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

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Understanding potential ways 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 same shifts affect each other's performance. We find strong empirical evidence that physicians affect each other's speed and quality, and scheduling diverse peers during the same shift could have a positive net impact on the operations of a hospital Emergency Department (ED). Specifically, our results show that a faster (slower) peer decreases (increases) the average speed of a focal physician compared to a same-speed peer. Similarly, a higher- (lower-) quality peer decreases (increases) a focal physician's average quality. Furthermore, the presence of a less-experienced peer improves a focal physician's average speed. However, in contrast to the conventional wisdom, we do not find any evidence that more-experienced physicians can affect the performance of their less-experienced peers. We investigate various mechanisms that might be the driving force behind our findings, including psychological channels such as learning, social influence, and homophily as well as resource spillover. We identify resource spillover as the main driver of the effects we observe and show that, under high ED volumes (i.e., when the shared resources are most constrained), the magnitude of the observed effects increases. 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 influenced than others by 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 and/or training programs that require physicians to work during same shifts.

Key words: Physician Performance; Physician Diversity; Emergency Department Operations; Propensity Score Matching

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1. Introduction

Understanding the impact of peers on an individual's performance is an important aspect of operations management and has been studied in a diverse set of occupations including supermarket cashiers (Mas and Moretti 2009), physicians (Chan 2016), sales teams (Chan et al. 2014), and scientists (Waldinger 2012). In this study, we examine how physicians who work alongside each other influence each other's speed and quality in the context of an Emergency Department (ED) setting. EDs provide interesting study settings 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 methods (e.g., physician pairing and scheduling) that can ultimately lead to more effective and efficient care delivery mechanisms.

In order to identify and quantify the potential effects 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), experience (measured in years after graduation from medical school), 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 peer in our setting as a physician who is scheduled to work side-by-side with him/her. We measure a physician's performance in terms of his/her speed and quality using 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.

To correctly estimate the impact that physicians have on each other's speed and quality, we consider potential sources of endogeneity and confounding in our dataset. For example, although there exists no systematic scheduling scheme in our setting, physicians' preferences in shift assignments might still cause endogeneity problems. In addition, simultaneous measurement of physicians' performance might confound our findings as peer and focal physicians simultaneously affect each other's performance.

To overcome these concerns, our empirical strategy involves correcting for the effects of non-random assignment of physicians such that we isolate the effect of a focal physician's peer from other factors affecting the physician's performance. 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]. In addition, we conduct various robustness tests which address physicians' selection into peer groups, to mitigate the concern of spurious correlations with omitted variables. We further show how our empirical strategy addresses the simultaneous influence of physicians on each other's performance.

Our results establish statistically significant evidence for peer physician influence which, in turn, has important implications for improving the operations of EDs. Specifically, we find that on average a faster peer has a negative effect on a focal physician's speed. Our results also document a positive effect on the focal physician's average speed when working alongside a slower peer. In addition, on average 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. We also observe an increase in the average physician's speed when s/he is scheduled to work with a less-experienced peer. Furthermore, we find the effect estimates of slower and lower-quality peers to be larger in magnitude compared to the effect estimates of faster and higher-quality peers, respectively. This suggests that incorporating diversity with respect to physicians' relative speed and quality could have a positive net impact on the ED's performance. We examine several mechanisms including psychological channels such as learning, social influence, and homophily as well as resource spillover that might be driving our results. 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 is an important insight with 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 examine whether the effects we establish on the influence of physicians on each other's performance 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

[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.

physician's average speed throughout our study period, indicating that peers' influence on a focal physician's speed is persistent over time. In contrast, the effects with respect to physicians' relative quality and experience 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 ED.

Our findings have important practice-related implications for improving the operations of hospital EDs. First, our results are useful in devising effective physician staffing strategies where one needs to decide which providers should be scheduled during the same shift. Importantly, 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 workloads by making use of our results on how physicians affect each other's performance. Specifically, our findings suggest that scheduling physicians with diverse peers with whom they utilize shared resources more efficiently would have a positive effect on the operations of EDs. Second, our findings can be used in areas such as physician training where one needs to provide guidance to physicians with ways to improve their operational efficiency. Lastly, 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.

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, 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. 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). 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.

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. Although such studies prove the existence of peer effects among physicians, their context-specific nature limits the generalizability and applicability of their findings. Unlike this literature, our study contributes by documenting the existence and magnitude of peer influence on a focal physician's speed and quality by examining the effects of various characteristics of peer physicians.

Our study is also related to the operations management literature surrounding physicians' speed and quality. Prior research has identified several factors affecting the performance of physicians. 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. 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. 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. Furthermore, our findings suggest that during high-volume shifts when resources are more constrained, peers' influence 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 is 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. We find evidence of negligible patient hand-off in our data. As such, the physician assigned to each patient in almost all cases is considered his/her primary care provider.

4. Methodology

To examine whether 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

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

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 indicating whether peer physician j has a higher speed, higher quality, more years of experience, a different medical degree, and is of the opposite gender compared to focal physician i.

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. 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. This is based on the assumption that the estimated effects of physicians on each other is a function of physicians' past performance measured in terms of speed and quality. Employing this approach, we do not face the simultaneity issue (a.k.a the reflection problem) (see Manski 1993), which arises due to the simultaneous effects of physicians on each other's performance.

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)

[2] In Section 10, we re-run our analyses by considering different measures of quality.

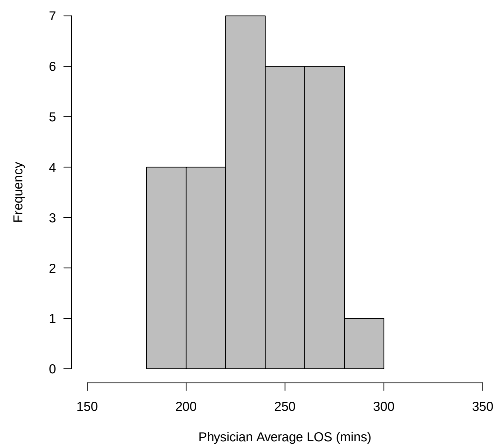

Figure 1 **Distribution of Physicians' Average LOS (in Minutes)**

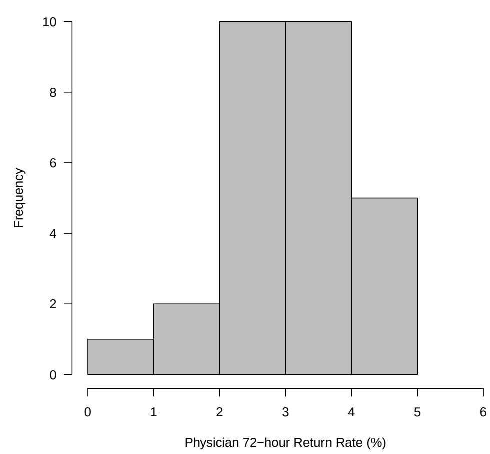

Figure 2 **Distribution of Physicians' 72-hr Rate of Return (in Percentage)**

and 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.

In order to correctly examine peer influence, however, we need to ensure that any differences between the treated and control physician groups are due to the treatment itself. Tables 1-8 in Online 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 distribution of ED volume and covariates related to physician characteristics are relatively unbalanced across the treated and control groups.

To arrive at a balanced set of covariates, we use the nearest-neighbor propensity score matching without replacement to construct a well-matched sample of focal-peer physician pairs that achieve balance across all covariates. Tables 9-16 in Online Appendix A illustrate how matching improves the balance in the means of the covariates across the treatment and control samples. 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 Online Appendix B plot the kernel density of the matching covariates for the faster peer effect analysis. We observe the same level of overlap for all other peer characteristics as well.

Having formed a balanced set of covariates, we then estimate the effects 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} is the treatment variable coded as 1 if peer physician j holds an opposite characteristic relative to that of physician i 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 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 effects of peers on a focal physician's speed and quality, respectively.

5. Results and Discussion

Using a propensity-score matched sample of treated and control physician groups, we derive estimates of peer effects on a focal physician's performance. Table 2 presents the effect estimates of faster (slower) peers on a focal physician's speed and quality. The coefficient estimate of a faster (slower) peer effect on the focal physician's average patient LOS is positive (negative) and statistically significant ($p < 0.001$). Our results demonstrate that in the presence of a faster (slower) peer, a focal physician's patient LOS increases by 1.4 minutes (decreases by 5.2 minutes) on average.

To illustrate a more clear picture of the implications of these effects, in Table 2 we also present 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. As shown in Table 2, we do not find statistically significant evidence for the effect of a faster (slower) peer on a focal physician's average quality.

Table 3 presents the effect estimates of a higher- (lower-) quality peer on a focal physician's speed and quality. We document a statistically significant negative (positive) effect of a higher- (lower-) quality peer on a focal physician's average quality. In particular, 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. We do not, however, find statistically significant evidence for the influence of higher- (lower-) quality peers on a focal physician's average speed. It is important to note that the effect estimates of both slower and lower-quality peers are larger in magnitude compared to the effect estimates of faster and higher-quality peers, respectively (see Tables 2 and 3). This suggests that scheduling diverse physicians with respect to their relative speed and quality during the same shift could have a positive net effect on the performance of the ED. To ensure that these insights are not due to the measure of quality we use—the 72-hour rate of return—in Section 10, 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- (same-) degree peer (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.

Table 2 Speed Effect Estimates

	Faster Peer	Same-Speed Peer	Slower Peer
Length of Stay (LOS)	1.3717***	-0.5166	-5.1593***
	(0.4804)	(0.4324)	(0.5864)
Rate of Return	0.0073	-0.0283	0.0387
	(0.0229)	(0.0312)	(0.0324)
Observations	121,564	128,314	210,780
Time Fixed Effects	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 3 Quality Effect Estimates

	Higher-Quality Peer	Same-Quality Peer	Lower-Quality Peer
Length of Stay (LOS)	-0.7553	0.0667	0.6836
	(0.6697)	(0.5936)	(0.8513)
Rate of Return	0.0850*	0.0319	-0.2036***
	(0.0459)	(0.0424)	(0.0533)
Observations	200,922	154,480	196,434
Time Fixed Effects	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 4 Degree Effect Estimates

	Different-Degree Peer	Same-Degree Peer
Length of Stay (LOS)	1.6196	4.6037
	(1.0182)	(3.6240)
Rate of Return	0.0044	-0.0514
	(0.0448)	(0.0018)
Observations	91,618	102,322
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Our effect estimates of a more- (less-) experienced peer are presented in Table 5. We document a statistically significant increase in a focal physician's speed when s/he is scheduled to work with a less-experienced peer.

Table 5 Experience Effect Estimates

	More-Experienced Peer	Same-Experience Peer	Less-Experienced Peer
Length of Stay (LOS)	-0.6290	-0.4444	-1.2842***
	(0.6271)	(1.2773)	(0.4700)
Rate of Return	-0.0080	-0.0577	-0.0040
	(0.0374)	(0.0522)	(0.0269)
Observations	214,574	20,860	208,688
Time Fixed Effects	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01		

Specifically, our results document an increase of 1.28 minutes in a focal physician's average speed when s/he works alongside a less-experienced peer. We do not, however, observe a statistically significant effect on a focal physician's quality. Furthermore, in contrast to the conventional wisdom, we find no evidence that more-experienced physicians affect the performance of their less-experienced peers.

With regards to a peer's gender, our results (presented in Table 6) 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.

Figures 3-5 summarize all documented estimates of peer influence on a focal physician's average speed and quality. As illustrated in Figure 3, the largest effect on a focal physician's average speed is observed when s/he works alongside a slower peer. Similarly, scheduling a focal physician with a lower-quality peer results in the largest average increase in the focal physician's average quality (Figure 4). In addition, comparing the marginal effects (i.e., effects compared to a same-level peer) of the documented estimates reveals that slower and lower-quality peer influence estimates on a focal physician's speed and quality are larger than those of the faster and higher-quality peers, respectively. As noted earlier, this suggests that scheduling physicians with diverse characteristics could positively impact the operations of an ED. In closing this section, we note that our results presented above have important implications for hospital administrators. We discuss these implications in Section 11.

6. 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 addition, we find that less-experienced peers have a positive effect on a focal physician's speed on average. In this section,

Table 6 Gender Effect Estimates

	Opposite-Gender Peer	Same-Gender Peer
Length of Stay (LOS)	0.6650	-2.2945
	(0.7033)	(0.9967)
Rate of Return	0.0116	-0.0090
	(0.0222)	(0.0345)
Observations	123,202	246,752
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

we explore several mechanisms which may drive these observed opposite-direction effects. We divide these mechanisms into two broad categories: psychological and resource spillover mechanisms.

6.1. Psychological Mechanisms

A large body of literature has documented the psychological channels through which individuals affect each other. Below, we outline a few of these channels that might be driving our results.

6.1.1. Learning

Learning is defined as obtaining information from a peer as how to succeed in performing a task (Buechel et al. 2018). Prior studies have discussed the learning mechanism in several different settings (Moretti 2004a, Broadie 2014, Pope et al. 2011). In our setting, learning could occur when physicians who work during the same shift ask each other questions about the best course of action for their patients. If learning was indeed the main mechanism driving our results, we would expect to find same-direction effects as opposed to our opposite-direction results. That is, we would expect to see faster and/or higher-quality physicians positively impact the performance of their peers. Furthermore, the fact that our results provide no evidence for the positive effect of more-experienced peers on a focal physician's performance casts further doubt that learning is the main driver of our results.

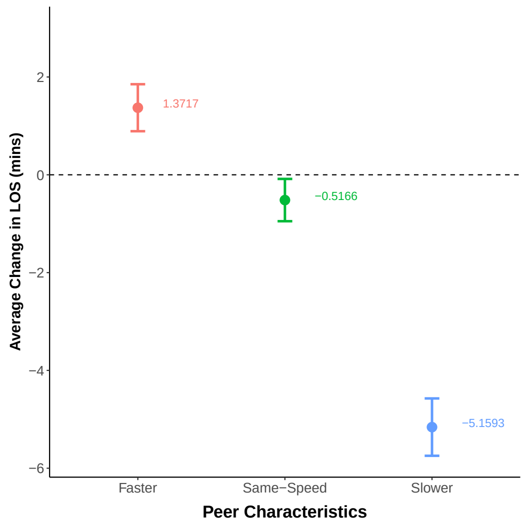

Figure 3 Effect Estimates - Speed

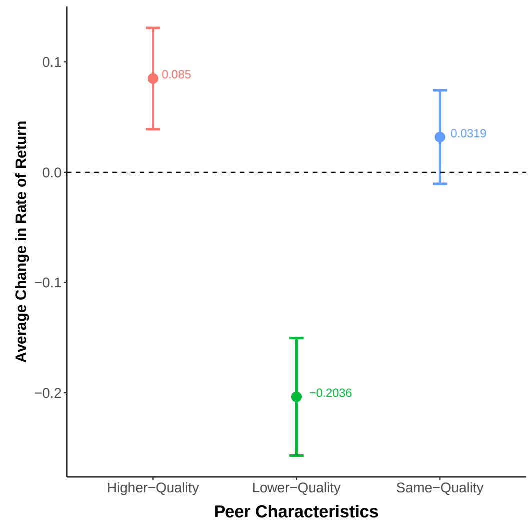

Figure 4 Effect Estimates - Quality

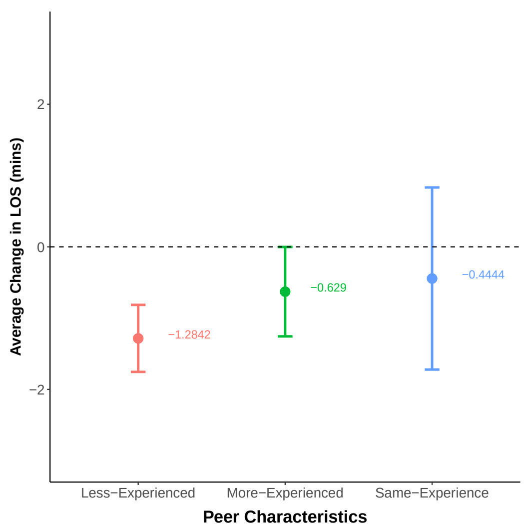

Figure 5 Effect Estimates - Experience

6.1.2. 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 samples. Comparing the magnitude of the observed effects across the two samples (presented in Tables 7 and 8) provides no statistically significant evidence that social influence is the driving force behind our results.

6.1.3. Homophily

A psychological mechanism referred to as "homophily" indicates that working with homogeneous peers could improve an individual's performance. For example, Carrell et al. (2013) suggest homophily as a potential explanation for the positive peer effects among students with the same level of ability. The authors show that students identify peers with similar ability levels as friends and prefer to study with them.

Our baseline results presented in Section 5 provide no statistically significant evidence that same-level physician peers influence the performance of each other. Thus, homophily is unlikely to be the driving force behind our findings.

6.2. 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 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 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 a 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 9 and 10, we observe that the effects corresponding to high-volume shifts are indeed larger in magnitude compared to

Table 7 Effect Estimates - Below Average Familiarity

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	0.8542*	-2.9700***	-1.3397	0.4147	-1.5260**
	(0.4698)	(1.1083)	(0.9491)	(1.1249)	(0.6506)
Rate of Return	-0.0098	0.0641**	0.1603***	-0.2763***	0.0282
	(0.0329)	(0.0292)	(0.0530)	(0.0743)	(0.0490)
Observations	59,320	58,888	116,778	109,866	123,472
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 8 Effect Estimates - Above Average Familiarity

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	1.5088*	-2.0560***	-0.3429	0.5544	-1.2669
	(0.7987)	(0.6804)	(1.1021)	(1.0734)	(0.8836)
Rate of Return	0.0124	0.0398	0.0503	-0.0117	-0.0519
	(0.0341)	(0.0490)	(0.0526)	(0.0561)	(0.0411)
Observations	46,500	43,314	84,154	86,602	96,714
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

those associated with low-volume shifts. This suggests that resource spillover is more likely than other mechanisms to be the driving force behind our opposite-direction effects. Nevertheless, 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.

7. 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 divide our dataset into two sub-samples each corresponding to observations in the first and second half of our study period. 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 11-15 present the results. Tables 11 and 12 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.

Table 9 Effect Estimates - Below Average ED Volume

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	2.0990***	-2.3293***	-1.2995***	0.5966	-1.6567***
	(0.6046)	(0.4333)	(0.3658)	(0.5485)	(0.5624)
Rate of Return	0.0422	-0.0107	0.0881*	-0.1339*	0.0135
	(0.0371)	(0.0397)	(0.0509)	(0.0726)	(0.0330)
Observations	101,006	111,282	101,392	97,520	104,580
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 10 Effect Estimates - Above Average ED Volume

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	4.3900***	-4.2014***	0.3032	0.9142	-2.0605**
	(0.8955)	(0.7952)	(0.9338)	(1.0909)	(0.9709)
Rate of Return	-0.0035	0.0813	0.1399***	-0.2231***	-0.0038
	(0.0323)	(0.0368)	(0.0478)	(0.0678)	(0.0386)
Observations	111,914	99,498	99,600	99,016	104,188
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 11 Faster Peer Influence 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 12 Slower Peer Influence 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	

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 13 and 14) are statistically significant only in the first half of our study period. This suggests that peer influence on quality is short-lived. Similarly, our findings with regards to less-experienced peers (presented in Table 15) show statistically significant effect estimates only in the first sub-sample, implying that the influence of less-experienced peers disappears over time. This suggests that senior physicians' responsiveness to their junior peers' presence fades over time.

8. 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 the peer group), 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 16 and 17. Our results show that while the magnitude of the faster peer influence is slightly larger for physicians with 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 typically have less experience working in the ED and are more sensitive to the spillover effect from their peers.

Table 13 Higher-Quality Peer Influence 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 14 Lower-Quality Peer Influence 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	

Table 15 Less-Experienced Peer Influence Estimates

	First Half	Second Half
LOS	-2.4048***	0.5121
	(0.8145)	(0.6450)
Rate of Return	0.0045	0.0056
	(0.0411)	(0.0403)
Observations	90,554	98,986
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

The effect estimates of higher-quality and less-experienced physicians provide no statistically significant evidence for the heterogeneity of these effects 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 18 and 19, 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 effect estimates of other peer characteristics (e.g., lower-quality, less-experienced).

Figures 6-10 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 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 same shifts.

9. Robustness Checks

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

9.1. Sensitivity to Matching

We start by testing whether our analysis is sensitive to the choice of our matching technique. We use alternative matching approaches including one-to-one matching with and without replacement and coarsened exact matching. In each case, our inferences remain unchanged.

9.2. 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 assignments to shifts in our setting mitigates the potential endogeneity issue, we conduct robustness tests to address this concern.

Table 16 Effect Estimates - Tenure Less than 7 years

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	1.2616**	-3.3777***	-0.8818	2.9275	-1.0735
	(0.5876)	(1.1843)	(1.0631)	(2.1000)	(1.2118)
Rate of Return	-0.0052	-0.0151	0.1117	-0.3021***	-0.0360
	(0.0446)	(0.0486)	(0.0689)	(0.0813)	(0.0361)
Observations	115,338	126,476	80,236	85,728	66,102
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 17 Effect Estimates - Tenure More than 7 years

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	1.6374***	-2.7112**	-0.6302	0.7438	-2.0477***
	(0.4431)	(1.1023)	(0.7578)	(0.7731)	(0.5802)
Rate of Return	0.0329	0.1700	0.0672	-0.1471**	0.0198
	(0.0514)	(0.0368)	(0.0574)	(0.0722)	(0.0306)
Observations	171,182	146,790	118,954	108,186	141,532
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 18 Effect Estimates - Below Average Performers

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	1.0902***	-1.0049*	-0.4698	0.2149	-1.0643
	(0.6243)	(0.4923)	(0.8008)	(0.5591)	(0.3238)
Rate of Return	0.1136***	-0.0203	0.1329*	-0.1791***	0.0501
	(0.0401)	(0.0364)	(0.0537)	(0.0506)	(0.0344)
Observations	130,764	43,752	102,094	109,504	102,452
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 19 Effect Estimates - Above Average Performers

	Faster Peer	Slower Peer	Higher-Quality Peer	Lower-Quality Peer	Less-Experienced Peer
LOS	1.5171***	-2.3178***	-1.8067*	0.6185	-0.6270
	(0.3186)	(0.5760)	(0.8674)	(1.0410)	(0.5460)
Rate of Return	-0.0086	0.0017	0.1899***	-0.1000**	-0.0487
	(0.0284)	(0.0506)	(0.0669)	(0.1127)	(0.0358)
Observations	26,102	131,034	98,898	67,536	55,934
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Physician Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01				

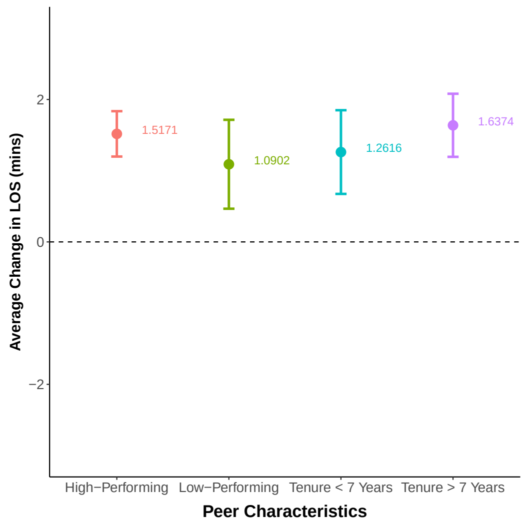

Figure 6 Effect Estimates-Faster Peer

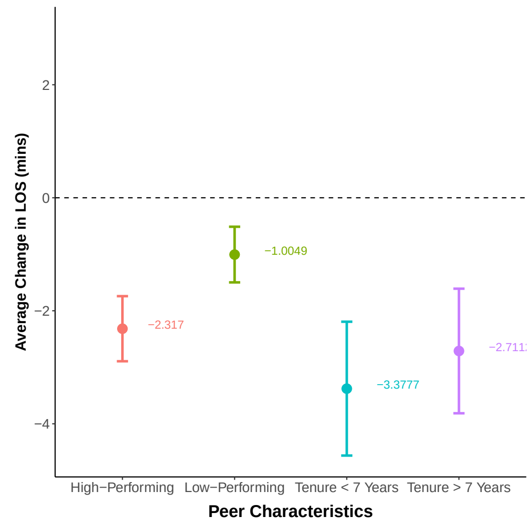

Figure 7 Effect Estimates-Slower Peer

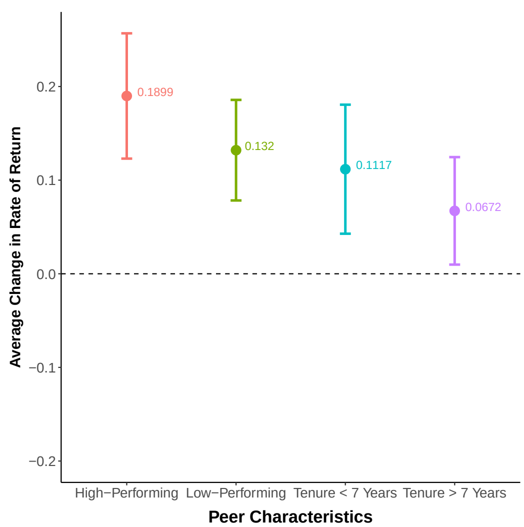

Figure 8 Effect Estimates-Higher Quality Peer

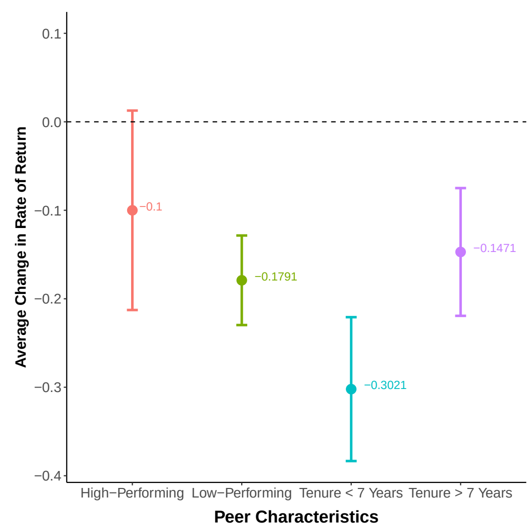

Figure 9 Effect Estimates-Lower Quality Peer

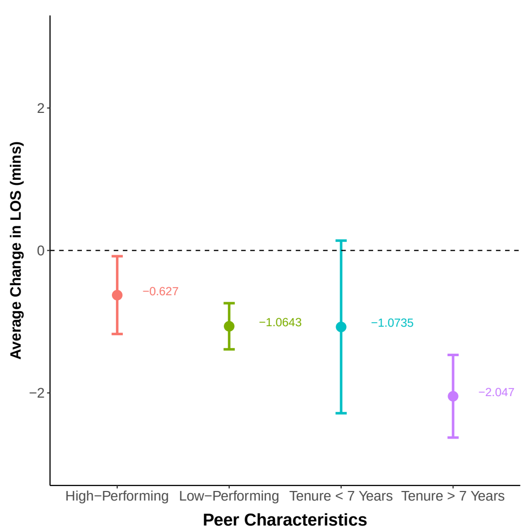

Figure 10 Effect Estimates-Less-Experienced Peer

In the first test, we address physicians' 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 peer across the sample period. We re-run our matching and regression analyses on this sub-sample and find the results (presented in Tables 20-24) 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. It is important to note that physician i's patients are excluded from ED volume calculation in order to avoid the problem of autocorrelation. 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:

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

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_i is an indicator variable coded as 1 if physician i is a higher-than-average performer in terms of speed and 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.

Table 20 Speed Effect Estimates

	Faster Peer	Slower Peer
Length of Stay (LOS)	6.3821***	-3.9734*
	(1.6332)	(2.2060)
Rate of Return	0.0853	0.0574
	(0.1080)	(0.0826)
Observations	27,248	38,166
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 21 Quality Effect Estimates

	Higher-Quality Peer	Lower-Quality Peer
Length of Stay (LOS)	-0.0703	0.6872
	(0.5571)	(0.9795)
Rate of Return	0.2769**	-0.2187*
	(0.1096)	(0.1228)
Observations	43,512	41,244
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 22 Experience Effect Estimates

	More-Experienced Peer	Less-Experienced Peer
Length of Stay (LOS)	0.3794	-2.8233*
	(1.6367)	(1.5573)
Rate of Return	0.0128	0.1471
	(0.1062)	(0.1407)
Observations	29,446	24,012
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 23 Gender Effect Estimates

	Opposite-Gender Peer	Same-Gender Peer
Length of Stay (LOS)	6.1811	-2.1703
	(5.8639)	(2.9488)
Rate of Return	-0.0281	-0.0612
	(-0.0111)	(0.0412)
Observations	10,342	10,324
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 Degree Effect Estimates

	Different-Degree Peer	Same-Degree Peer
Length of Stay (LOS)	-1.4180	-0.3933
	(2.3507)	(1.9619)
Rate of Return	0.0856	0.0130
	(0.0976)	(0.0764)
Observations	17,372	17,284
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

According to the results presented in Tables 25 and 26, we find no statistically significant relationship between ED volume and the number of high-performing physicians. The 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.

10. Alternative Quality Measures

In our analysis thus far, we utilize the 72-hour return rate to measure physician quality. In this section, we estimate the effects of higher- and lower-quality peers using alternative quality metrics 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.

Table 25 Effect Estimates - Faster Peer

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

Table 26 Effect Estimates - Higher-Quality Peer

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

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 patient.[3] Tables 27 and 28 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 earlier using the 72-hour rate of return as the measure of quality.

[3] 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 27 Overcall Effect Estimates

	Higher-Quality Peer	Lower-Quality Peer
Length of Stay (LOS)	-1.8123	1.8464
	(1.0624)	(1.1749)
12-Hour Discharge	0.0193	-0.0273
	(0.1065)	(0.0890)
Observations	55,856	55,936
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 28 Undercall Effect Estimates

	Higher-Quality Peer	Lower-Quality Peer
Length of Stay (LOS)	-1.3584	0.7552
	(1.0719)	(1.1258)
24-Hour Upgrade	0.6956***	-0.5078***
	(0.1630)	(0.1361)
Observations	27,600	26,622
Time Fixed Effects	Yes	Yes
Physician Fixed Effects	Yes	Yes
Controls	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

11. 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. We find the marginal effects of working alongside physician peers with opposite characteristics to be greater than those of the baseline case of working with homogeneous peers. 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. Similarly, scheduling more-experienced physicians with junior physicians could not only have a positive impact on the performance of senior physicians but also provide a learning opportunity for less-experienced 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. 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.

12. Limitations

It is important to note the limitations of our study. 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 we have not considered. 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). Although we could not identify any significant learning effect (see the results in Section 6.1), 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.

13. Conclusions

In this study, we examine the effects of different characteristics of physician peers including relative speed, quality, experience, 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. In addition, we find that the presence of a less-experienced peer has a positive effect on an average physician's speed. Our findings identify resource spillover from peers as the main driver of peer influence and indicate that diverse physicians with regards to speed, quality, and experience utilize shared resources more efficiently.

We further examine the persistence of these effects over time and find the effects with respect to relative quality and experience 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 are fairly heterogeneous and depend 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 of hospital EDs. Given the importance of gaining such understanding, we hope to see further studies that quantify mechanisms through which physicians impact their peers.

References

Abualenain J, Frohna WJ, Smith M, Webb C, Milzman D, Pines JM (2013) The prevalence of quality issues and adverse outcomes among 72-hour return admissions in the emergency department. *Journal of Emergency Medicine* 45:281-8.

Anderson D, Golden B, Jank W, Wasil E (2012) The Impact of Hospital Utilization on Patient Readmission Rate. *Health Care Management Science* 15(1):29-36.

Armony M, Shlomo I, Avishai M, Marmor Y, Tseytlin Y, Yom-Tov G (2015) Patient flow in hospitals: A data-based queuing-science perspective. *Stochastic Systems* 5(1):1-194.

Azoulay P, Graff Zivin JS, Wang J (2010) Superstar Extinction. *Quarterly Journal of Economics* 125(2):549-589.

Batt R, Terwiesch C (2017) Early Task Initiation and Other Load-adaptive Mechanisms in the Emergency Department. *Management Science* 63(11):3531-3551.

Berry Jaeker J, Tucker A (2017) Past the Point of Speeding Up: The Negative Effects of Workload Saturation on Efficiency and Patient Severity. *Management Science* 63(4):1042-1062.

Broadie M (2014) Assessing Golfer Performance on the PGA Tour. *Interfaces* 42(2):146-165.

Buechel B, Mechtenberg L, Petersen J (2018) If I can do it, so can you! Peer effects on perseverance. *Journal of Economic Behavior and Organization* 155:301-314.

Chan DC (2016) Teamwork and moral hazard: Evidence from the emergency department. *Journal of Political Economy* 124(3):734-770.

Chan T, Li J, Pierce L (2014) Compensation and Peer Effects in Competing Sales Teams. *Management Science* 60(8):1965-1984.

Chan TY, Li J, Pierce L (2014) Learning from peers: Knowledge transfer and sales force productivity growth. *Marketing Sci.* 33(4):463-484.

Cornelissen T, Dustmann C, Schnberg U (2017) Peer Effects in the Workplace. *American Economic Review* 107(2):425-56.

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

Edmondson A, Bohmer RM, Pisano G (2001) Disrupted routines: Team learning and new technology implementation in hospitals. *Admin. Sci. Quart.* 46(4):685-716.

Emergency Department Cases (2015) Emergency Physician Speed-Solutions to Physician Productivity. Retrieved February 26, 2019, https://emergencymedicinecases.com/emergency-physician-speed-and-productivity-solutions/.

Falk A, Ichino A (2006) Clean Evidence on Peer Effects. *Journal of Labor Economics* 24:39-58.

Gerla M, Kleinrock L (1980) Flow control: A comparative survey. *IEEE Transactions on Communications* 28(4):553-574.

Horrace WC, Liu X, Patacchini E (2016) Endogenous Network Production Functions with Selectivity. *Journal of Econometrics* 190(2):222-232.

Huang J, Carmeli B, Mandelbaum A (2015) Control of Patient Flow in Emergency Departments, or Multiclass Queues with Deadlines and Feedback. *Operations Research* 63(4) 892-908.

Huckman RS, Staats BR, Upton DM (2009) Team Familiarity, Role Experience, and Performance: Evidence from Indian Software Services. *Management Science* 55(1):85-100.

Iyengar R, Van den Bulte C, Lee J (2015) Social Contagion in New Product Trial and Repeat. *Marketing Science* 34(3):408-429.

Jackson CK, Bruegmann E (2009) Teaching students and teaching each other: The importance of peer learning for teachers. *American Economic Journal: Applied Economics* 1(4):85-108.

Keele L (2009) An Overview of Rbounds: An R Package for Rosenbaum Bounds Sensitivity Analysis with Matched Data. White Paper, Columbus, OH, 1-15.

Klasco RS, Wolfe RE, Wong M (2015) Assessing the Rates of Error and Adverse Events in the ED. *American Journal of Emergency Medicine* 33:178-69.

Krochmal P, Riley TA (1994) Increased Health Care Costs Associated with ED Overcrowding. *American Journal of Emergency Medicine* 12(3):265-6.

Kuntz L, Mennicken R, Scholtes S (2011) Stress on the Ward: An Empirical Study of the Nonlinear Relationship Between Organizational Workload and Service Quality (Ruhr-Universitaet Bochum, Bochum, Germany).

Lindquist MJ, Sauermann J, ZenouY (2015) Network Effects on Worker Productivity. Discussion Paper, C.E.P.R., 109-28.

Manchanda P, Xie Y, Youn N (2008) The role of targeted communication and contagion in new product adoption. *Marketing Science* 27(6):961-976.

Manski C (1993) Identification of endogenous social effects: the reflection problem. *Review of Economic Studies* 60:531-542.

Mas A, Moretti E (2009) Peers at Work. *American Economic Review* 99:112-145.

Moretti, E (2004a) Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data. *Journal of Econometrics* 121(12):175212.

Nair HS, Manchanda P, Bhatia T (2010) Asymmetric Social Interactions in Physician Prescription Behavior: The Role of Opinion Leaders. *Journal of Marketing Research* 47(5):883-895.

Olmos A, Govindasamy P (2015) Propensity Scores: A Practical Introduction Using R. *Journal of Multidisciplinary Evaluation* 11(25):68-88.

Pham JC, Kirsch TD, Hill PM, DeRuggerio K, Hoffmann B (2011) Seventy two-hour returns may not be a good indicator of safety in the emergency department: a national study. *Academic Emergency Medicine* 18:39-07.

Pope DG, Schweitzer ME (2011) Is Tiger Woods Loss Averse? Persistent Bias in the Face of Experience, Competition, and High Stakes. *American Economic Review* 101(1):129-57.

Powell A, Savin S, Savva N (2012) Physician Workload and Hospital Reimbursement. *Manufacturing and Service Operations Management* 14(4):512-528.

Rosenbaum PR, Rubin DB (1985) Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician* 39(1):33-38.

Rosenbaum PR (2002) *Observational Studies*, 2nd ed. (Springer, New York).

Saghafian S, Hopp WJ, Van Oyen MP, Desmond JS, Kronick SL (2012) Patient Streaming as a Mechanism to Improve Responsiveness in Emergency Departments. *Operations Research* 60(5):1080-1097.

Saghafian S, Hopp WJ, Iravani SMR, Cheng Y, Diermeier D (2018) Workload Management in Telemedical Physician Triage and Other Knowledge-Based Service Systems. *Management Science* 64(11):5180-5197.

Salway RJ, Valenzuela R, Shoenberger JM, Mallon WK, Viccellio A (2017) Emergency Department (ED) Overcrowding: Evidence-Based Answers To Frequently Asked Questions. *Revista Mdica Clnica Las Condes* 28(2):213-219.

Steinbach D, Tatsi E (2016) The Effect of Team Production on Individual Performance. Working Paper, Goethe University Frankfurt, Department of Management and Microeconomics, and Stockholm University, Swedish Institute for Social Research (SOFI).

The Becker's Hospital Review (2016) Hospitals: Is your ED's length of stay costing you millions?. Retrieved September 20, 2018, https://www.beckershospitalreview.com/finance/hospitals-is-your-ed-s-length-of-stay-costing-you-millions.html.

Traub SJ, Stewart CF, Didehban R, Bartley AC, Saghafian S, Smith VD, Silvers SM, LeCheminant R, Lipinski CA (2016) Emergency Department Rotational Patient Assignment. *Annals of Emergency Medicine* 67(2):206-215.

Trusov M, Bodapati AV, Bucklin RV (2010) Determining influential users in internet social networks. *Journal of Marketing Research* 47(4):643-658.

Waldinger, F (2012) Peer Effects in Science-Evidence from the Dismissal of Scientists in Nazi Germany. *Review of Economic Studies* 79(2):838-861.

Woehr D, Arciniega J, Poling L (2013) Exploring the Effects of Value Diversity on Team Effectiveness. *Journal of Business and Psychology* 28(1):107-121.

Yang M, Lien H, Chou S (2014) Is There a Physician Peer Effect? Evidence from New Drug Prescriptions. *Economic Inquiry* 52:116-137.

Zoogah D, Vora D, Richard O, Peng M (2011) Strategic alliance team diversity, coordination, and effectiveness. *The International Journal of Human Resource Management* 22(3):510-529.