: To examine whether recently-hired physicians are more sensitive to their peers' influence, we partition our data into two sub-samples: one corresponding to physicians who have worked less than 7 years (the median employee tenure) and one corresponding to those who have more than 7 years of experience working in the current setting. We re-run our matching and regression analyses on both sub-samples and present the results in Tables 27 and 28. Our results show that while the magnitude of the faster peer influence is slightly larger for physicians with

Table 27 Effect Estimates - Tenure Less than 7 years

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	1.2616**	-3.3777***	-0.8818	2.9275
	(0.5876)	(1.1843)	(1.0631)	(2.1000)
Rate of Return	-0.0052	-0.0151	0.1117	-0.3021***
	(0.0446)	(0.0486)	(0.0689)	(0.0813)
Observations	115,338	126,476	80,236	85,728
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 28 Effect Estimates - Tenure More than 7 years

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	1.6374***	-2.7112**	-0.6302	0.7438
	(0.4431)	(1.1023)	(0.7578)	(0.7731)
Rate of Return	0.0329	0.1700	0.0672	-0.1471**
	(0.0514)	(0.0368)	(0.0574)	(0.0722)
Observations	171,182	146,790	118,954	108,186
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

more years of tenure, the effect estimates of both slower and lower-quality peers are larger for newly-hired physicians. This suggests that newly-hired physicians are more responsive to the positive influence of their peers. This is expected since recently-hired physicians have less experience working in our partner ED and are more sensitive to the spillover effect from their peers. The effect estimate of higher-quality peers provides no statistically significant evidence for the heterogeneity of peer influence with respect to job tenure in our sample.

Performance: We also investigate the heterogeneity of peer influence among low- and high-performing physicians by constructing sub-samples of physicians who perform above and below the average with respect to the speed and quality measures. As demonstrated in Tables 29 and 30, we find that the effect estimates of faster, slower, and higher-quality peers are larger in magnitude among higher-than-average performers. This suggests that high-performers are more responsive to the influence of their peers compared to low-performing physicians. Our results offer no statistically significant evidence for the heterogeneity in the effect estimate of lower-quality peers.

Figures 3-6 summarize the documented effect estimates across heterogeneous groups of physicians. Put together, our results indicate that newly-hired physicians and/or high-performing ones are typically more influenced by their peers than others. Our results are also consistent with the

Table 29 Effect Estimates - Below Average Performers

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	1.0902***	-1.0049*	-0.4698	0.2149
	(0.6243)	(0.4923)	(0.8008)	(0.5591)
Rate of Return	-0.0255	-0.0203	0.1329*	-0.1791***
	(0.0369)	(0.0364)	(0.0537)	(0.0506)
Observations	130,764	43,752	102,094	109,504
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

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

Table 30 Effect Estimates - Above Average Performers

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer
LOS	1.5171***	-2.3178***	-0.7235	0.6185
	(0.3186)	(0.5760)	(0.7312)	(1.0410)
Rate of Return	-0.0086	0.0017	0.1899***	-0.1000**
	(0.0284)	(0.0506)	(0.0669)	(0.1127)
Observations	26,102	131,034	98,898	67,536
Time Fixed Effects	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

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

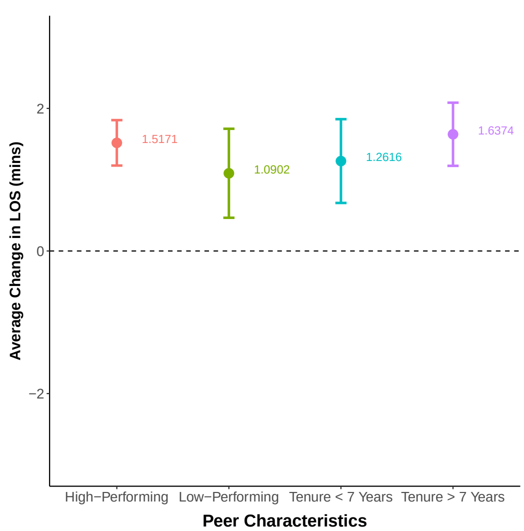

Figure 3 Effect Estimates - Faster Peer

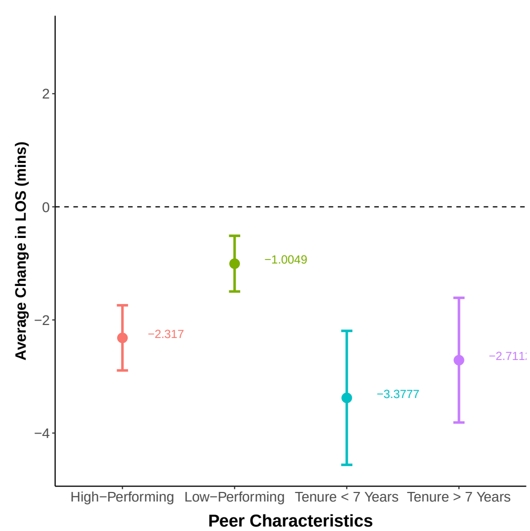

Figure 4 Effect Estimates - Slower Peer

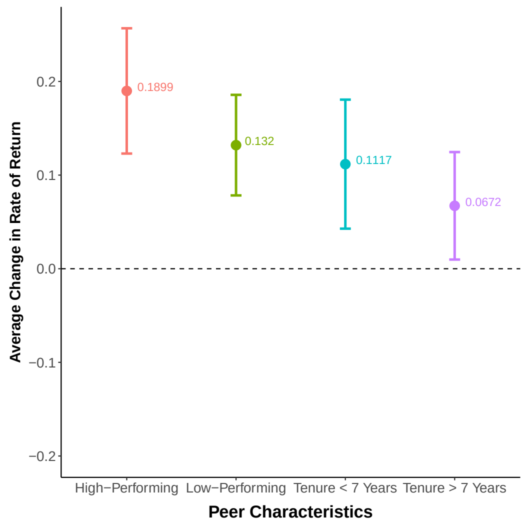

Figure 5 Effect Estimates - Higher-Quality Peer

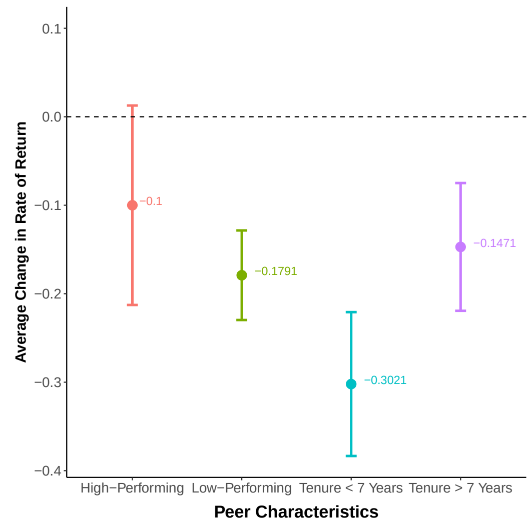

Figure 6 Effect Estimates - Lower-Quality Peer

notion that scheduling a diverse mix of physicians during the same shift could have a positive net effect on the performance of the ED. For example, scheduling high-performing physicians with low-performing peers would have a positive overall effect compared to scheduling only high- or low-performing physicians during the same shifts. To gain further confidence, we have re-run our analysis using interaction terms. The results (presented in Appendix G) confirm that our findings remain unchanged.

11. Alternative Quality Measures

In this section, we estimate the effects of higher- and lower-quality peers using alternative quality metrics (instead of the 72-hour return rate) to ensure that our results are not merely due to the specific measure of quality we use. Specifically, we repeat our matching and regression analyses using two alternative quality metrics: one capturing how often a physician 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. We define the overcall metric as the percentage of a physician's patients who are admitted to the hospital 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 the needs and illness severity of his/her patients.[6] Tables 31 and 32 present the effect estimates of higher- and lower-quality peers using

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

Table 31 Overcall Effect Estimates

	Higher-Quality Peer	Lower-Quality Peer
LOS	-1.8123	1.8464
	(1.0624)	(1.1749)
12-Hour Discharge	0.0193	-0.0273
	(0.1065)	(0.0890)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 32 Undercall Effect Estimates

	Higher-Quality Peer	Lower-Quality Peer
LOS	-1.3584	0.7552
	(1.0719)	(1.1258)
24-Hour Upgrade	0.6956***	-0.5078***
	(0.1630)	(0.1361)
Observations	253,921	253,921
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

these overcall and undercall measures, respectively. In both cases, our inferences are similar to those made earlier using the 72-hour rate of return as the measure of quality. Specifically, the effect estimates of a higher and lower -quality peers with respect to the overcalling rate (presented in Table 31) although not statistically significant, are positive and negative, respectively. This shows that consistent 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. Similarly, the results presented in Table 32 show statistically significant effect estimates of higher- and lower-quality peers with respect to the undercalling rate on a focal physician's average quality, respectively.

12. Managerial Implications

We now summarize some of the main implications of our results. First, hospital administrators can benefit from our findings in constructing the optimal mix of physicians to schedule during the same shift. Overall, our results suggest that scheduling diverse peers during the same shift would positively affect the performance of physicians. This is consistent with the literature on teamwork that identifies team diversity as an important component of effective teams (Woehr et al. 2013, Zoogah et al. 2011). 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.

Finally, it is important to consider the financial implications of our findings for hospitals. Given the financial burden of prolonged ED LOS and unnecessary return visits on hospitals, our results may lead to significant cost savings for hospitals. This is because reducing LOS has both direct and indirect positive effects on the financial status of hospitals. It has a direct positive effect through decreasing the costs of patient care, facility and staffing expenses. It has an indirect positive effect by minimizing the risk of hospital-acquired infections and improving a variety of other patient safety metrics. Thus, reducing LOS by even a few minutes could have significant financial implications for hospitals (Krochmal and Riley 1994, The Beckers Hospital Review 2016). Similarly, improving the ED return rates or how often patients' illness severity are undercalled or overcalled even by small amounts can have significant direct and indirect financial benefits for hospitals. Our study sheds light on ways to improve the performance of ED physicians by pairing them with the "right" peers. Specifically, 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 of physicians. Importantly, unlike many other process or quality improvement interventions, our findings allow hospitals to gain such financial benefits without substantial investments and by only changing how physicians are paired.

13. Limitations

Our study has some important limitations. First, while we control for the 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 peers shapes 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). Future research can make use of randomized experiments to gain deeper insights into potential learning effects that are 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.

14. Conclusions

In this study, we examine the effects of different characteristics of physician peers including relative speed, quality, gender, and medical degree on a focal physician's performance in an ED setting. We document statistically significant evidence for opposite-direction peer influence. In particular, our results demonstrate that a faster peer has a negative effect and a slower peer has a positive effect on a focal physician's speed on average. 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. Table 33 presents a summary of our results. Our findings identify resource spillover from peers as the main driver of peer influence and indicate that diverse physicians with regards to speed and quality utilize shared resources more efficiently.

We further examine the persistence of these effects over time and find the effects with respect to relative quality to be short-lived. In contrast, the effects with respect to relative speed are shown to persist over time. Moreover, our results indicate that physician peer influence is fairly heterogeneous and depends on the focal physician's characteristics. For example, we establish evidence that newly-hired physicians and high-performing ones are more sensitive to the influence of their peers.

Our findings have important practical implications for improving the performance of physicians by highlighting the need to consider peer influence 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. Considering the importance of gaining such understanding, we hope to see further studies that quantify mechanisms through which physicians impact their peers.

Table 33 Summary Results (Impact of the Paired Peer on the Focal Physician's Performance)

	FS	SS	HQ	LQ
Effect on Speed	-	+	0	0
Effect on Quality	0	0	-	+

Note: FS: Paired physician has a faster speed compared to the focal physician; SS: Paired physician has a slower speed compared with the focal physician; HQ: Paired physician has a higher quality compared to the focal physician; LQ: Paired physician has a lower quality compared with the focal physician +: Positive impact; -: Negative impact; 0: No impact.

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