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Team-Specific Human Capital and Team Performance: Evidence from Doctors†

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This paper studies whether team members' past collaboration creates team-specific human capital and influences current team performance. Using administrative Medicare claims for two heart procedures, I find that shared work experience between the doctor who performs the procedure ("proceduralist") and the doctors who provide care to the patient during the hospital stay for the procedure ("physicians") reduces patient mortality rates. A one standard deviation increase in proceduralist-physician shared work experience leads to a 10–14 percent reduction in patient 30-day mortality. Patient medical resource use also declines with shared work experience, even as survival improves. (*JEL* I10, J24, M12, M54)

Teams are widespread in the organization of work. Many firms use teams to organize production and many tasks require coordinated input from multiple workers (e.g., Delarue et al. 2008, Deloitte 2016). Yet we have relatively little economic evidence on how to organize teams to achieve higher productivity. An important and underexplored question is: is team productivity contingent on team members' collaboration histories? Conceptually, past collaboration may build skills and knowledge for coordination in the specific collaborative relationship, creating *team-specific human capital* that cannot be fully transferred to collaboration with other workers. Understanding the role of past collaboration for team productivity is highly relevant given its potential implications for optimal team organization and the pervasiveness of teamwork in many industries.

In this paper, I study whether team members' past collaboration creates team-specific human capital and influences current team performance in the context of health care—one of the most teamwork-intensive industries.[1] Using Medicare

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[1] For example, a single outpatient visit may involve teamwork among a multidisciplinary group of health care providers, an inpatient stay may require collaboration among multiple physicians. Many policies (e.g., accountable

claims data, I investigate whether shared work experience between doctors impacts outcomes of patients undergoing two procedures: (i) percutaneous coronary intervention (PCI); and (ii) coronary artery bypass grafting (CABG)—two of the most common medical procedures among the US elderly population and both of which are associated with high medical spending and high mortality rates.[2] PCI and CABG are often used for treating heart attacks. Treatments for a patient undergoing PCI or CABG typically require inputs from two types of doctors during the patient's hospital stay: (i) the surgeon/interventional cardiologist who performs the procedure—hereafter, "proceduralist"; and (ii) the doctors who provide preprocedure inpatient care and postprocedure recovery treatments—hereafter, "physicians."[3] Teamwork between proceduralists and physicians is an important feature of care for patients since each proceduralist and physician in a team may have her own distinct approach to the procedure, but their tasks are interdependent. Experience working together may be a potential way to gain skills and knowledge for better collaboration with each other. This paper studies whether shared work experience between the proceduralist who performs the PCI/CABG and the physicians who provide care to the patient during the hospital stay impacts the patient's treatment outcomes.

This setting is well suited to study the returns to shared work experience for several reasons. First, there exists a well-defined and welfare-relevant measure of doctor performance with respect to PCI and CABG—patient mortality, which can be accurately measured. Second, care for patients undergoing PCI and CABG requires teamwork between proceduralists and physicians, and team switches between proceduralists and physicians are frequent; these provide an opportunity to examine how team members' past collaboration influences current team performance. Third, the acute nature of heart attacks requires immediate care and generally precludes patients from selecting or being selected by doctors. This restricts the possibility of patients sorting into doctor teams with differing shared work experience. Finally, from a policy perspective, understanding doctors' team production in PCI and CABG is in itself important given the significant costs and high mortality rates associated with these two procedures.[4] The results can also generate important welfare implications given the widespread nature of teamwork in health care.

To estimate the causal effect of past collaboration experience, I use two complementary quasi-experimental strategies. The first strategy leverages within-proceduralist variation in shared work experience among patients admitted to the hospital through the emergency department (ED). Physician work schedules are generally set well in advance (e.g., several weeks ahead of the shift). Yet for PCI and CABG patients admitted to the hospital through the ED, the admission is typically unanticipated

care organizations and bundled payments) have been implemented to promote care coordination among providers, making teamwork increasingly important in health care.

[2] Medical costs of PCI and CABG totaled \$28 billion in the United States in 2014 (estimated based on the number of PCI and CABG performed in 2014 (Benjamin et al. 2018) and the mean cost per PCI or CABG hospitalization reported by Centers for Disease Control and Prevention (2015), inflation adjusted to 2014 dollars). 30-day mortality rates among Medicare beneficiaries undergoing PCI and CABG are, respectively, 5 and 6 percent (estimated based on all PCI/CABG patients in the 20 percent Medicare claims files).

[3] Although proceduralists are also physicians, I refer to doctors who perform the procedure as proceduralists and doctors who provide hospital care as physicians throughout this paper for distinction. I use doctors to refer to both proceduralists and physicians.

[4] See footnote 2 for medical spending and mortality rates associated with PCI and CABG.

and requires immediate care. These institutional features restrict the possibility of patients selecting into or being selected by doctor teams with differing shared work experience, holding the proceduralist fixed. By comparing patients within proceduralists, I show evidence that shared work experience is unrelated to patient characteristics that are predictive of health risks, and the estimated returns to shared work experience are robust to including a broad set of physician characteristics (including individual work experience) that may independently affect patient treatment outcomes. In additional analyses, I demonstrate in greater detail that the effects I measure are specific to shared work experience, not driven by patient or physician variation.

In the second empirical strategy, I include all patients undergoing PCI and CABG, regardless of whether admitted through the ED. The empirical specification is a two-way fixed effects model that includes proceduralist fixed effects, physician fixed effects, and a variable tracking shared work experience of the proceduralist-physician team that treats the patient. Proceduralist and physician fixed effects separate the effect of shared work experience from outcomes related to doctor-patient sorting in the non-ED setting as well as those due to differences in doctor time-invariant characteristics that may influence patient treatment outcomes. The two-way fixed effects model allows me to examine the effect of shared work experience among both ED and non-ED patients; the larger and more heterogeneous sample relative to that of the first strategy also allows me to explore heterogeneity in the returns to shared work experience.

Measuring shared work experience by the number of times that proceduralists and physicians have worked together in the past, I find that team performance improves when proceduralists and physicians accumulate experience working with each other. My estimates from the first empirical strategy indicate that a one standard deviation increase in shared work experience lowers patient 30-day mortality rates by 0.6 and 1.2 percentage points—or equivalently, 10 and 14 percent compared to the mean—for patients undergoing PCI and CABG, respectively. This evidence implies that shared work experience has substantial value for patient mortality, approximately equal to the returns to a one standard deviation increase in hospital spending (Doyle et al. 2015).[5] Results from my second empirical strategy—the two-way fixed effects model—show a comparable effect of shared work experience: a one standard deviation increase in shared work experience reduces patient 30-day mortality by 10 and 13 percent for PCI and CABG, respectively. The large returns to shared work experience imply a substantial role of team composition in shaping health care quality and, importantly, saving lives. This paper provides the first evidence (to my knowledge) that, even holding medical technology and the pool of health care providers fixed, reorganizing provider teams based on collaboration histories can significantly improve patient survival.

To further examine the effect of shared work experience, I rule out a competing explanation that is not specific to returns to shared work experience: proceduralist-physician matching, which refers to the possibility that proceduralists

[5] Doyle et al. (2015) finds that a one standard deviation increase in hospital spending (approximately $1,800) leads to a 10 percent reduction in one-year mortality among patients brought to the hospital because of emergency health conditions.

and physicians who are a better match for each other work together more frequently and a higher-quality match (rather than shared work experience per se) results in better patient outcomes. Both institutional features and empirical evidence provide little support for such a matching explanation. Institutionally, the quasi-random overlap in doctors' work schedules restricts the possibility of matching. Empirically, the proceduralist-physician team fixed effects model that captures constant match quality within teams yields similar estimates and results in only a minimal improvement in explanatory power relative to my baseline model. I also examine matching by restricting the sample to patients treated by proceduralists and physicians who likely are unable to choose collaboration intensity; I find similar returns to shared work experience. Finally, I construct an alternative measure of shared work experience using past collaboration that was unanticipated; the results consistently show that shared work experience reduces mortality.

Next, I investigate two potential mechanisms that may generate the effect of shared work experience: (i) improved productivity versus (ii) increased inputs. Over the course of a collaboration, proceduralists and physicians may learn how to best collaborate with each other, which in turn improves productivity and therefore team performance. As such, we could achieve better patient outcomes with the same or even fewer medical inputs. On the other hand, if proceduralists and physicians increase treatment intensity (i.e., use more medical inputs) when they are familiar with each other, team performance could also improve, even without any rise in productivity. Previous studies have found positive returns to treatment intensity among patients with emergency health conditions (e.g., Doyle 2011, Doyle et al. 2015, Silver 2021). Sorting out the relative importance of the improved productivity hypothesis and the increased inputs view is important since the former implies welfare improvements, whereas the latter may have a less clear welfare implication if extra inputs are costly. My results show that several measures of medical resource use decline with shared work experience, even as survival improves. This evidence supports models in which the productivity hypothesis outweighs the input view. In sum, past collaboration creates team-specific human capital that raises productivity, and enables doctors to achieve better patient outcomes—with even lower medical costs.

Finally, I explore how general human capital may substitute for or complement team-specific human capital. A large literature has documented the role of individual work experience as a source of general human capital and worker productivity (e.g., Shaw and Lazear 2008; Levitt, List, and Syverson 2013; Lafontaine and Shaw 2016; Haggag, McManus, and Paci 2017). It is thus possible that an experienced doctor works well with any doctor regardless of shared work experience, resulting in decreased importance of team-specific human capital when general human capital increases. In contrast, there may exist complementarities between general and team-specific human capital, so that team-specific human capital is more effective among agents with greater general human capital. To explore these possibilities, I examine heterogeneity in the effect of shared work experience by doctors' individual work experience. The results show that the effect of shared work experience on reducing patient mortality declines with doctors' own experience. However, the decline is small. For example, for patients undergoing PCI, a proceduralist's own experience needs to be about four standard deviations higher than that of an average proceduralist to eliminate the effect of shared work experience. In sum, although general human capital can substitute for team-specific human capital, the extent of the substitution is limited.

This paper contributes to three strands of literature. First, this paper contributes to the growing body of research on variation in the quality and cost of care provided by doctors. Prior work has linked a variety of factors to doctors' quality and cost performance, including, for example, financial incentives (e.g., Gaynor, Rebitzer, and Taylor 2004; Clemens and Gottlieb 2014; Johnson and Rehavi 2016), medical skill (e.g., Currie and MacLeod 2017; Chan, Gentzkow, and Yu 2019), and intrinsic motivation to perform well (e.g., Kolstad 2013). Different from the main focus on skills and incentives of individual doctors, this paper contributes to the literature by showing that the performance of a doctor depends importantly on team members.

Second, this paper contributes to the literature on teamwork. Teams are pervasive in the workplace and a large number of studies have investigated determinants of team performance, predominantly from the perspectives of moral hazard (e.g., Alchian and Demsetz 1972, Holmström 1982, Chan 2016), peer pressure (e.g., Kandel and Lazear 1992; Bandiera, Barankay, and Rasul 2005; Mas and Moretti 2009; Silver 2021), and team incentives (e.g., Hamilton, Nickerson, and Owan 2003; Bandiera, Barankay, and Rasul 2013; Friebel et al. 2017). This line of research emphasizes changes in efforts to production by influencing the preferences of agents. My study contributes to the literature by showing that team performance may also improve without explicit incentive schemes: past collaboration creates team-specific human capital and raises the productivity (and value) of a team.

Third, this paper contributes to the literature on human capital accumulation. While a large body of research has highlighted the role of work experience as a source of human capital and worker productivity (e.g., Levitt, List, and Syverson 2013; Lafontaine and Shaw 2016; Haggag, McManus, and Paci 2017), whether returns to workers' experience are team-specific is much less studied. My focus on team-specific human capital relates to Jaravel, Petkova, and Bell (2018), which shows the importance of team-specific human capital by showing that the premature death of an inventor significantly lowers co-inventors' earnings and innovation. In investigating mechanisms, the paper finds that the earning and innovation loss is larger among co-inventors who have a longer potential collaboration length with the deceased—a relationship consistent with the hypothesis that past collaboration creates team-specific human capital. My study also relates to Kellogg (2011) which shows that repeated interactions between firms improve firms' productivity, to Bartel et al. (2014) which shows that nurses' performance depends more on experience at the specific working unit than on general experience across all units, and to the management studies (e.g., Reagans, Argote, and Brooks 2005; Boh, Slaughter, and Espinosa 2007; Akşin et al. 2021) that find positive relationships between workers' past interactions and current performance.[6] My paper contributes to the literature by directly measuring workers' past collaboration intensity and leveraging plausibly exogenous variation in past collaboration to show causal evidence that

[6]While these management studies find positive relationships, it is difficult to exclude the possibility that the relationships are driven by variation in tasks/or workers' characteristics that are systematically correlated with both past collaboration intensity and current performance.

past collaboration between workers creates team-specific human capital and enables workers to achieve higher productivity—i.e., generating better performance with even fewer inputs. Such causal evidence remains thin in the literature but is highly relevant given its important implications for team productivity and the pervasiveness of teamwork in modern economies.

The remainder of this paper proceeds as follows. Section I describes the institutional setting. Section II introduces the data. Section III presents identification strategies and discusses main results. Section III also rules out proceduralist-physician matching as an alternative explanation and reports a series of robustness checks. Section IV examines mechanisms behind the effect of shared work experience. Section V explores heterogeneity in the effect of shared work experience. Section VI discusses the implications of my findings, and Section VII concludes the paper.

I. Institutional Setting

Both PCI and CABG are procedures often used for treating heart attacks, a sudden and severe condition that typically results in emergency hospitalizations. The condition develops when one or more of the coronary arteries become suddenly blocked, resulting in limited blood flow to the heart and the risk of death. PCI reestablishes blood to the heart by a catheter with a tiny balloon and stent to widen the diseased artery. CABG restores blood flow by creating a bypass around the clogged artery. CABG is more invasive than PCI and is often recommended as the strategy for patients with severe clinical conditions.

Like many other procedures, treatments for patients undergoing PCI and CABG typically require inputs from two types of doctors during the patient's hospital stay: (i) the proceduralist who leads the procedure; and (ii) the physicians (one or more than one) who provide pre- and postprocedure inpatient care. Teamwork between proceduralists and physicians is an important feature of care for patients given that the two types of doctors' tasks are, to a large extent, interdependent. For example, before the procedure, since physicians evaluate and medically manage the patient, they tend to have better information—which may not be complete in medical records—about the patient's clinical status than the proceduralist. Physicians' communication about the patient's clinical status could be an important input to the proceduralist's decision about the optimal procedure timing and strategy—i.e., proceduralists' tasks require inputs from physicians. On the other hand, physicians' tasks would also require inputs from proceduralists. For example, after the procedure, physicians continue to evaluate and manage the patient, whose clinical status may fluctuate and depend on events during the procedure. If complications occur, physicians may contact the proceduralist for additional consultation or a repeat operation. The interdependency in tasks between proceduralists and physicians could make their quality of collaboration important for patient treatment outcomes.

Prior experience working together may influence current patient outcomes since each proceduralist and physician in a team can have her own distinct way of performing tasks, making it valuable for proceduralists and physicians to learn how to collaborate with the specific team member. For example, for the same patient, different physicians may interpret the patient's disease status differentially and may have different communication styles, resulting in variation in information the proceduralist receives about the patient's disease progress. Past collaboration may help proceduralists learn how to better interpret the specific physician's messages or lack thereof. In addition, for the same procedure (e.g., within PCI), proceduralists may have differing skills and distinct ways of performing the procedure. The more knowledge physicians have about a proceduralist's ability and style, the better they can tailor their postprocedure treatment plans or develop skills that are specific to the proceduralist's distinct approach to the procedure. These may be particularly important in health care, in which patients' complex disease progress and doctors' various communication and practice styles could complicate teamwork. A significant number of medical studies have emphasized the importance of teamwork quality for patient treatment outcomes (e.g., Gawande et al. 2003, Christian et al. 2006, Mazzocco et al. 2009).

I conducted interviews with proceduralists and physicians to understand the possible effects of shared work experience.[7] The following quotes provide additional intuitions about how shared work experience may affect team performance:

(i) Example from physicians about how past collaboration influences current work with proceduralists:

[*If we have worked together often*,] *I know better what drugs they* [*proceduralists*] *would like to use*, …, *what stents they will use*, *and when to allow the patient out of bed after the surgery.*

(ii) Example from proceduralists about how past collaboration influences current work with physicians:

[*If we have worked together often*,] *the physicians are more likely to communicate to me if any complications occur to the patient after the procedure*, *rather than waiting for several days until I discover it. I can then deal with the complication more in time*, *for example*, *sending the patient back to the surgery room in a more timely way.*

(iii) Example from both proceduralists and physicians (though in slightly different words) on the value of past collaboration:

We have better communication and we trust each other more if we have worked together often.

The institutional background and doctors' quotes shed light on the potential effect of proceduralist-physician shared work experience on patient treatment outcomes. Next, I turn to the empirical investigation of this effect.

[7] I spoke with nine proceduralists and physicians affiliated with Stanford University, Stanford Hospital, or Palo Alto Medical Foundation in 2018 and 2019.

II. Data

The primary data for this study are administrative claim records for a 20 percent random sample of Medicare beneficiaries from 2008 to 2016 (Centers for Medicare and Medicaid Services (CMS) 2008–2016). Medicare claims cover a large number of patients undergoing PCI and CABG and provide rich administrative data for tracking doctors' collaboration histories. The Medicare data also provide information on patient demographic characteristics and medical histories. Vital statistics that record patient death dates are linked to Medicare claims, allowing me to measure my primary analysis outcome: patient 30-day mortality.

I supplement Medicare claims with two other datasets—Medicare Data on Provider Practice and Specialty (MD-PPAS 2008–2016) and Physician Compare (Physician Compare 2014–2017)—which contain information on proceduralists' and physicians' characteristics, such as specialty, age, gender, and medical school attended.

To identify the proceduralist and the set of physicians who treat a patient during the hospital stay, I link the carrier file (the Medicare claims that record doctor services) to the MedPAR file (the Medicare data that contains information on inpatient stays). The carrier file records all services provided by doctors to a patient and provides information on service procedure code, service date, and provider ID. The MedPAR file includes information on hospitalized patients' admission and discharge dates. By linking the carrier file to the MedPAR data using patient ID, I identify the proceduralist as the doctor who leads the patient's procedure during the hospital stay and the physicians as the doctors who provide hospital care to the patient after the admission date but before the discharge date.[8] Each of the analyzed patients has only one proceduralist by design but can be associated with multiple physicians.

A. *Sample Construction*

I construct slightly different analytic samples for the two empirical strategies. In my first empirical strategy that compares ED patients within proceduralists, I restrict the sample in the following ways. First, I restrict the sample to PCI and CABG patients admitted to the hospital through the ED.[9] Second, I include only patients aged 65 to 100 years. Third, I exclude cases in which I cannot observe any physician

[8] I use the following process to pick the lead proceduralist for each patient. First, I restrict the data to procedure claims billed for doctors in the relevant specialties for PCI and CABG (e.g., interventional cardiology for PCI and cardiac/thoracic surgery for CABG). Second, I drop claims billed for assistant proceduralists or proceduralists who provide only the supervision and interpretation portion of the procedure if there are multiple proceduralists. Third, a small number of patients still have more than one observed proceduralist; I thus pick the one with the highest allowable charge as the lead proceduralist. Finally, I drop a small number of patients who still have two or more proceduralists (mostly two) after the above process.

[9] Based on the recommendation by the CMS Research Data Assistance Center (ResDAC 2015), I define a hospital stay as admitted through the ED if it has an emergency room charge amount >\$0 in the MedPAR file. Though ResDAC (2015) also suggests using revenue center codes in the Medicare Outpatient file to identify ED visits, such a method tends to overclassify ED visits and hence hospital admissions through the ED (see a similar finding in, e.g., Venkatesh et al. 2017). In addition, if admitted for inpatient care, the majority of ED patients (87 percent) identified in this way are reported to be transferred to another hospital rather than being admitted to the current hospital. Therefore, I use the stringent definition that categorizes an inpatient stay as admitted through the hospital's ED if it has an emergency room charge >\$0 in the MedPAR file (i.e., has ED visits with the current

visits in the first two days after admission or the last two days before discharge. The purpose of this third sample restriction is to exclude (i) patients covered by bundled payments or Medicare Advantage,[10] whose physicians are not observable in the carrier file, and (ii) patients whose hospital care is provided by the proceduralist who performs the procedure and thus are not associated with any physicians during the hospital stay.[11] Finally, I exclude a small number of patients treated by proceduralists who have only one patient in my data, since comparing outcomes within the same proceduralist is not feasible among these patients. I also drop a small number of observations with missing patient or physician characteristics. The final sample includes approximately 76,000 PCI observations and 14,000 CABG observations. Panel A of online Appendix Table A1 reports changes in the sample size resulting from the above restrictions.

In my second empirical strategy that controls for proceduralist and physician fixed effects (i.e., the two-way fixed effects model), I make the same sample restrictions as those in the first empirical strategy except with the following two changes: (i) I include all patients undergoing PCI and CABG regardless of whether they are admitted to the hospital through the ED or not; and (ii) I exclude patients treated by proceduralists or physicians (rather than only proceduralists) who have only one patient during the years of observation, since comparing outcomes within the same proceduralist or the same physician is not feasible among these observations. The final sample consists of approximately 92,000 and 50,000 PCI and CABG observations, respectively.[12] Panel B of online Appendix Table A1 reports changes in the sample size resulting from the above restrictions.

Online Appendix Table A2 presents summary statistics on the number of proceduralists, physicians, and physicians per team in my data. The ED analysis sample (empirical strategy I) includes approximately 7,500 PCI and 1,900 CABG proceduralists; the two-way fixed effects sample (empirical strategy II) includes approximately 7,400 PCI and 2,400 CABG proceduralists. While, by definition, each team has only one proceduralist, the average number of physicians per team is about 3 and 6 for PCI and CABG, respectively.[13]

B. *Primary Variables*

Shared Work Experience.— Physicians' care to hospitalized patients is recorded as hospital visits in Medicare claims. I thus define the shared work experience between a proceduralist and a physician as the number of hospital visits the physician

hospitalization). This method also captures ED admissions identified by revenue center codes in the Medicare Inpatient file (ResDAC 2020).

[10] The MedPAR file contains some patients covered by Medicare Advantage, but these patients are not included in the carrier claims file.

[11] For PCI, which is less invasive than CABG and hence typically involves a shorter hospital stay, I further exclude patients without any physician visits in the first day after the hospital admission.

[12] Approximately 61 and 25 percent of PCI and CABG patients, respectively, are admitted to hospitals through the ED (based on an emergency room charge amount >\$0 in the MedPAR file). Yet we do not see a commensurate increase in sample size from the first to the second empirical strategy. This is because, compared to the first empirical strategy, the second strategy further excludes patients treated by physicians who have only one observed patient during the years of analysis.

[13] Since CABG is more invasive than PCI, CABG patients generally stay in the hospital longer and thus tend to be associated with a larger number of physicians during the hospital stay.

provided to the proceduralist's PCI/CABG patients in the past two years, i.e., in the proceeding 730 days. Specifically,

$$E(j,k;t) \;=\; \sum_{\tau=t-730}^{t-1} N_{j,k;\tau}, \tag{1}$$

where $E(j,k;t)$ is the shared work experience between physician j and proceduralist k on day t; $N_{j,k;\tau}$ is the number of hospital visits physician j provided to proceduralist k's patients at day $\tau \in [t-730, t-1]$.[14]

I measure shared work experience based on collaboration in the past two years because studies have shown that the effect of experience decays with time (e.g., Benkard 2000, Kellogg 2011). As a result, experience gained in the distant past may not be relevant for current teamwork. In robustness checks, I also measure shared work experience in alternative time windows and as a function of a decay parameter that captures experience depreciation over time.

Although there is only one proceduralist who leads the procedure, there are often multiple physicians providing care to the patient during the hospital stay.[15] As a natural benchmark, I measure shared work experience for each patient as the average of the shared work experience between the proceduralist and each of the physicians treating the patient during the hospital stay, to account for the fact that each physician contributes to the patient's hospital care. I also weight the average by the share of visits provided by each physician to the patient, to reflect that each physician may account for a differential share of care. This weighted average considers each physician's shared work experience with the proceduralist and the differential share of care contributed by each physician. In robustness checks, I also define shared work experience in a variety of alternative ways, including the median and mode of the shared work experience between the proceduralist and each of the physicians treating the patient, as well as the shared work experience between the proceduralist and the first physician who treats the patient.

In the main analysis, shared work experience for patient i is measured as follows:

$$E_i \;=\; \sum_{j \in J(i)} \sigma_{ij} \times E\big(j, k(i); t(i)\big), \tag{2}$$

where $J(i)$ indicates the set of physicians who provide visits to i during the current hospital stay, $k(i)$ indicates i's proceduralist, and $t(i)$ indicates the day i was admitted to the hospital. The term σ_{ij} is the share of hospital visits associated with i in her current hospital stay that is provided by physician j; specifically,

$$\sigma_{ij} \;=\; \frac{\sum_{v \in V_i} I\big(j(v) \;=\; j\big)}{\|V_i\|}, \tag{3}$$

[14] To the extent that I measure doctors' shared work experience based on collaboration in the past two years and my data start in the year 2008, my empirical regression restricts the sample to patients admitted to the hospital in 2010 or after to allow for at least a two-year look-back window to measure doctors' shared work experience.

[15] For example, 15 percent of the PCI and CABG patients admitted through the ED are treated by only one physician during the hospital stay; 22, 18, and 45 percent of these ED patients are treated by two, three, and more than three physicians during the hospital stay, respectively. As discussed in Section IIA, an average PCI and CABG team consists of approximately 3 and 6 physicians, respectively.

where V_i is the set of all physician visits provided to i during the hospital stay, and $I\big(j(v) = j\big)$ is an indicator that equals one if the visit was provided by physician j. In the extreme, if a single physician provides all the hospital visits to the patient, i.e., $J(i) = j$, then σ_{ij} equals one and E_i is equivalent to $E\big(j, k(i); t(i)\big)$.

Online Appendix Figure A1 plots the distribution of shared work experience measured based on equation (2). Perhaps surprisingly, many teams have not worked together often. A large proportion of doctors, especially proceduralists, are not employed by a specific hospital but rather practice in multiple facilities through contractual relationships.[16] Such a pattern may result in few interactions between a specific proceduralist and physician. Perhaps also a contributing factor, most proceduralists and physicians co-treating a patient are from different practice groups, which may lower the shared work experience for these proceduralist-physician pairs if belonging to the same organization increases the probability of working together. Finally, to the extent that my data is a 20 percent sample, I may underestimate the shared work experience between a proceduralist and a physician since I cannot observe every collaboration between them. Such a measurement error issue may add noise to my estimation. Online Appendix Section A explores the effect of measurement error by simulations and shows that, if anything, the measurement error would lead to an underestimated effect of shared work experience on reducing mortality.

Individual Work Experience.—A proceduralist's individual work experience is measured as the number of PCI and CABG procedures the proceduralist performed in $\big[t(i) - 730, t(i) - 1\big]$ for patient i undergoing PCI and CABG, respectively.[17] A physician's individual work experience is the number of hospital visits the physician provided to PCI and CABG patients in $\big[t(i) - 730, t(i) - 1\big]$ for i undergoing PCI and CABG, respectively. As a patient may be cared for by more than one physician during the hospital stay, following the main measure of shared work experience, I define physicians' individual work experience for a patient as the weighted average individual work experience of all the physicians treating the patient during the hospital stay. The weights are σ_{ij}.[18] A more general version of individual work experience—years of practice—is also included in my analysis.

[16] For example, data from the American Medical Association show that in 2011 (around the middle of my study period), only 7.5 percent of surgeons and 12.3 percent of physicians were full-time hospital employees (Charles et al. 2013). Less than 30 percent of doctors in the United States in 2011 were employed by physician groups owned by a hospital or hospital group (https://www.nytimes.com/2019/10/03/health/sutter-hospitals-medical-bills.html, accessed October 1, 2019).

[17] Specifically, I measure proceduralists' individual work experience as

$$E\big(k(i); t(i)\big) = \sum_{\tau=t(i)-730}^{t(i)-1} \sum_{i' \in \{i' : t_{i'} = \tau\}} I\big(k_{i'} = k(i)\big),$$

where $t_{i'}$ is the day the procedure was performed, and $I\big(k_{i'} = k(i)\big)$ is an indicator that equals one if the procedure for patient i' was provided by proceduralist $k(i)$.

[18] Specifically, a physician's individual work experience for patient i is defined as: $E\big(J(i); t(i)\big) = \sum_{j \in J(i)} \sigma_{ij} \times E\big(j; t(i)\big)$, where

$$E\big(j; t(i)\big) = \sum_{\tau=t(i)-730}^{t(i)-1} \sum_{v \in \{v : t_v = \tau\}} I\big(j(v) = j\big),$$

where t_v is the day the hospital visit was provided, and $I\big(j(v) = j\big)$ is a dummy that equals one if visit v was provided by physician j.

Outcome Variables.— My main measure of doctors' team performance is patient 30-day mortality, which indicates whether the patient dies within 30 days after the hospital discharge.[19,20] Patient mortality is a broadly used performance measure for PCI and CABG in the medical literature;[21] it can be accurately measured and is characterized by sufficient variation across doctors that allows for meaningful comparisons. Patient mortality is also the performance measure of many report card programs for cardiac surgery.[22] My main analysis focuses on 30-day mortality, which is a commonly used mortality measure for PCI and CABG.[23] In robustness checks, I investigate the effect when considering mortality outcomes over a shorter or longer period.

I also include the following frequently used measures of medical resource use as outcome variables: (i) length of hospital stay, which is the number of days the patient stays in the hospital for the current procedure; (ii) number of tests and exams performed on the patient during the current hospital stay; and (iii) Medicare outlier payments, which is a dummy that equals one if the patient's current hospital stay has an unusually long length or high cost according to the definition by Medicare. I also consider three common measures of postdischarge health care use: (i) whether the patient is discharged to skilled nursing or rehabilitation facilities; (ii) 30-day inpatient readmission—whether the patient is rehospitalized within 30 days of the discharge; and (iii) 30-day outpatient visits—the number of physician office and ED visits in the 30 days after the discharge.

III. Effect of Shared Work Experience

An ideal experiment to assess the effect of past collaboration would randomly assign patients to doctor teams with randomly varied shared work experience, so that (i) patient potential outcomes are balanced across shared work experience and (ii) shared work experience is not correlated with other doctor variation that may influence patient treatment outcomes. Lacking random assignment, I leverage two quasi-experimental strategies to estimate the effect of past collaboration. In this section, I describe the two empirical strategies and their analysis results. I begin with the estimation that focuses on patients admitted to the hospital through the ED (i.e., empirical strategy I). Then, I describe the two-way fixed effects model (i.e., empirical strategy II). The two strategies show a consistent pattern that shared work experience significantly reduces patient mortality. Next, I rule out proceduralist-physician matching as a competing explanation. Lastly, I assess the robustness of my estimates to a series of additional checks.

[19] As the data track patient mortality up to December 31, 2016, I restrict my sample to patients discharged from the hospital on or before December 1, 2016 to allow for a 30-day observation window after the hospital discharge.

[20] In robustness checks (Section IIID), I also measure 30-day mortality from the day of the hospital admission.

[21] See, e.g., Wennberg et al. (2004), Shroyer et al. (2017), and Thiele et al. (2018).

[22] Several states, including California, Massachusetts, New Jersey, New York, and Pennsylvania, use patient mortality as the performance measure of their report card programs for cardiac procedures.

[23] See, e.g., Wennberg et al. (2004), Joynt et al. (2012), Menees et al. (2013), and Myles et al. (2016).

A. *Empirical Strategy I: Patients Admitted through the ED*

Identification.—My first empirical strategy restricts the sample to patients admitted to the hospital through the ED and leverages *within-proceduralist* variation in shared work experience. As a result of changes in physicians on duty, a proceduralist works with different physicians for patients admitted to the hospital on different days, leading to variation in shared work experience across patients within proceduralists. Physician work schedules are typically set well in advance of a patient's admission date. Yet for patients admitted via the ED, the admission is unanticipated and requires immediate treatment from the physicians on duty. These two institutional features—predetermined physician work schedules and unanticipated patient admissions—limit patient selection to physicians. As a result, assignments of patients to proceduralist-physician teams with differing shared work experience may be considered quasi-random, holding the proceduralist fixed. My first empirical strategy exploits such quasi-random assignments within proceduralists. One possible issue is that patients may be sorted into physicians among the set of physicians on duty. For instance, riskier patients may be assigned to on-call physicians who have more collaboration experience with the proceduralist. Yet, in speaking with physicians, they pointed out that this seems unlikely since patients are typically assigned sequentially to available physicians. Further, it is difficult to require physicians who are not on duty to see a specific patient. The acute nature of the conditions related to PCI and CABG also generally precludes patients from waiting until a preferred physician is available. These institutional features restrict the possibility of physician selection. Finally, this issue boils down to whether patient health risks are systematically correlated with shared work experience, which, as I show below, has little supportive evidence.

By randomly drawing proceduralists from the data, I find large and quasi-normally distributed variation in shared work experience across ED patients admitted on different days within each proceduralist.[24] Figure 1 systematically shows the within-proceduralist variation in shared work experience by residualizing shared work experience by proceduralist identities using all ED patients in the data. The figure exhibits substantial within-proceduralist variation in shared work experience.

A natural question is what drives the variation in shared work experience. Note that to have shared work experience, a proceduralist's and a physician's clinical schedules of seeing patients must overlap. Two institutional features could result in quasi-random overlap in doctors' clinical shifts. First, besides seeing patients, doctors are often responsible for nonclinical duties such as administration; many doctors also have teaching and research responsibilities. The latter is likely given that hospitals that are able to perform PCI and CABG are relatively large hospitals and are more likely to be academic medical centers. Doctors set schedules to fit various tasks, making it difficult to schedule shifts to work with a particular doctor. Second,

[24] Specifically, I randomly draw proceduralists from the analysis sample and plot shared work experience for ED patients treated by each randomly picked proceduralist. The data shows large within-proceduralist variation in shared work experience across ED patients admitted on different days. Though I do not report these detailed results, I include the code in the online replication folder in case readers are interested in replicating.

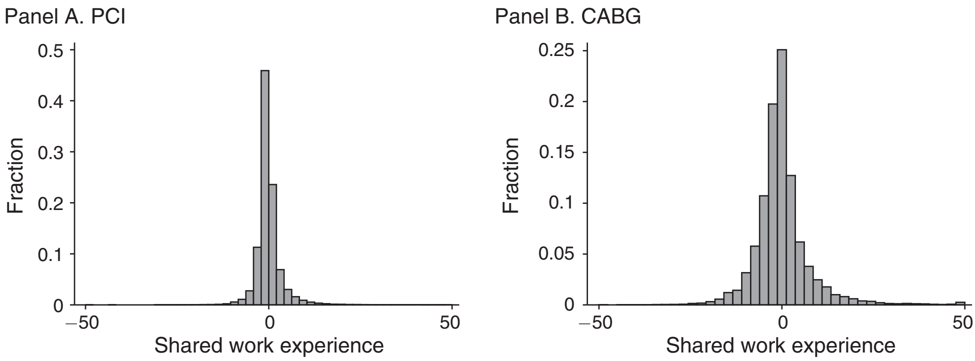

Figure 1. Distribution of Shared Work Experience

Notes: These figures plot the distribution of shared work experience after residualizing by proceduralist identities for patients included in empirical strategy I (the ED analysis). Residualized shared work experience is winsorized at values of –50 and 50 for improved readability.

most proceduralists and physicians in my data are from different practices;[25] arranging shifts to work together is difficult among doctors who belong to different practices and these doctors generally set schedules independently. Importantly, the above institutional features hold regardless of whether the patient is admitted through the ED.

The identifying assumptions in empirical strategy I are the following.

ASSUMPTION 1.1 (Independence): *Conditional on proceduralist identities, admission hospital-time categories (e.g., hospital-year, day of the week) and individual work experience, potential outcomes of patients admitted through the ED are mean independent of shared work experience.*

ASSUMPTION 1.2 (Exclusion): *Conditional on proceduralist identities, admission hospital-time categories (e.g., hospital-year, day of the week) and individual work experience, physician characteristics that may affect outcomes of patients admitted through the ED are mean independent of shared work experience.*

The institutional feature that patients' admissions are unanticipated but physicians' work schedules are set well in advance lends credibility to the independence assumption. To empirically assess the independence assumption, I first check whether patient characteristics are balanced across shared work experience. Table 1 compares patients treated by a proceduralist-physician team with high versus low shared work experience. The table shows balance in patient demographics as well as recorded comorbidities (conditional on the conditioning variables). In Figure 2,

[25] For example, in the ED analysis sample, 75 and 91 percent of patients undergoing PCI and CABG, respectively, are treated by proceduralists and physicians who belong to different practices. I identify proceduralists' and physicians' practices by their tax identification number (TIN). A proceduralist and a physician are defined as belonging to the same practice if they report the same TIN in Medicare claims. A patient is defined as being treated by proceduralists and physicians from the same practice if more than 95 percent of the patient's care is provided by physicians who work in the same practice as the proceduralist.

Table 1—Balance in Patient Characteristics: ED Patients

	Shared work experience below mean	Shared work experience above mean	p-value
Panel A. PCI			
Age	76.13	76.18	0.36
	(6.21)	(6.48)	
Female	0.437	0.436	0.77
	(0.425)	(0.447)	
Black	0.081	0.080	0.70
	(0.211)	(0.224)	
Hispanic	0.017	0.016	0.27
	(0.102)	(0.109)	
Medicaid	0.168	0.165	0.18
	(0.302)	(0.321)	
Disabled	0.159	0.156	0.32
	(0.310)	(0.328)	
Number of comorbidities	2.284	2.272	0.30
	(1.373)	(1.452)	
Predicted 30-day mortality (percent)	5.952	5.946	0.75
(by patient characteristics)	(2.324)	(2.462)	
Observations	53,940	21,991	
Panel B. CABG			
Age	74.47	74.49	0.75
	(4.77)	(4.99)	
Female	0.336	0.333	0.65
	(0.362)	(0.389)	
Black	0.068	0.064	0.18
	(0.187)	(0.191)	
Hispanic	0.016	0.018	0.30
	(0.093)	(0.095)	
Medicaid	0.144	0.139	0.25
	(0.256)	(0.273)	
Disabled	0.138	0.137	0.82
	(0.264)	(0.285)	
Number of comorbidities	1.825	1.829	0.87
	(1.107)	(1.176)	
Predicted 30-day mortality (percent)	9.059	9.074	0.81
(by patient characteristics)	(3.400)	(3.553)	
Observations	9,438	4,684	

Notes: This table shows average characteristics of patients treated by proceduralist-physician teams with shared work experience below versus above the mean of the sample. The sample includes all patients included in empirical strategy I (the ED analysis). Standard deviations are reported in parentheses. Each characteristic is residualized with respect to the set of nonpatient controls included in empirical strategy I. The unconditional mean of each characteristic is added back for ease of interpretation. Predicted 30-day mortality is generated based on logistic regressions of patient actual 30-day mortality outcomes on patient covariates that include five-year age bin fixed effects, gender, Black race, Hispanic, Medicaid coverage, disability status, and dummies for the patient's health history of common comorbidities that include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease, and cancer. p-values of t-tests for the equivalence of means between the two subgroups are shown in the last column.

I further show that patient *predicted* 30-day mortality as a function of demographics and comorbidities is nearly identical across shared work experience.[26] Despite

[26] The predicted 30-day mortality is generated based on logistic regressions of patient actual 30-day mortality outcome on patient demographics and comorbidities, which include five-year age bin fixed effects, gender, Black

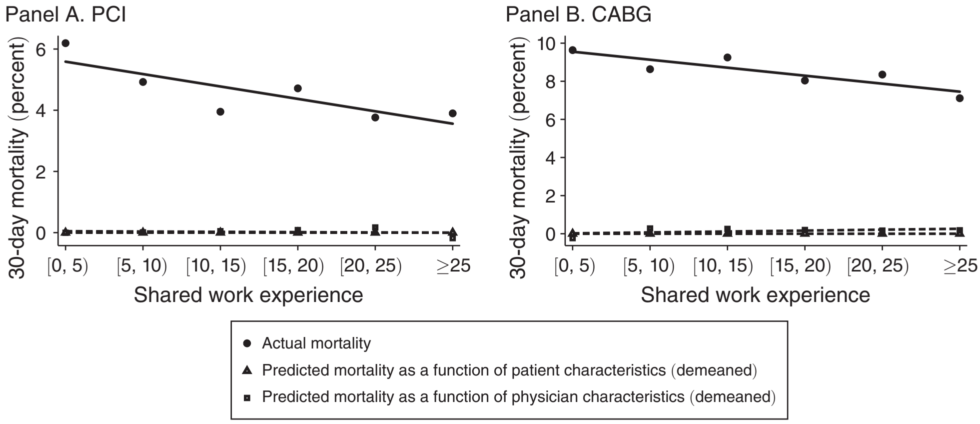

FIGURE 2. ACTUAL AND PREDICTED 30-DAY MORTALITY VERSUS SHARED WORK EXPERIENCE: ED PATIENTS

Notes: These figures plot actual 30-day mortality (circles), predicted 30-day mortality as a function of patient characteristics (triangles), and predicted 30-day mortality as a function of physician characteristics (squares) for patients treated by proceduralist-physician teams with different levels of shared work experience. The sample includes all patients included in empirical strategy I (the ED analysis). The solid/dashed lines show the best linear fit through the binned data. Predicted 30-day mortality as a function of patient characteristics is generated based on logistic regressions of actual 30-day mortality outcomes on patient covariates that include five-year age bin fixed effects, gender, Black race, Hispanic, Medicaid coverage, disability status, and dummies for the patient's health history of common comorbidities that include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease, and cancer. Predicted mortality based on patient characteristics is residualized with respect to the set of nonpatient controls included in empirical strategy I. Predicted 30-day mortality as a function of physician characteristics is generated by first regressing patient actual 30-day mortality on physician characteristics (age, gender, years of practice, rank of medical school attended, and specialties), conditioning on the covariates in empirical strategy I. Coefficients from this regression are then used to predict patient mortality as a function of physician characteristics. Predicted mortality outcomes are generated separately for PCI and CABG.

having no relationship with shared work experience, patient demographics and comorbidities are nonetheless significant predictors of 30-day mortality: even conditional on the conditioning variables specified in the independence assumption, the F-statistics for joint significance of patient characteristics on 30-day mortality are 32.23 (p-value: 0.00) and 9.06 (p-value: 0.00) for patients undergoing PCI and CABG, respectively.[27] To further test the independence assumption, I show in the empirical results below that (i) adding patient demographics and comorbidities in the specification results in virtually no change in my estimates and (ii) unobserved patient variation is unlikely to be driving my results.

For the exclusion assumption, the plausibly quasi-random overlap in doctors' work schedules provides support for it. To empirically assess the assumption, I conduct four sets of tests. First, Figure 2 shows balance in physician observable characteristics (summarized by patient predicted 30-day mortality as a function of physician characteristics) across shared work experience. Specifically, I regress

race, Hispanic, Medicaid coverage, disability status, and dummies for the patient's health history of common comorbidities that include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease, and cancer (lung/breast/colorectal/endometrial/prostate cancer).

[27] The lower F-statistic for CABG than for PCI could result from the relatively smaller sample for CABG, rather than the notion that patient characteristics are less important predictors of mortality for CABG.

patient actual 30-day mortality on key characteristics of physicians, conditional on patient covariates and the conditioning variables specified in the exclusion assumption. I then use the coefficients from this regression to predict patient mortality as a function of physician characteristics. The physician characteristics used in the prediction include years of practice, specialties, age, gender, and rank of medical school attended. Despite the fact that these characteristics are strong predictors of patient mortality outcomes (with an F-statistic of 94.33 for PCI and 16.65 for CABG, conditional on patient characteristics and the conditioning variables in Assumption 1.2), Figure 2 shows that these characteristics are balanced across shared work experience. As a second test for the exclusion assumption, I show in the results below that my estimates remain stable when controlling for detailed physician covariates. Third, I adopt an approach by Oster (2019) and show that my estimates are unlikely to be explained away by *un*observed physician characteristics. Fourth, in Section IIIC, I show evidence from four different empirical tests that the matching hypothesis (i.e., doctors who are better matched tend to work together more often) is unlikely to be driving the estimated effect of shared work experience.

Empirical Specification.—My empirical specification takes the following form:

$$y_i = \alpha E_i + \theta_{k(i)} + \mathbf{T}_i \eta + \mathbf{F}_i \gamma + \bar{\mathbf{H}}_{J(i)} \lambda + \mathbf{X}_i \beta + \varepsilon_i, \tag{4}$$

where y_i is the outcome (e.g., 30-day mortality) of patient i admitted to the hospital on day $t(i)$, and E_i is the shared work experience of the proceduralist-physician team that treats i. The coefficient of interest is α, which identifies the extent to which shared work experience influences patient outcomes. Standard errors are clustered at the proceduralist level.[28] The term $\theta_{k(i)}$ is proceduralist fixed effects; $\mathbf{T}_i$ is a set of fixed effects that includes hospital-year fixed effects, patient admission month fixed effects, and admission day of the week fixed effects.

The term $\mathbf{F}_i$ includes proceduralists' and physicians' individual work experience (details of the variable construction described in Section IIB). In the main specification, I control for individual work experience as a linear term. In robustness checks (Section IIID), I control for individual experience in six different forms: (i) linear splines; (ii) restricted cubic splines; (iii) polynomials that include both a linear and a quadratic term; (iv) polynomials that include a linear, a quadratic, and a cubic term; (v) splines and interactions of the splines;[29] and (vi) nonparametrically by fixed effects.

The term $\bar{\mathbf{H}}_{J(i)}$ is a set of physician characteristics, including weighted averages of the physicians' years of practice, age, gender, and rank of medical school attended, where the weights are the share of hospital visits provided by each physician to that patient.[30] I also include in $\bar{\mathbf{H}}_{J(i)}$ weighted percentages of the physicians that are in

[28] In robustness checks (Section IIID), I show results under different clustering approaches.

[29] I include interactions of the splines in case there are interaction effects between proceduralists' and physicians' individual work experience.

[30] Specifically, each of the weighted average characteristics, $\bar{h}_{J(i)}$, included in $\bar{\mathbf{H}}_{J(i)}$ is defined as

$$\bar{h}_{J(i)} = \sum_{j \in J(i)} \sigma_{ij} \times h_j,$$

where h_j is the characteristic of physician j, and σ_{ij} is defined in equation (3).

each of the five noncardiology specialties that most frequently provide care to PCI and CABG patients for patients undergoing PCI and CABG, respectively. This can be viewed as controlling for specialty fixed effects, with cardiology omitted as the base group and weighting each specialty by its share of care to the patient.[31]

The term $\mathbf{X}_i$ is a set of patient characteristics. The full set of $\mathbf{X}_i$ includes five-year age bin fixed effects, gender, Black race, Hispanic, Medicaid coverage, disability status, and dummies for the patient's health history of common comorbidities that include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease (ESRD), and cancer (lung/breast/colorectal/endometrial/prostate cancer). Finally, ε_i indicates the error term.

Results

Descriptive Evidence: As a descriptive exercise, Figure 2 plots the means of patient 30-day mortality rates against shared work experience between the proceduralist and the physicians who treat the patient during the hospital stay. Despite the fact that patient predicted 30-day mortality rates based on patient characteristics and physician characteristics are well balanced across doctor teams with differing shared work experience, patient actual 30-day mortality declines notably with doctors' shared work experience. For example, for patients undergoing PCI, 30-day mortality among the lowest shared work experience group is 6.2 percentage points, yet it is only 3.9 percentage points among the highest shared work experience group. For CABG, 30-day mortality rates among the lowest and highest shared work experience groups are 9.6 and 7.1 percentage points, respectively.

Regression Estimates: Table 2 presents regression evidence regarding the effect of shared work experience. For ease of interpretation, I standardize shared work experience by dividing it by the sample standard deviation. Column 1 reports the baseline specification, which controls for only proceduralist fixed effects. The results imply that a one standard deviation increase in shared work experience reduces PCI and CABG patients' 30-day mortality rates by 0.77 and 1.19 percentage points, respectively.

In column 2, I add hospital-year fixed effects and fixed effects for patient admission month and day of the week as controls. The coefficient estimates show a consistent pattern that shared work experience reduces patient mortality.

If a doctor's individual work experience is positively correlated with her experience working with other doctors and individual work experience also contributes to better patient outcomes, I would overestimate the beneficial effect of shared work experience. To mitigate this concern, Column 3 adds controls for proceduralists' and physicians' individual work experience. The results consistently show a significant effect of shared work experience on reducing mortality: the coefficient remains

[31] The analysis does not include all specialties because many specialties constitute only a small share of care for a minor proportion of patients. The estimated effect of shared work experience based on the main specification is statistically similar to that controlling for the top 10 or 15 noncardiology specialties, or treating all noncardiology specialties outside of the top five as a separate group and controlling for it in the regression.

TABLE 2—SHARED WORK EXPERIENCE AND 30-DAY MORTALITY: ED ANALYSIS

	(1)	(2)	(3)	(4)	(5)
Panel A. PCI					
Shared work experience	−0.772	−0.980	−0.852	−0.586	−0.588
	(0.099)	(0.121)	(0.144)	(0.139)	(0.139)
Proceduralist fixed effects	Yes	Yes	Yes	Yes	Yes
Hospital-year/admission time fixed effects		Yes	Yes	Yes	Yes
Individual work experience			Yes	Yes	Yes
Physician covariates				Yes	Yes
Patient characteristics					Yes
Mean dependent variable	5.95	5.95	5.95	5.95	5.95
SD dependent variable	23.66	23.66	23.66	23.66	23.66
Observations	75,931	75,931	75,931	75,931	75,931
Panel B. CABG					
Shared work experience	−1.191	−1.530	−1.716	−1.279	−1.242
	(0.288)	(0.429)	(0.612)	(0.606)	(0.593)
Proceduralist fixed effects	Yes	Yes	Yes	Yes	Yes
Hospital-year/admission time fixed effects		Yes	Yes	Yes	Yes
Individual work experience			Yes	Yes	Yes
Physician covariates				Yes	Yes
Patient characteristics					Yes
Mean dependent variable	9.06	9.06	9.06	9.06	9.06
SD dependent variable	28.71	28.71	28.71	28.71	28.71
Observations	14,122	14,122	14,122	14,122	14,122

Notes: This table reports results from regressing patient 30-day mortality on shared work experience based on empirical strategy I (the ED analysis). Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are shown in parentheses. For each panel, Column 1 controls for only proceduralist fixed effects. Column 2 adds hospital-year fixed effects and patient admission month and admission day of the week fixed effects. Column 3 adds individual work experience of the proceduralist and the physicians who treat the patient during the hospital stay. Column 3 controls for doctors' individual work experience linearly. In robustness checks (Section IIID), I control for individual work experience in six different forms, including adding higher-order polynomials, controlling for individual experience as splines, and controlling for individual experience nonparametrically by fixed effects. Column 4 adds weighted average characteristics (years of practice, age, gender, rank of medical school attended, and specialty) of the physicians who treat the patient during the hospital stay. Column 5 adds patient covariates, including five-year age bin fixed effects, gender, Black race, Hispanic, Medicaid coverage, disability status, and dummies for the patient's health history of common comorbidities that include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease, and cancer. In addition, online Appendix Section B adopts an approach by Oster (2019) and infers the robustness of my estimates to physician and patient unobservables.

stable from −0.98 to −0.85 for PCI and from −1.53 to −1.72 for CABG upon adding controls for individual work experience. Column 3 controls for doctors' individual work experience linearly. In robustness checks (Section IIID), I control for individual work experience in six different forms: (i) linear splines; (ii) restricted cubic splines; (iii) polynomials that include both a linear and a quadratic term; (iv) polynomials that include a linear, a quadratic, and a cubic term; (v) splines and interactions of the splines; and (vi) nonparametrically by fixed effects. In all these specifications, the coefficients for shared work experience remain remarkably stable.

Controlling for physician individual work experience also allows for the possibility that physicians in some specialties only care for patients with severe conditions, and consequently these physicians may have less experience working with proceduralists than do physicians in specialties that care for all risk types of patients. Such a scenario may result in a negative correlation between patient health risks and doctors' shared work experience, biasing upward the returns to shared work experience. Both controlling for physician individual work experience (column 3) and controlling for physician specialties (column 4) restrict such a potential bias. Finally, this issue boils down to the independence assumption (Assumption 1.1), which, as discussed both above and below, is unlikely to be violated in my setting.

In column 4, I report specifications that add controls for physician characteristics (weighted averages of years of practice, specialties, rank of medical school attended, age, and gender). The estimated coefficients for shared work experience are not statistically distinguishable from those in column 3 and consistently show that shared work experience lowers mortality, in support of the exclusion assumption (Assumption 1.2). To further assess the exclusion assumption, I examine the robustness of my results to unobserved physician characteristics: I adopt an approach by Oster (2019) and report the adjusted coefficient estimates by allowing for selection on physician unobservables. Using the parameterization recommended by Oster (2019), the adjusted coefficients are -0.50 and -1.14 for PCI and CABG, respectively—statistically indistinguishable from the baseline estimates of -0.59 and -1.28 for PCI and CABG, respectively (see online Appendix Section B and online Appendix Table A3 for details). These findings lend credence to the exclusion assumption.

As an additional test of the exclusion assumption, I add controls for physician fixed effects. Note that because there could be multiple physicians associated with a patient during the hospital stay, it is difficult to observe exactly the same group of physicians working together again with the same distribution of share of care contributed by each physician. This makes it difficult to control for physician group fixed effects. As a robustness check, I control for fixed effects for the main physician, i.e., the physician who provides the largest share of hospital care to the patient during the hospital stay.[32] Specifically, I replace $\bar{\mathbf{H}}_{J(i)}$ with fixed effects for the main physician and the weighted average characteristics of physicians (if any) other than the main physician.[33] Online Appendix Table A4 reports the results. The sample becomes smaller because patients treated by singleton main physicians (i.e., main physicians who have only one patient in the data) are dropped from the analysis. The estimates are relatively noisy as a result, but they consistently show that shared work experience lowers mortality: the estimated coefficient is -0.60 for PCI and -1.26 for CABG, both of which are close to my main estimates reported in Table 2.

Finally, in column 5, I add controls for a rich set of patient characteristics. If sorting based on patient characteristics is driving the results (i.e., the independence in Assumption 1.1 is violated), we would expect the estimates to change sizably with these additional controls. Otherwise, we can be more confident that patient sorting is unlikely in my data. Column 5 adds patient controls that include gender, five-year age bin fixed effects, dummies for Black race, Hispanic, Medicaid coverage, and disability status, and comorbidities that include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, ESRD, and cancer, as controls. Results are stable with the inclusion of these patient controls.

[32] About 60 percent of hospital care to patients included in the ED analysis is provided by the main physician.

[33] The weights are the share of hospital visits (except those provided by the main physician) that are provided by each physician to that patient.

As a further check on the independence assumption, I examine the robustness of my estimates to the inclusion of different sets of patient controls. Specifically, from the 14 patient demographic and comorbidity variables described above, I randomly select subsets of n covariates to include in the regression for each integer $n = 0, 1, \ldots, 14$. By definition, only $C_{14}^{0} = C_{14}^{14} = 1$ set of patient controls is available when $n = 0$ or $n = 14$. For $n = 1, 2, \ldots, 13$, I repeat 14 random draws for each n (where 14 is the maximum number of possible sets of patient controls when $n = 1$ or $n = 13$). Figure 3 shows the range of the coefficients for shared work experience across the $C_{14}^{0} + 14 \times 13 + C_{14}^{14} = 184$ different specifications. Specifically, for each n on the x-axis, I plot the maximum, mean, and minimum of the estimated coefficients for shared work experience. The figure shows that my estimates remain stable with any subset of patient controls, providing further credence to the independence assumption. I also use an approach by Oster (2019) and examine the robustness of my estimates to selection on patient unobservables. The results consistently suggest that my estimates are unlikely to be explained away by patient unobservables.[34]

Column 5 of Table 2 implies that a one standard deviation increase in shared work experience reduces 30-day mortality rates by 0.59 and 1.24 percentage points—or equivalently, 10 and 14 percent compared to the mean—for patients undergoing PCI and CABG, respectively. These estimates imply the substantial value of doctors' shared work experience for patient mortality, approximately equal to the returns to a one standard deviation (about \$1,800) increase in hospital spending (Doyle et al. 2015).

Interpretation of One Standard Deviation and Measurement Error in Shared Work Experience.—A one standard deviation increase in shared work experience is equal to an increase of 4.8 and 10.7 hospital visits among the analyzed ED patients for PCI and CABG, respectively. Note that we may not interpret the estimates as the effect of a 4.8 or 10.7 hospital visits increase, since there may exist collaboration between a proceduralist and a physician that is not observable in the 20 percent Medicare data, and the standard deviation of shared work experience is likely higher among the population than among the analyzed patients. In online Appendix Section A, I run a series of simulations to estimate the amount of one standard deviation in the population and examine how potential measurement error in shared work experience due to a 20 percent random sample may affect my estimates. In sum, the simulation suggests that the standard deviation of shared work experience is equal to 41.1 and 95.5 hospital visits for ED patients undergoing PCI and CABG, respectively. If anything, measurement error would lead to an underestimated effect of shared work experience on reducing mortality rates.

B. *Empirical Strategy II: Two-Way Fixed Effects Model*

Identification.—In this section, I consider an alternative empirical strategy that includes all patients, regardless of whether admitted through the ED. This strategy

[34] Specifically, using the parameterization recommended by Oster (2019), the coefficient estimates adjusting for possible selection on patient unobservables are −0.59 and −1.21 for PCI and CABG, respectively. Online Appendix Section B and online Appendix Table A3 provide the details.

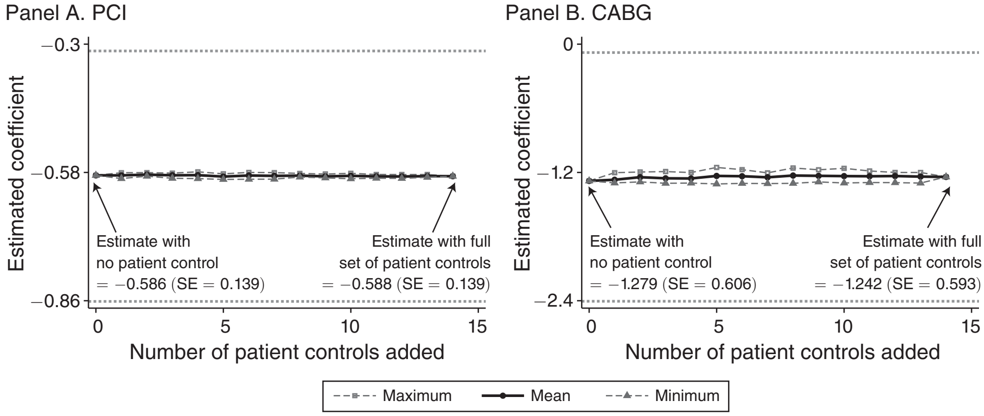

Figure 3. Sensitivity of Effect of Shared Work Experience on 30-Day Mortality: ED Analysis

Notes: These figures plot the estimated effect of shared work experience on 30-day mortality with the inclusion of different sets of patient controls based on empirical strategy I (the ED analysis). Specifically, from the 14 patient demographic and comorbidity variables described under Table 2, I randomly select subsets of n covariates to include in the regression for each integer $n = 0, 1, \ldots, 14$. By definition, only $C_{14}^{0} = C_{14}^{14} = 1$ set of patient controls is available when $n = 0$ or $n = 14$. For $n = 1, 2, \ldots, 13$, I repeat 14 (the maximum number of possible subsets of patient controls when $n = 1$ or $n = 13$) random draws for each n. Therefore, each panel summarizes results from $C_{14}^{0} + 14 \times 13 + C_{14}^{14} = 184$ different regression specifications. I plot the maximum, mean, and minimum of the estimated coefficients for shared work experience for each integer $n = 0, 1, \ldots, 14$. To provide a benchmark, I show in short-dashed lines 95 percent confidence intervals of the coefficient estimates with the full set of patient controls.

allows me to examine the effect of shared work experience among both emergency and nonemergency patients. The larger and relatively more heterogeneous sample compared to that used in the previous empirical strategy also allows me to investigate heterogeneity in the effect of shared work experience. To deal with the possibility of proceduralist- and physician-patient sorting among patients not admitted through the ED, I include both proceduralist and physician fixed effects in my estimation. Specifically, the empirical specification is a two-way fixed effects model that includes proceduralist fixed effects, physician fixed effects, and a variable tracking shared work experience of the proceduralist-physician team that treats the patient. Proceduralist and physician fixed effects separate the effect of shared work experience from outcomes related to potential doctor-patient sorting as well as those due to differences in doctor time-invariant characteristics that may affect patient treatment outcomes.

An empirical challenge in carrying out this analysis is that comparing outcomes of patients treated by exactly the same group of physicians is difficult. As discussed earlier, since there could be multiple physicians associated with a patient during the hospital stay, it is difficult to observe exactly the same group of physicians working together again. Therefore, instead of controlling for physician group fixed effects, I control for fixed effects for the main physician, i.e., the physician who provides the largest share of hospital visits to the patient during the inpatient stay. I also control for weighted average characteristics of physicians other than the main physician. Thus, the two-way fixed effects model compares patients within the same proceduralist and treated by the same main physician and the same (linear) composition of other physicians (in terms of observable characteristics).[35]

The identifying assumptions in the two-way fixed effects model are as follows.

ASSUMPTION 2.1 (Independence): *Conditional on proceduralist identities, physician group (main physician identities and non-main physician characteristics), admission hospital-time categories (e.g., hospital-year, day of the week), and individual work experience, patient potential outcomes are mean independent of shared work experience.*

ASSUMPTION 2.2 (Exclusion): *Conditional on proceduralist identities, physician group (main physician identities and non-main physician characteristics), admission hospital-time categories (e.g., hospital-year, day of the week), and individual work experience, physician unobserved characteristics that may affect patient outcomes are mean independent of shared work experience.*

Online Appendix Table A5 assesses Assumption 2.1 by reporting the balance of patient characteristics across shared work experience for the sample used in the two-way fixed effects estimation. The table shows that, conditional on the conditioning variables, patient observable characteristics that are predictive of health risks are well balanced across shared work experience. Further, similar to that in empirical strategy I, I test the robustness of my estimates by including $C_{14}^{0} + 14 \times 13 + C_{14}^{14} = 184$ different sets of patient covariates. Online Appendix Figure A2 shows that the estimates are stable across different sets of patient controls. These results lend credence to Assumption 2.1.

For Assumption 2.2, I admittedly cannot rule out the possibility of violation. Yet institutionally, the plausibly quasi-random overlap in doctors' work schedules described in Section IIIA is supportive of the assumption. Empirically, controlling for main physician fixed effects and the use of physician characteristics that may affect patient treatment outcomes make a plausible case that I am isolating the effect of shared work experience. Intuitively, the two-way fixed effects model compares patients within the same proceduralist and treated by the same main physician and the same (linear) composition of other physicians (in terms of observables). In Section IIIC, I also show that proceduralist-physician matching is unlikely to drive my estimates. Finally, estimates from the two-way fixed effects model are similar to the quasi-random estimates obtained from empirical strategy I, lending credence to both Assumption 2.1 and Assumption 2.2.

[35] About 60 percent of inpatient care to the patients in the two-way fixed effects sample is provided by the main physician. As a robustness check, I control for fixed effects for the top two main physicians, i.e., the physicians who provide the largest and the second-largest share of care to the patient during the hospital stay. The top two main physicians constitute on average approximately 80 percent of care to PCI and CABG patients. The sample size declines with the inclusion of the second main physician fixed effects (since patients without a second physician and patients treated by a second main physician with only one patient in the data are dropped from the analysis), but the results consistently show that shared work experience reduces mortality.

Empirical Specification.—The specification in this approach takes the following form:

$$y_i = \alpha E_i + \boldsymbol{\theta}_{d(i)} + \bar{\mathbf{H}}_{\check{J}(i)} \lambda + \mathbf{T}_i \eta + \mathbf{F}_i \gamma + \mathbf{X}_i \beta + \varepsilon_i, \tag{5}$$

where α is the coefficient of interest that measures how patient mortality rates change with shared work experience. Standard errors are clustered at the proceduralist level. The term $\boldsymbol{\theta}_{d(i)}$ includes both proceduralist fixed effects $(\theta_{k(i)})$ and main physician fixed effects $(\theta_{\hat{j}(i)})$; $\bar{\mathbf{H}}_{\check{J}(i)}$ is the weighted average characteristics of the physicians, aside from the main physician, who treat the patient.[36] These characteristics include specialties, years of practice, age, gender, and rank of medical school attended. The weights are the share of hospital visits (except those provided by the main physician) that are provided by each physician to that patient.

Results.—Figure 4 and Table 3 report results from the two-way fixed effects estimation. Similar to the ED analysis, the results show a significant effect of shared work experience on reducing patient 30-day mortality rates. Figure 4 uses the original shared work experience; for ease of interpretation, Table 3 standardizes shared work experience by dividing it by the sample standard deviation. The results show that, among patients undergoing PCI, a one standard deviation increase in shared work experience reduces 30-day mortality rates by 0.51 percentage points, or, equivalently, 10 percent compared to the mean. For CABG, a one standard deviation increase in shared work experience reduces patient 30-day mortality by 0.75 percentage points, which is 13 percent of the mean.[37]

C. *Ruling Out Proceduralist-Physician Matching*

In this section, I show that the mortality decline with shared work experience does not stem from proceduralist-physician matching, which refers to the possibility that proceduralists and physicians who are a better match for each other work together more frequently and a higher-quality match results in better patient outcomes. Such a matching hypothesis contrasts with the central explanation that past collaboration experience improves current team performance. Intuitively, the two competing views (i.e., experience and matching) can be written as

$$y_{jk}(e) = A_{jk}(e) + M_{jk}, \tag{6}$$

[36] For patients treated by only one physician (i.e., only the main physician), $\bar{\mathbf{H}}_{\check{J}(i)}$ by definition contains missing values; I hence replace the missing values with zero and add a dummy that equals one if the variable is missing.

[37] A one standard deviation increase in shared work experience is equal to an increase of 8.5 and 16.5 hospital visits among the two-way fixed effects estimation sample for PCI and CABG, respectively. Similar to the discussion in Section IIIA, we may not interpret the estimates as, for example, an increase of 8.5 hospital visits reduces PCI patients' 30-day mortality by 0.51 percentage points, since there may exist collaboration between a proceduralist and a physician that is not observed in Medicare data and the standard deviation of shared work experience is likely higher among the population than among the analyzed patients. In online Appendix Section A, I run a series of simulations to infer the standard deviation of shared work experience among the population. I also show that, if anything, the potential measurement error in shared work experience due to a 20 percent sample would lead to an underestimated effect of shared work experience on reducing mortality.

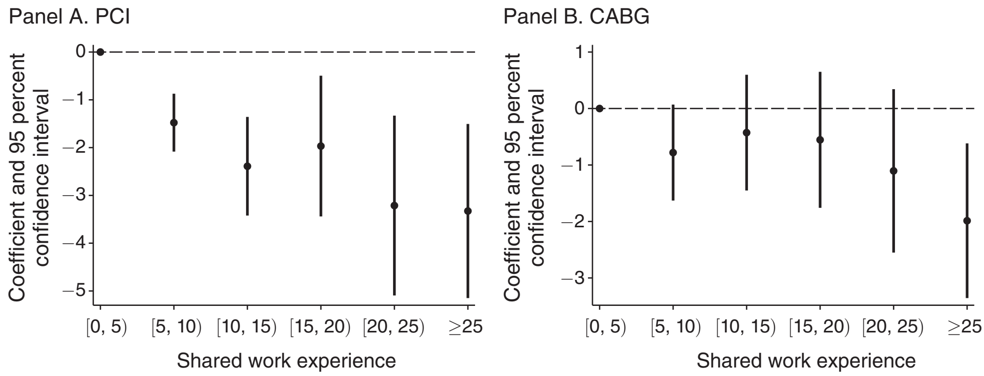

Figure 4. Effect of Shared Work Experience on 30-Day Mortality: Two-Way Fixed Effects Model

Notes: These figures plot coefficients from regressing 30-day mortality on shared work experience based on empirical strategy II (the two-way fixed effects model). Shared work experience is not scaled in units of standard deviations. The empirical specification is the same as equation (5), except that shared work experience is categorized into groups. Ninety-five percent confidence intervals of the estimated coefficients are shown in solid lines. Standard errors are clustered at the proceduralist level. Coefficients for patients treated by teams with shared work experience in the lowest range are normalized to zero.

Table 3—Shared Work Experience and 30-Day Mortality: Two-Way Fixed Effects Model

	PCI (1)	CABG (2)
Shared work experience	−0.508	−0.754
	(0.224)	(0.255)
Full control	Yes	Yes
Mean dependent variable	5.09	5.85
SD dependent variable	21.97	23.47
Observations	91,847	49,699

Notes: This table reports results from regressing patient 30-day mortality on shared work experience based on empirical strategy II (the two-way fixed effects model). The set of full controls includes proceduralist fixed effects, main physician fixed effects, weighted average characteristics (years of practice, age, gender, rank of medical school attended, and specialty) of physicians other than the main physician who treat the patient during the hospital stay, proceduralists' and physicians' individual work experience, hospital-year fixed effects, fixed effects for patient admission month and admission day of the week, and patient covariates specified under Table 2. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses.

where $y_{jk}(e)$ is team performance of proceduralist k and physician j with shared work experience e, $A_{jk}(e)$ is the component of team performance that varies with shared work experience e, and M_{jk} is the quality of match between j and k and is independent of e.

It is important to distinguish between the experience and the matching view since they have distinct implications. The experience view indicates that team performance improves over time with the accumulation of shared work experience. Thus, frequent team membership reshuffling may result in significant performance losses. Yet the match view suggests that the mortality decline is driven by proceduralist-physician match quality instead of shared work experience. Frequent team switches, therefore, should be encouraged to improve the quality of match between collaborators.

However, both institutional features and empirical evidence suggest that proceduralist-physician matching is unlikely to be driving the estimated effect of shared work experience. Institutionally, as discussed in Section IIIA, besides seeing patients, doctors are often responsible for nonclinical duties such as administration and may have teaching and research responsibilities. Doctors set schedules to fit various responsibilities, making it difficult to coordinate clinical schedules of seeing patients with a specific coworker. Second, most patients are treated by proceduralists and physicians who belong to different practice groups.[38] For proceduralists and physicians from different practices, it is generally difficult to arrange shifts to work on the same patient. These institutional features could restrict the possibility that well-matched doctors arrange to work together more often.

To empirically test whether matching is driving the mortality decline with shared work experience, I first use a proceduralist-physician team fixed effects model. I define the match component as constant within teams over time, while, by construction, shared work experience varies over the course of a collaboration. Therefore, how changes in shared work experience within each team impact patient outcomes would tell us the effect of shared work experience without that of proceduralist-physician matching.

However, as discussed earlier, it is difficult to observe exactly the same group of physicians working together multiple times. For this reason, controlling for team fixed effects for the exact proceduralist-physician team that treats a patient is difficult. I thus define a team as the combination of the proceduralist and the main physician (i.e., the physician who provides the largest share of care to the patient during the hospital stay) and control for proceduralist-main physician team fixed effects in regressions. Intuitively, matching would be more likely between the proceduralist and the main physician than between the proceduralist and any other physician who accounts for only a minimal share of care for the patient.

The empirical specification takes the following form:

$$y_i = \alpha E_i + \theta_{\hat{j}(i)k(i)} + \bar{\mathbf{H}}_{\check{J}(i)}\lambda + \mathbf{T}_i\eta + \mathbf{F}_i\gamma + \mathbf{X}_i\beta + \varepsilon_i, \tag{7}$$

where $\theta_{\hat{j}(i)k(i)}$ is the proceduralist-main physician team fixed effects.

Columns 3 and 4 of Table 4 show results from the proceduralist-main physician team fixed effects estimation. Since results from the ED analysis and the two-way fixed effects model are similar, Table 4 reports results based on the sample used in the two-way fixed effects estimation. Results using the ED analysis sample are similar and shown in online Appendix Table A6. Sample sizes in columns 3 and 4 of Table 4 are smaller than those reported in Table 3 because patients treated by singleton proceduralist-main physician teams (i.e., proceduralist-main physician teams that have only one observed patient) are removed from the analysis.

[38] In the ED analysis sample, 75 and 91 percent of patients undergoing PCI and CABG, respectively, are treated by proceduralists and physicians who belong to different practices. In the two-way fixed effects estimation sample, 69 and 89 percent of PCI and CABG patients, respectively, are treated by proceduralists and physicians from different practices.

Table 4—Excluding Matching as a Mechanism

	Two-way fixed effects		Team fixed effects		Different practices		Shared experience by ED patients	
	PCI (1)	CABG (2)	PCI (3)	CABG (4)	PCI (5)	CABG (6)	PCI (7)	CABG (8)
Shared work experience	−0.662	−0.925	−0.993	−1.314	−0.864	−0.874	−0.696	−1.155
	(0.234)	(0.331)	(0.229)	(0.339)	(0.294)	(0.291)	(0.281)	(0.651)
Full control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.14	0.13	0.15	0.13				
Mean dependent variable	4.32	5.42	4.32	5.42	6.09	5.92	5.09	5.85
SD dependent variable	20.34	22.64	20.34	22.64	23.91	23.59	21.97	23.47
Observations	46,108	34,215	46,108	34,215	57,419	42,995	91,847	49,699

Notes: Columns 1 and 2 report the estimates from the two-way fixed effects model using the sample analyzed in columns 3 and 4, respectively. Columns 3 and 4 report the estimates using the team fixed effects model. Sample sizes in columns 1–4 are smaller than those reported in Table 3 because patients treated by proceduralist-main physician teams with only one observed patient are dropped from the analysis. Columns 5 and 6 report the results using patients treated by proceduralists and physicians from different practice groups. Columns 7 and 8 report the results using shared work experience measured based on patients admitted through the ED. Adjusted R^2 are reported for the two-way fixed effects and the team fixed effects estimation to compare the explanatory power of the two models. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses.

Although a proceduralist may have treated several patients and a physician may have cared for many patients on a separate basis, the combination of the proceduralist and the physician being the main physician for a patient may not occur as often. This could contribute to the large decline in sample size when dropping singleton proceduralist-physician teams from the analysis. To facilitate comparison, I also report results for the two-way fixed effects model based on the same sample used in the team fixed effects estimation (in columns 1 and 2 of Table 4). The coefficients for shared work experience are not significantly different between the two estimations, suggesting limited confounding effects of proceduralist-main physician matching.

Second, I examine the matching explanation by restricting the sample to patients treated by proceduralists and physicians who belong to different practice groups. As discussed earlier, matching is less likely among doctors from different practices since coordinating shifts to work on the same patient is difficult. Focusing on this subset of patients further reduces concerns about potential confounding bias due to proceduralist-physician matching. The results are reported in columns 5 and 6 of Table 4, which show a similar effect of shared work experience on lowering patient 30-day mortality rates.[39]

Third, as a further step to examine the matching explanation, I measure shared work experience between a proceduralist and a physician using only patients

[39] While 69 percent of PCI patients and 89 percent of CABG patients are treated by proceduralists and physicians from different practices, sample sizes in columns 5 and 6 of Table 4 are slightly smaller than 69 and 89 percent of those reported in columns 1 and 2 of Table 3, respectively; this is because, to include proceduralist and main physician fixed effects, patients treated by proceduralists or main physicians with only one patient treated by proceduralists and physicians from different practices are excluded from the analysis in columns 5 and 6 of Table 4.

admitted through the ED that the two doctors have treated together.[40,41] The unanticipated nature of ED cases further increases the likelihood that past collaboration is random, making it less likely to be driven by matching. Online Appendix Figure A3 compares my baseline measure of shared work experience based on all patients in the data and the measure using only patients admitted through the ED. The figure shows an essentially linear relationship between the two measures of shared work experience, supporting the quasi-random variation of my baseline measure. Columns 7 and 8 of Table 4 report the regression results using shared work experience measured by only ED patients. The estimates show a consistent pattern that shared work experience reduces patient mortality. In fact, such findings not only imply that matching is unlikely to be driving my estimates, but also underscore the credibility of the exclusion assumption (Assumptions 1.2 and 2.2), since the unexpected nature of ED admissions makes it more unlikely that past collaboration is endogenous to physician characteristics.

Finally, I examine changes in the explanatory power of the regression model when replacing separate proceduralist and main physician fixed effects with proceduralist-main physician team fixed effects. If match effects are important, the fully saturated model that replaces separate fixed effects with team fixed effects would much better predict the outcome variable.[42] Yet the team fixed effects model has an only minimally better fit: the adjusted R^2 changes only slightly from 0.14 to 0.15 for PCI and remains stable at 0.13 for CABG.

Taken together, the documented effect of shared work experience does not appear to be driven by proceduralist-physician matching. This points to the view that past experience working together improves current team performance. Put another way, the performance of a team improves with the accumulation of shared work experience.

D. *Additional Results and Robustness Checks*

Ruling Out Other Alternative Explanations.—In this section, I investigate the role of four additional alternative explanations for the estimated returns to shared work experience. I show that these explanations do not appear to be operative.

First, the evidence suggests that the mortality decline associated with shared work experience does not seem to be driven by hospital-specific human capital. That is, doctors who frequently practice at a hospital may be (i) more familiar with procedures at the hospital, which may improve care quality, and (ii) more likely to exhibit high shared work experience when practicing at the hospital. Online Appendix Table A7 shows that my estimates are robust in specifications that flexibly control for proceduralists' and physicians' patient volume or years of practice at the hospital. Online Appendix Table A8 shows similar-magnitude returns to shared work

[40] Specifically, I define this measure of shared work experience as

$$E'(j,k;t) \;=\; \sum_{\tau=t-730}^{t-1} N'_{j,k;\tau},$$

where $N'_{j,k;\tau}$ is the number of hospital visits physician j provided on day τ to proceduralist k's patients admitted through the ED.

[41] I thank one referee for suggesting this measure of shared work experience.

[42] See Card, Heining, and Kline (2013) for discussions.

experience when restricting the sample to patients treated by doctors who have been practicing at the hospital in the last two years. These findings support the view that hospital-specific human capital is unlikely to be driving my estimates.

Second, though the empirical evidence has suggested little estimation bias due to patient predetermined characteristics (demographics and comorbidities), a related question is whether variation in the severity of the current condition may confound my estimates. To mitigate this concern, I examine the robustness of my estimates to controlling for patient current diagnosis fixed effects. Specifically, I control for fixed effects for the 4-digit ICD-10 code of the patient's primary diagnosis in the current hospital stay.[43] These codes provide information on patient disease types. For example, ST elevation versus non-ST elevation myocardial infarction, which is an important predictor of heart attack severity. Online Appendix Table A9 shows that the results are stable when I control for 4-digit ICD-10 codes, mitigating the concern on estimation bias due to the severity of the current disease.

Third, a related question is whether patients select into different procedures based on available proceduralist-physician teams. For example, a patient may undergo PCI instead of CABG (or nonprocedural treatments) if there is an available PCI doctor team with high shared work experience. Online Appendix Section C discusses this possibility and shows that there is little evidence of procedure selection.

Fourth, perhaps a question of interest is the role of health professionals other than the proceduralists and physicians (e.g., nurses) who care for the patient during the hospital stay. Online Appendix Section D discusses this question and shows that the presence of these health professionals is unlikely to affect my estimates.

Additional Robustness Checks.—Online Appendix Tables A10 and A11 measure shared work experience in multiple alternative ways, including (i) in different time windows—the past year and the past three years; (ii) in different functional forms—as the median and the mode of the shared work experience between the proceduralist and each of the physicians treating the patient during the hospital stay; (iii) as the shared work experience between the proceduralist and the first physician who treats the patient during the hospital stay; and (iv) as a function of a decay parameter that captures experience depreciation over time. Online Appendix Section E describes the details and shows that the results are consistent.

Online Appendix Tables A12–A16 report additional robustness checks showing that the results are robust to controlling for doctors' individual work experience in multiple alternative forms, are similar when considering mortality outcomes measured from the day of the hospital admission or measured over a period longer or shorter than 30 days after the discharge, are robust to clustering standard errors at different levels, and are stable when excluding patients treated by proceduralists or physicians with only a few patients in the data. The last test is to mitigate the concern that my estimates based on a fixed effects model may be estimated with noise given the presence of proceduralists or physicians with a small number of analyzed patients.

[43] For years before the implementation of ICD-10, I convert ICD-9 to ICD-10 using crosswalks (obtained from National Bureau of Economic Research 2020). For ICD-9 codes with multiple ICD-10 codes, I take the lowest-value ICD-10 code. Results are robust to alternative rules: the highest or the median value.

IV. Mechanisms

Having established evidence for the existence and substantial magnitude of returns to shared work experience, I next investigate the underlying mechanisms. I first distinguish between two mechanisms that may generate the effect of shared work experience: (i) improved productivity versus (ii) increased inputs. I find evidence in support of improved productivity. I then discuss possible mechanisms behind the productivity improvement.

A. *Improved Productivity versus Increased Inputs*

Two competing mechanisms could drive the mortality effect of shared work experience: (i) improved productivity versus (ii) increased inputs. First, repeated interactions may enhance workers' productivity with the specific team members, much like the firm-specific human capital literature which hypothesizes that experience in a firm enables workers to develop firm-specific expertise and enhances workers' productivity at the specific firm (Becker 1962, Parsons 1972). Intuitively, through shared work experience, team members may gain skills and knowledge about how to work with each other (i.e., build teammate-specific expertise) that facilitate collaboration, which in turn could improve productivity and team performance. Better collaboration could be particularly important in health care, in which complex and largely unpredictable patient disease progress complicates teamwork. A substantial number of medical studies have documented poor teamwork between doctors as a key contributor to low quality of care.[44] Under the improved productivity mechanism, proceduralists and physicians can achieve better patient outcomes with the same or even fewer inputs.

Second, patient outcomes may improve if, when proceduralists and physicians are familiar with each other, they are more willing to increase treatment intensity to improve teamwork. Intuitively, if more prior experience working together implies a higher probability of future encounters and playing a repeated game reduces moral hazard, team members would be more willing to exert effort (e.g., prescribe/perform more treatments, extend patient length of stay) when shared work experience increases. Additionally, if shared work experience raises the value of the collaborative relationship over time (e.g., team members may prefer familiar peers), team members may be more willing to exert effort to preserve the relationship.[45] The resulting increased medical inputs could lead to better patient outcomes. Studies have shown positive returns to treatment intensity for patients with emergency health conditions (e.g., Doyle 2011, Doyle et al. 2015, Silver 2021). Under the increased inputs mechanism, we can achieve better patient outcomes even without any improvement in productivity.

Specifically, these two mechanisms (improved productivity and increased inputs) can be written as

$$A_{jk}(e) = a_{jk}(e) \cdot f\big(I_{jk}(e)\big), \tag{8}$$

[44] See, e.g., Gawande et al. (2003), Christian et al. (2006), Mazzocco et al. (2009), and Frasier et al. (2017).

[45] This intuition relates to relational contracting, i.e., the value of relationships can serve as informal enforcement that increases coordinative behaviors among peers. See, MacLeod and Malcomson (1989); Baker, Gibbons, and Murphy (2002); and Levin (2003) for theoretical discussions. See, Jackson and Schneider (2011), Antràs and Foley (2015), and Macchiavello and Morjaria (2015) for empirical evidence.

where $A_{jk}(e)$ is the component of team performance between proceduralist k and physician j that evolves over time with the accumulation of shared work experience, $a_{jk}(e)$ is the productivity of the team, and $I_{jk}(e)$ is the inputs used by the team. The improved productivity mechanism refers to the hypothesis that past collaboration experience improves current team performance through enhancing $a_{jk}(e)$ (i.e., doctors operate on an improved production function), while the increased inputs mechanism implies that team performance improves with shared work experience by raising $I_{jk}(e)$ (i.e., doctors operate on the same production function but choose a higher level of inputs).

Understanding the relative importance of the improved productivity and the increased inputs mechanism is important since they have different implications. The former implies improvements in productive efficiency, while the latter may have a less clear implication for productive efficiency given the extra inputs required. Table 5 investigates the relative importance of these two mechanisms by examining how medical resource use changes with shared work experience. If the dominant mechanism is increased inputs, to achieve lower mortality rates, we should find a positive relationship between shared work experience and medical resource use. In contrast, a negative relationship would indicate the improved productivity mechanism dominates.

Table 5 shows that the three commonly used measures of medical resource use (length of hospital stay, number of tests and exams performed on the patient during the hospital stay, and whether the hospital stay incurs Medicare outlier payments) all decline with shared work experience. Among patients undergoing PCI, a one standard deviation increase in shared work experience is associated with a 6.1, 4.3, and 14.0 percent reduction (compared to the mean) in length of hospital stay, number of tests and exams, and probability of incurring Medicare outlier payments, respectively. For CABG, a one standard deviation increase in shared work experience reduces patient length of hospital stay, number of tests and exams, and probability of incurring Medicare outlier payments by 4.5, 4.8, and 4.3 percent (compared to the mean), respectively.[46] Table 5 reports results based on the two-way fixed effects model; results based on the ED analysis are qualitatively similar and are reported in online Appendix Table A17.

Online Appendix Table A18 shows that lower medical resource use during the hospital stay is not at the cost of higher postdischarge health care use: there is no significant positive correlation between shared work experience and the probability of discharge to skilled nursing or rehabilitation facilities, 30-day inpatient readmission rates, or the number of outpatient visits in the 30 days after the hospital

[46] Table 5 has a smaller sample than does Table 3. This is because patients who died during the hospital stay are excluded from Table 5. Including these patients may bias downward (toward zero) the effect of shared work experience on reducing medical resource use. For example, patients treated by low shared-work-experience teams are less likely to be kept alive and thus may not have lived to the full length of hospital stay they would otherwise have. We would then observe patients treated by low shared-work-experience teams experience shorter hospital stays, biasing downward the effect of shared work experience on reducing length of stay.

A possible concern is that such a restriction may lead to unbalanced patient samples across shared work experience. In particular, high shared-work-experience teams would be left with riskier patients who would otherwise have died if they were treated by doctors with low shared work experience. This suggests that Table 5 still underestimates the effect of shared work experience on reducing patient medical resource use.

Table 5—Shared Work Experience and Medical Resource Use: Two-Way Fixed Effects Model

	PCI			CABG		
	Length of stay (1)	Number tests exams (2)	Outlier payments (3)	Length of stay (4)	Number tests exams (5)	Outlier payments (6)
Shared work experience	−0.256	−0.315	−0.007	−0.460	−0.811	−0.006
	(0.075)	(0.116)	(0.002)	(0.083)	(0.140)	(0.004)
Full control	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	4.18	7.27	0.05	10.33	16.81	0.14
SD dependent variable	4.31	6.37	0.22	6.81	11.75	0.35
Observations	88,022	88,022	88,022	46,884	46,884	46,884

Notes: This table reports results from regressing patient medical resource use outcomes on shared work experience based on empirical strategy II (the two-way fixed effects model). The dependent variables in columns 1–3 are, respectively, length of hospital stay, number of tests and exams performed on the patient during the hospital stay, and whether the stay incurs outlier payments. Columns 4–6 repeat the same set of dependent variables. Sample sizes are smaller than those reported in Table 3 because patients who died during the hospital stay are excluded from the analysis. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses.

discharge. If anything statistically significant, shared work experience appears to lower postdischarge health care use.

Taken together, these findings support the existence of improved productivity and the view that the improved productivity mechanism is more important than the increased inputs channel in generating the effect of shared work experience. Put differently, past collaboration experience enables teams to achieve better outcomes, with even fewer inputs.

B. *Mechanism behind Improved Productivity*

What drives the productivity increase with shared work experience? Though a full exploration of the underlying mechanisms is beyond the scope of this paper, prior research suggests that repeated interactions between firms enable firms (and possibly their personnel) to learn about how to work with one another, which in turn enhances firms' productivity (Kellogg 2011). In interviews, doctors also brought up a similar hypothesis of learning about how to work with each other as a key mechanism.[47] The main implication of the learning hypothesis could be that shared work experience should be more effective when there are fewer ex ante specified rules for how to work together, making ex post learning for coordination more important. I test two predictions of this implication: first, task complexity would raise the returns to shared work experience given the fewer routines for more complex tasks (Autor, Levy, and Murnane 2003); second, belonging to the same organization may be correlated with a smaller productivity effect of shared work experience since organizations provide specified rules for coordination among coworkers (Dessein, Galeotti, and Santos 2016) and opportunities for informal interactions besides directly working together (formal interactions) that facilitate learning about how to work with

[47] For example, doctors pointed out that past collaboration facilitates learning about how to best communicate with one another and learning about each other's specific practice style.

each other. Section VB tests these two heterogeneity patterns and finds evidence consistent with the prediction.

V. Heterogeneity in the Effect of Shared Work Experience

Given the substantial magnitude of returns to team-specific human capital accumulated through shared work experience, this section investigates how the effect of shared work experience varies across patient and physician characteristics. As results from the ED analysis and the two-way fixed effects model are similar, this section uses the two-way fixed effects model to exploit the larger sample.

A. *Heterogeneity by Doctors' Individual Work Experience*

To investigate how general human capital accumulated through individual work experience may substitute for or complement team-specific human capital created by shared work experience, this section investigates heterogeneity in the effect of shared work experience by doctors' individual experience. The literature has widely documented the role of individual work experience as a source of general human capital and worker productivity (e.g., Shaw and Lazear 2008; Lafontaine and Shaw 2016; Haggag, McManus, and Paci 2017). It is thus possible that an experienced doctor works well with any doctor regardless of their prior experience working together. In this case, general human capital is a substitute for team-specific human capital and the returns to shared work experience would decline with individual work experience. In contrast, there may exist complementarities between general and team-specific human capital, so that team-specific human capital is more crucial when general human capital increases. For example, an experienced proceduralist may have developed a distinct way of performing the procedure, physicians therefore may need to work extensively with the proceduralist to learn and adjust to the proceduralist's unique style.

To explore whether general and team-specific human capital substitute for or complement each other, Table 6 reports heterogeneity in the effect of shared work experience by doctors' individual work experience using the following specification based on the two-way fixed effects model:

$$(9) \qquad y_i = \alpha_1 E_i \times E\big(d(i);t(i)\big) + \alpha_2 E_i + \boldsymbol{\theta}_{d(i)} + \bar{\mathbf{H}}_{\check{J}(i)} \lambda + \mathbf{T}_i \eta + \mathbf{F}_i \gamma + \mathbf{X}_i \beta + \varepsilon_i,$$

where $E_i \times E\big(d(i);t(i)\big)$ refers to the interaction between shared work experience E_i and proceduralists' or physicians' individual work experience—i.e., $E\big(k(i);t(i)\big)$ or $E\big(J(i);t(i)\big)$, both of which are included in $\mathbf{F}_i$. To facilitate interpretation, both $E\big(k(i);t(i)\big)$ and $E\big(J(i);t(i)\big)$ are standardized by subtracting the sample mean and dividing by the sample standard deviation.

Table 6 exhibits two notable patterns. First, the effect of shared work experience declines with individual work experience. Panel A shows that a one standard deviation increase in proceduralists' individual work experience is associated with a 0.27 percentage point decrease in the effect of shared work experience on reducing

Table 6—Substitution between Individual and Shared Work Experience: Two-Way Fixed Effects Model

	PCI (1)	CABG (2)
Panel A. Heterogeneity by proceduralists' individual work experience		
Shared work experience × proceduralist experience	0.272	0.128
	(0.051)	(0.224)
Shared work experience	−1.061	−0.868
	(0.216)	(0.310)
Full control	Yes	Yes
Observations	91,847	49,699
Panel B. Heterogeneity by physicians' individual work experience		
Shared work experience × physician experience	0.113	0.107
	(0.028)	(0.062)
Shared work experience	−1.068	−1.035
	(0.212)	(0.330)
Full control	Yes	Yes
Observations	91,847	49,699

Notes: This table shows heterogeneity in the effect of shared work experience on patient 30-day mortality by proceduralists' and physicians' individual work experience. The empirical specification is based on the two-way fixed effects model with an added interaction term between shared work experience and individual work experience (details in equation (9)). For ease of interpretation, individual work experience is demeaned and scaled in units of standard deviations. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses.

mortality among PCI patients. Table 6 also shows similar declines in the effect of shared work experience when physicians' individual work experience increases.[48]

A second finding in Table 6 is that, although the effect of shared work experience declines with proceduralists' and physicians' individual work experience, the extent of the decline is small. For example, for patients undergoing PCI, a proceduralist's individual work experience needs to be about four standard deviations higher than that of the average proceduralist to eliminate the effect of shared work experience. In sum, although general human capital acquired through individual work experience can substitute for team-specific human capital created by shared work experience, the extent of the substitution is limited. This points to the irreplaceability of team-specific human capital.

B. *Heterogeneity by Care Complexity and Doctor Practice Affiliation*

In this section, I examine more heterogeneity patterns in the effect of shared work experience. Table 7 reports α_1 and α_2 estimated from the following specification:

$$(10) \qquad y_i = \alpha_1 E_i \times g_i + \alpha_2 E_i + \alpha_3 g_i + \boldsymbol{\theta}_{d(i)} + \bar{\mathbf{H}}_{J(i)} \lambda + \mathbf{T}_i \eta + \mathbf{F}_i \gamma + \mathbf{X}_i \beta + \varepsilon_i,$$

[48] A potential question is whether the observed substitution between shared work experience and individual work experience is driven by nonlinear returns to the former. A positive correlation between these two types of experience and a decreasing return to shared work experience may lead to a lower effect of shared work experience when individual experience increases. To examine this possibility, online Appendix Table A19 incorporates the nonlinear returns to shared work experience in the estimation. The results show a consistent pattern that individual work experience can substitute for shared work experience, and the extent of the substitution is small.

Table 7—Heterogeneity in Effect of Shared Work Experience: Two-Way Fixed Effects Model

	PCI (1)	CABG (2)
Panel A. Heterogeneity by patient age		
Shared work experience × patient age in top quartile	−0.458	−0.551
	(0.179)	(0.308)
Shared work experience	−0.414	−0.661
	(0.210)	(0.257)
Panel B. Heterogeneity by patient predicted mortality		
Shared work experience × patient predicted mortality in top quartile	−0.508	−0.170
	(0.161)	(0.305)
Shared work experience	−0.390	−0.713
	(0.209)	(0.263)
Panel C. Heterogeneity by whether patient has uncommon comorbidities		
Shared work experience × patient has uncommon comorbidities	−0.270	−0.101
	(0.117)	(0.243)
Shared work experience	−0.397	−0.728
	(0.211)	(0.258)
Panel D. Heterogeneity by proceduralist/physician from different practices		
Shared work experience × proceduralist/physician different practices	−1.062	−0.264
	(0.212)	(0.367)
Shared work experience	0.018	−0.528
	(0.193)	(0.379)
Full control	Yes	Yes
Observations	91,847	49,699

Notes: This table shows heterogeneity in the effect of shared work experience on patient 30-day mortality. The empirical specification is based on the two-way fixed effects model with an added interaction term between shared work experience and the dummy listed in the top row of each panel (details in equation (10)). Each of the interacted dummies is also included in the corresponding regression. The dummies in panels A–D are, respectively, indicators that take a value of one if the patient's age is in the top quartile of the sample, the patient's predicted mortality is in the top quartile of the sample, the patient has uncommon comorbidities, and the patient is treated by proceduralists and physicians from different practices. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses.

where g_i is the heterogeneity variable of interest (attributes of the patient or the proceduralist-physician team that treats the patient).

Two findings stand out in Table 7. First, the effect of shared work experience is larger when care tends to be more complex. Fewer ex ante specified rules for complex care may make ex post coordination more important. Past collaboration experience that enables team members to learn how to work with each other thus may be more crucial. In contrast, in less complex production processes, following standard procedures may suffice. Consistent with this intuition, Table 7 shows that, for PCI, the effect of shared work experience is larger among patients with less common comorbidities,[49] higher predicted 30-day mortality, and older ages. Care for these patients tends to be more complex given patients' sicker conditions and less predictable disease progress. Online Appendix Table A20 divides the mortality reduction in each group of PCI patients by its mean mortality and similarly shows

[49] This is whether the patient has any of the four lowest-prevalence comorbidities in the sample: Alzheimer's disease/dementia, stroke, end-stage renal disease, and cancer.

a larger percentage decline relative to the mean when care is more complex. For CABG, though the heterogeneity pattern is less pronounced given the smaller sample size relative to PCI, Table 7 shows a consistent pattern that the effect of shared work experience is significantly larger among older patients.

Second, Table 7 shows that the effect of shared work experience is larger when proceduralists and physicians are from different practice groups than when they are from the same practice. As discussed earlier, if organizations provide tacit knowledge for how to work with each other (Dessein, Galeotti, and Santos 2016) or opportunities for informal interactions besides directly working together (formal interactions), past collaboration experience would be less important when doctors are from the same practice group.

VI. Discussion

The finding that doctors' past collaboration significantly lowers patient mortality could have important implications, particularly for policies that aim to improve health care productivity. To put the effect magnitude in perspective, it may be useful to evaluate the mortality reduction in a hypothetical scenario in which we re-arrange proceduralist-physician teams to achieve higher shared work experience. I consider a stylized setting where, in each hospital, (i) holds fixed the number of patients and the number of hospital visits associated with each patient, (ii) reduces the number of unique physicians a proceduralist collaborates with by half (i.e., a way to increase shared work experience by reducing the frequency of team switches),[50] and (iii) evenly distributes patient care to each proceduralist-physician pair. The third assumption is to simplify the scenario and keep my estimates trackable. In the extreme, one can assign all the patients to only one proceduralist-physician pair to maximize shared work experience and survival gains. Yet this may not be feasible in reality given doctors' time constraints. Assuming that reorganizing doctor teams only acts via shared work experience, this hypothetical scenario would yield a mortality decline of 0.2 percentage points—or, equivalently, 4 percent of the mean mortality—for all patients undergoing PCI and CABG in my years of analysis (2010–2016). Online Appendix Section F provides details of the simulation algorithm.

To put the magnitude of this hypothetical mortality decline in perspective, it may be useful to compare it to the returns to two often-discussed policy instruments for improving patient outcomes: (i) health insurance coverage, and (ii) the adoption of new medical technologies. First, within my application of Medicare patients admitted to the hospital due to emergency conditions, Card, Dobkin, and Maestas (2009) estimates that being covered by Medicare (relative to no or other insurance coverage) lowers patient 28-day mortality by 9 percent. This suggests that the reduction in mortality through reorganizing doctors to increase shared work experience is approximately equal to one-half of the returns to Medicare coverage. Second, the decline in mortality is more than one-tenth of the magnitude of the

[50] This is equivalent to a decline of approximately 0.5 standard deviations in the number of physicians for both PCI and CABG proceduralists, or equivalently, a decline from an average of about 150 unique physicians to 75 over a two-year window.

mortality reduction associated with the key technology advance in heart attack treatment—primary angioplasty, which is shown by randomized trials to reduce patient 30-day mortality by 38 percent more than does a conventional therapy (Weaver et al. 1997).

Perhaps a question of interest is, given the productivity gains from shared work experience, why continued collaboration is not already more widespread. One possible interpretation, paralleling the argument of Bloom et al. (2013), is that although some practices can enhance productivity, firms may not be aware of them or their productivity-enhancing effects. This restricts the adoption of these practices. Information dissemination about these practices and their productivity effects can be an effective way to increase adoption (Bloom et al. 2013, Gibbons and Henderson 2012). Another explanation, which is particularly relevant for health care, could be the fragmented organizational structure of health care providers (Cebul et al. 2008). For example, as doctors are typically independent of hospital management, hospitals have limited ability to arrange doctors' schedules to foster continued collaboration. In addition, most proceduralists and physicians belong to different practices, which complicates shift coordination. These suggest that leveraging the recently developed accountable care organizations, which provide a platform for health care providers to coordinate, may be a potential way to increase continued collaboration. A third possible explanation could be that continued collaboration may be at the cost of, for example, a high productivity loss when a teammate the worker has extensively collaborated with is no longer available. Investigating the implications of such a trade-off remains a valuable subject for future research.

VII. Conclusion

This study shows that team members' past collaboration creates team-specific human capital and raises team productivity. In the context of two common medical procedures, I find that past collaboration between the proceduralist who performs the procedure and the physicians who provide care to the patient during the hospital stay for the procedure substantially lowers patient mortality rates. Patient medical resource use also declines with shared work experience—even as survival improves. These findings point to increased productivity with the accumulation of shared work experience. Further, although general human capital acquired through individual work experience can substitute for team-specific human capital created by shared work experience, the extent of the substitution is small.

These findings suggest two important implications. First, even holding medical technology and the pool of doctors fixed, we can achieve higher health care productivity—i.e., yield better patient survival with even fewer medical inputs—by reorganizing health care providers, which has typically been neglected but could generate important productivity gains. Second and more broadly for contexts outside health care, these findings show that the productivity (and value) of a team increases with the accumulation of shared work experience, instead of being fixed with a constant quality of match between team members. Past collaboration creates team-specific human capital that enables teams to achieve better performance—with even fewer inputs.

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