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

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Abstract

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 10-13 percent reduction in patient 30-day mortality. Patient medical resource use also declines with shared work experience, even as survival improves.

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1 Introduction

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 under-explored 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 the potential implications for optimal team organization and the pervasiveness of teamwork in many industries. Yet empirical evidence remains thin.

In this paper, I study whether team members' past collaboration creates team-specific human capital and influences current team performance in the context of healthcare—one of the most teamwork-intensive industries.[1] Using Medicare 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 pre-procedure inpatient care and post-procedure 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 his or her own distinct approach to the procedure, but their tasks are interdependent. Past experience working together may be a potential way

[1] For example, a single physician visit may involve teamwork among a multidisciplinary group of clinicians; an inpatient stay may require collaboration among multiple physicians. Many policies (e.g., accountable care organizations and bundled payments) have been implemented to promote care coordination among providers, which makes teamwork increasingly important in healthcare.

[2] Medical costs of PCI and CABG totaled $28 billion in the U.S. 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 for this estimation). 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.

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 team production in healthcare.

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 determined well in advance (e.g., several weeks ahead of the shift). Yet for PCI/CABG patients admitted to the hospital through the ED, the admission is typically unanticipated 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 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. I use a "two-way fixed effects" model that includes proceduralist fixed effects, physician fixed effects, and a variable tracking shared work experience of the

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

proceduralist-physician team that treats the patient. This strategy allows me to examine the effect of shared work experience among both ED and non-ED patients. 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.

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 reduces patient 30-day mortality rates by 0.6 and 1.0 percentage points—or equivalently, 10 and 12 percent compared to the mean—for patients undergoing PCI and CABG, respectively. This evidence implies substantial value of shared work experience 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 healthcare quality and, importantly, saving lives. This paper provides the first evidence (to my knowledge) that, even holding medical technology and the pool of healthcare providers fixed, reorganizing provider teams based on collaboration histories can significantly improve patient survival.

Next, I examine the mechanisms behind the effect of shared work experience. I start by ruling out a competing mechanism that is not specific to returns to shared work experience: 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 (rather than shared work experience per se) results in better patient outcomes. Yet both institutional features and empirical evidence provide little support for such a matching hypothesis. Empirically, proceduralist-physician team fixed effects model that captures constant match quality within teams yields similar estimates and results in only a small improvement in explanatory power relative to my baseline model. I also check for matching by restricting the sample to proceduralists and physicians who likely are unable to match; I find similar returns to shared work experience.

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

I then 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., Card et al. 2009; Doyle 2011; Doyle et al. 2015). Sorting out the relative importance of the improved productivity hypothesis and the increased inputs view is important since the former implies welfare improvements, while the latter may result in a welfare loss if the cost of extra inputs outweighs the benefit of better team performance. 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 produce 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 et al. 2013; Lafontaine and Shaw 2016; Haggag et al. 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 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 many factors to doctors' quality and cost performance, including, for example, financial incentives (e.g., Gaynor et al. 2004; Clemens and Gottlieb 2014; Johnson and Rehavi 2016), medical skill (e.g., Currie and MacLeod 2017; Chan et al. 2019), practice environment (e.g., Chandra and Staiger 2007; Frakes 2013; Molitor 2018), and intrinsic motivation to perform well (e.g., Kolstad 2013). In contrast to the typical assumption that doctors' performance depends only on individual doctors, this paper contributes to the literature by showing that the performance of a doctor also depends importantly on team members.

Second, this paper relates 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; Holmstrom 1982; Bonatti and Hörner 2011; Chan 2016), peer pressure (e.g., Kandel and Lazear 1992; Bandiera et al. 2005; Mas and Moretti 2009; Silver 2020), and team incentives (e.g., Hamilton et al. 2003; Bandiera et al. 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 experience creates team-specific human capital that raises the productivity (and value) of a team.

Third, this paper contributes to the literature on human capital accumulation. A large body of research has highlighted the role of work experience as a source of human capital and worker productivity (e.g., Shaw and Lazear 2008; Levitt et al. 2013; Lafontaine and Shaw 2016; Haggag et al. 2017). Less studied, though, is whether returns to experience are specific to teams—whether workers can fully transfer the performance improvements gained through experience at the current team to their work in another. My focus on team-specific human capital relates to Kellogg (2011) which shows that repeated interactions between firms improve firm productivity in joint production, and to Jaravel et al. (2018) which examines how the unexpected death of collaborators affects inventors' earnings and innovation. This paper also relates to Agha et al. (2018) which examines how referral concentration of referral physician-specialist teams affects healthcare costs, and to Huckman and Pisano (2006) and Bartel et al. (2014) which show that the performance of healthcare providers at a hospital or a unit depends more on their experience at that specific facility than on general experience across all facilities.

The remainder of this paper proceeds as follows. Section 2 describes the institutional setting. Section 3 introduces my data and measure of shared work experience. Identification strategies and

results on the effect of shared work experience are presented in Section 4. Section 5 examines mechanisms behind the effect of shared work experience. Section 6 investigates heterogeneity in the effect of shared work experience. Section 7 discusses and concludes the paper.

2 Institutional Setting

Both PCI and CABG are procedures that are 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 risks 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 post-procedure 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 on the optimal procedure timing and strategy—i.e., proceduralists' tasks require inputs from physicians. One 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 some 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 his/her own distinct way of performing tasks, making it valuable for proceduralists and physicians to learn how to collaborate with each other. 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 a 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 that physicians learn about a proceduralist's abilities and style, the better physicians can tailor their post-procedure treatment plans or develop skills that are specific to the proceduralist's idiosyncratic approach to the procedure. These may be particularly important in healthcare, 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 effect of shared work experience.[6] The following are a few quotes that provide more intuitions about how shared work experience may affect team performance:

1. 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.

2. 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.

3. 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.

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

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

3 Data

The primary data for this study are claim records for a 20 percent random sample of Medicare beneficiaries from 2008 through 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 history. Vital statistics that record patient death dates are linked to Medicare claims, which allows me to measure my primary analysis outcome—patient 30-day mortality.

I supplement Medicare claims with two other datasets—Physician Compare and Medicare Data on Provider Practice and Specialty (MD-PPAS)—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 that treat a patient during her 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 based on 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.[7] Each of the analyzed patients has only one proceduralist by design but can be associated with multiple physicians.

[7] I use the following process to pick the lead proceduralist for each patient during the hospital stay. 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. 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.

3.1 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. Second, I only include patients aged 65 to 100. Third, I exclude cases in which I cannot observe any physician visits in the first two days or in the last two days of the hospital stay. The purpose of this third sample restriction is to exclude (i) patients covered by bundled payments or Medicare advantage, whose physicians are not observable in the carrier file,[8] 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. 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. The final sample includes approximately 85,000 PCI patients and 18,000 CABG patients. Panel A of Appendix Table A1 reports changes in 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 patients. The final sample consists of approximately 92,000 and 50,000 PCI and CABG patients, respectively.[9] Panel B of Appendix Table A1 reports changes in sample size resulting from the above restrictions.

3.2 Measuring 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 provided to the proceduralist's patients in the past two years, i.e., in the

[8] The MedPAR file covers some Medicare Advantage enrollees, but these enrollees are not included in the carrier file.

[9] About 70 and 30 percent of PCI and CABG patients, respectively, are admitted to the hospital through the ED. 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 patient in the years of observation.

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 $\tau \in [t-730, t-1]$.[10]

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; Thompson 2007; Ost 2014). As a result, experience gained in the distant past may not be relevant for current teamwork. In robustness checks (Section 4.3), I 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.[11] As a natural benchmark, I measure shared work experience for each patient case as the average of the shared work experience between the proceduralist and each of the physicians treating the case, 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 case, to reflect that each physician may account for a differential share of care. This weighted average considers both each physician's shared work experience with the proceduralist and the differential share of care contributed by each physician. In Section 4.3.2, I also define shared work experience for a case in a variety of alternative ways.

Specifically, in my main analysis, shared work experience for a patient case, i, is measured as:

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

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. σ_{ij} is the share of hospital visits associated with i in her current hospital stay that is provided by physician j; specifically,

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

[11] For example, 16 percent of the PCI and CABG patients admitted through the ED are treated by only one physician during the hospital stay. 22, 18, and 44 percent of these ED patients are treated by two, three and more than three physicians during the hospital stay, respectively.

$$\sigma_{ij} = \frac{\sum_{v \in V_i} I(j(v) = j)}{\parallel V_i \parallel} \tag{3}$$

where V_i is the set of all physician visits provided to i during the hospital stay, and $I(j(v) = j)$ is an indicator that equals one if the visit was provided by physician j.[12] 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 $E(j, k(i); t(i))$.

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.[13] 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. Appendix Section A.1 explores the effect of measurement error by simulations and shows that, if anything, the measurement error would lead to an underestimated mortality-reducing effect of shared work experience.

3.3 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.[14] Patient mortality is a broadly used performance measure for PCI and CABG in the medical literature;[15] it can be accurately mea-

[12] The mechanics of Equation (2) can be illustrated by the following example. Suppose i received three hospital visits during the hospital stay. One of the visits was provided by physician j_1, who had in total provided three hospital visits to proceduralist $k(i)$'s patients in the two years prior to the admission of i. The other two visits were provided by physician j_2, who had in total provided six hospital visits to proceduralist $k(i)$'s patients before i in the past two years. The shared work experience of the proceduralist-physician team that treated i is therefore $\frac{1}{3} \times 3 + \frac{2}{3} \times 6 = 5$.

[13] 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 are full-time hospital employees (Charles et al. 2013). Less than 30 percent of doctors in the United States in 2011 are employed by physicians 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).

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

[15] See, e.g., Wennberg et al. (2004), Newman et al. (2012), Shroyer et al. (2017), and Thiele et al. (2018).

sured 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.[16] My main analysis focuses on 30-day mortality, which is a commonly used mortality measure for PCI and CABG.[17] In robustness checks, I show that the results are qualitatively similar 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.[18] I also consider three common measures of post-discharge healthcare 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—number of physician and ED visits in the 30 days after the discharge.

4 Effect of Shared Work Experience

In this section, I describe my two empirical strategies and analysis results. I begin with the estimation that focuses on patients admitted to the hospital through the ED (i.e., empirical strategy I). I then describe the two-way fixed effects model (i.e., empirical strategy II). The two strategies show a consistent pattern that shared work experience significantly lowers patient 30-day mortality rates. Lastly, I assess the robustness of my estimates to a number of alternative explanations and specifications.

4.1 Empirical Strategy I: Patients Admitted through the ED

4.1.1 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

[16] 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.

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

[18] I do not use the amount of Medicare payments as an outcome because it largely reflects patient diagnosis-related group (DRG) and may reflect payments that are unrelated to medical resource use (e.g., indirect medical education costs). Focusing instead on Medicare outlier payments would better inform us variation in medical resource use among patients with similar disease severity.

in physicians on duty, a proceduralist would work 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 generally set well in advance of a patient's admission date. Yet for patients admitted via the ED, the admission is unanticipated and requires immediate treatments 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 to 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, physicians 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 below I show there is little supportive evidence.

Figure 1 illustrates variation in shared work experience across ED patients treated by an example proceduralist. To construct the figure, I first randomly pick a CABG proceduralist with 30 patient cases from the analysis sample. I then plot the level of shared work experience between the proceduralist and the physicians who care for the patient for each of the cases treated by the proceduralist and observed in the data. The figure shows large variation in shared work experience across patients within the specific proceduralist. Figure 2 shows systematically variation of shared work experience after residualizing by proceduralist identities for all patients included in the analysis.

The identifying assumptions in this empirical strategy are the following:

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

Assumption 1.2 (Exclusion): *Conditional on proceduralist identities, hospital-year, and time categories of the admission (month and day-of-the-week), 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 supports the validity of the independence assumption. To empirically assess the independence assumption, I first check whether patient characteristics are balanced across shared work experience, conditional on the conditioning variables specified above. 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. In Figure 3, I further show that patient *predicted* 30-day mortality as a function of demographics and comorbidities is nearly identical across shared work experience.[19] Despite having no relationship with shared work experience, patient demographics and comorbidities are nonetheless significant predictors of 30-day mortality: even conditional on physician characteristics and all the conditioning variables specified in the independence assumption, the F-statistics for joint significance of patient characteristics on 30-day mortality are 34.01 (p-value: 0.00) and 9.86 (p-value: 0.00) for patients undergoing PCI and CABG, respectively. To further test the independence assumption, below in empirical results, I show 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.

To assess the exclusion assumption, I conduct three tests. First, Figure 3 shows balance of physician characteristics—summarized by patient predicted 30-day mortality as a function of physician characteristics—across shared work experience. Specifically, I regress 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 that these characteristics are strong predictors of patient mortality outcomes (with an F-statistic of 110.60 for PCI and 21.33 for CABG, conditional on patient characteristics and all the conditioning variables), Figure 3 shows that these characteristics are well balanced across shared work experience. As a second test for the exclusion assumption, in the results presented

[19]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 race, Hispanic ethnicity, 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).

below I show that my estimates remain stable when controlling for detailed physician covariates. If the exclusion assumption is violated, we would expect the estimates to change sizably with these physician covariates. Otherwise, we can be more confident that the assumption holds. Third, to test the possible bias due to unobserved physician variation, in my empirical results I infer the robustness of my estimates to selection on physician unobservables.

4.1.2 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 case i admitted to the hospital at date $t(i)$. E_i is the shared work experience of the proceduralist-physician team that treats i. α is the coefficient of interest, which identifies the extent to which prior shared work experience influences current patient outcomes. Standard errors are clustered at the proceduralist level.[20] $\theta_{k(i)}$ is proceduralist fixed effects. $\mathbf{T}_i$ is a set of fixed effects that includes hospital-year fixed effects, and the patient's admission month fixed effects and admission day-of-the-week fixed effects. $\mathbf{T}_i$ absorbs potential differences in patient outcomes across hospital-year and admission time categories. $\bar{\mathbf{H}}_{J(i)}$ is a set of physician characteristics,[21] 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 that is provided by each physician to that patient (i.e., σ_{ij} defined in Equation (3)).[22] $\bar{\mathbf{H}}_{J(i)}$ also includes weighted percentages of the physicians that are in each of the five non-cardiology specialties that most frequently provide care to PCI and CABG patients for patients undergoing PCI and CABG,

[20] In robustness checks, I show results under different clustering approaches.

[21] As there are often multiple physicians associated with a patient during the hospital stay (16, 22, 18, and 44 percent of these ED patients are treated by one, two, three, and more than three physicians during the hospital stay, respectively), it is difficult to observe exactly the same group of physicians working together again with the same distribution of σ_{ij}. This makes it difficult to control for physician group fixed effects. As a robustness check, I control for fixed effects of the main physician, i.e., the physician who provides the largest share of hospital care to the patient during the hospital stay. Patients treated by singleton main physicians (i.e., patients treated by main physicians who have only one patient in the data) are dropped from the robustness check, leading to a smaller sample. The coefficients on shared work experience become noisy with this smaller sample, but still show a persistent role of shared work experience in reducing patient 30-day mortality and are not statistically different from the estimates based on my main specification. See details in Panel B of Appendix Table A12.

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

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

where h_j is the characteristic of physician j.

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.[23]

$\mathbf{F}_i$ includes proceduralists' individual work experience—$E(k(i);t(i))$, and physicians' individual work experience—$E(J(i);t(i))$. $E(k(i);t(i))$ is the number of PCI and CABG the proceduralist performed in $[t(i)-1,\, t(i)-730]$ for patient case i undergoing PCI and CABG, respectively. $E(J(i);t(i))$ is the weighted average of the number of hospital visits each physician treating the patient provided to PCI and CABG patients in $[t(i)-1,\, t(i)-730]$ for i undergoing PCI and CABG, respectively. The weights are σ_{ij}.[24] A more general version of physician individual work experience—years of practice—is also included in the estimation (as a covariate in $\bar{\mathbf{H}}_{J(i)}$).

$\mathbf{X}_i$ is a set of patient characteristics. The full set of $\mathbf{X}_i$ includes five-year age bin fixed effects, gender, black race, Hispanic ethnicity, 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). ϵ_{it} is the error term.

4.1.3 Results

Descriptive Evidence.—As a descriptive exercise, Figure 3 plots 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 that patient *predicted* 30-day mortality rates based on patient characteristics and physician characteristics are nearly constant 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

[23] Results are statistically similar when controlling for the top 10 non-cardiology specialties, or treating all non-cardiology specialties outside of the top 10 non-cardiology specialties as a separate group and controlling for it in the regression.

[24] Specifically,

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

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

$E(J(i);t(i)) = \sum_{j\in J(i)} \sigma_{ij} \times E(j;t(i))$, where

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

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

lowest shared work experience group is 6.2 percentage points, but is only 3.7 percentage points among the highest shared work experience group. For CABG, 30-day mortality among the lowest and the highest shared work experience group are 9.6 and 7.2 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 0.78 and 1.12 percentage points, respectively.

In Column 2, I add hospital-year fixed effects and fixed effects of patient admission month and and day-of-the-week as controls. The magnitude of the coefficients increases with these additional covariates, yet the change is non-significant.

A documented feature of medical procedures is the presence of a volume-outcome relationship: doctors with a higher patient volume may develop better skills that could result in improved patient outcomes (e.g., Halm et al. 2002; Hannan et al. 2003). If a doctors' individual work experience is also correlated with her experience working with other doctors, I would overestimate the beneficial effect of shared work experience. Column 3 therefore controls for proceduralists' and physicians' individual work experience. The estimates attenuate after adding the individual work experience controls (decline in magnitude from -0.98 to -0.89 and from -1.52 to -1.47 for PCI and CABG, respectively), but still point to a persistent role of shared work experience in reducing patient 30-day mortality rates. Column 4 controls for doctors' individual work experience linearly. In robustness checks, I add squared individual experience terms to allow for non-linearities in the returns to individual work experience; I also control for individual work experience as splines and nonparametrically by fixed effects.

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 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 estimation bias.

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 on shared work experience exhibit no significant change relative to Column 3. Therefore, in addition to the balance in physician characteristics across shared work experience (Figure 3), this robustness pattern provides another piece of evidence in support of the exclusion assumption that physician characteristics are mean independent of shared work experience. Further, to assess the potential bias due to *un*observable physician factors, I follow Oster (2019) who extends the approach by Altonji et al. (2005) and infer the degree of selection on physician unobservables relative to that on observables that would be needed to explain away the estimated effect of shared work experience. For PCI and CABG, respectively, the selection on physician unobservables would have to be 35 and 34 times as high as the selection on observables to fully account for the estimated effect of shared work experience, both of which seem unlikely. Altonji et al. (2005) suggests that a ratio above one, i.e., the unobservables are more important than the observables in explaining the treatment effect, be viewed as unlikely.

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 ethnicity, 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 remarkably robust to the inclusion of these patient controls.

As a further check on the independence assumption, I use a test similar to that used by Card et al. (2018) and examine the stability of my estimates to the inclusion of different sets of patient controls. Specifically, from the 14 patient demographic and comorbidity variables listed above, I randomly select subsets of n covariates to include in the regression and collect the coefficients on shared work experience for each integer $n = 0, 1, ..., 14$. By definition, only $C_{14}^{0} = C_{14}^{14} = 1$ set of patient controls is available when $n = 0$ or $n = 14$. For $n = 1, 2, .., 13$, 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 4 shows the range of the coefficients on 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, median, and minimum of the estimated coefficients on shared work experience. The figure shows that my estimates remain stable with any subset of patient controls. Based on

the logic of Altonji et al. (2005), this evidence suggests that adding other (unobserved) patient risk factors as covariates is unlikely to result in large changes in the estimated effect of shared work experience. I also use the approach by Oster (2019) to infer the robustness of my estimates to selection on patient unobservables, which, similarly, suggests that my estimates are unlikely driven by patient unobservables.[25]

Column 5 of Table 2 implies that a one standard deviation increase in shared work experience reduces 30-day mortality rates by 0.60 and 1.04 percentage points—or equivalently, 10 and 12 percent compared to the mean—for patients undergoing PCI and CABG, respectively. These estimates suggest 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).

Another important finding, as further discussed in Section 5, is that shared work experience also significantly reduces medical resource use—including length of hospital stay, number of tests and exams performed on the patient during the stay, and whether the stay incurs outlier payments. Taken together, these findings point to increased productivity and generate new insights about the healthcare production function: even holding medical technologies and the pool of healthcare providers fixed, reorganizing provider teams based on collaboration histories can enable doctors to achieve better patient survival outcomes—with even less medical spending.

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 5 and 12 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 5 or 12 hospital visits increase, since there may exist collaboration between a proceduralist and a physician that is not observed 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 Appendix Section A.1, 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 56 and 136 hospital visits for ED patients undergoing PCI and CABG,

[25]For CABG, the amount of selection on patient unobserved characteristics would have to be 43 times as high as that on the observed controls to explain away the estimated effect of shared work experience, which seems unlikely given the rich set of patient controls included in the analysis. For PCI, the coefficient moves slightly further away from zero (from -0.600 to -0.604), indicating that accounting for patient unobservables may yield even larger estimated returns to shared work experience.

respectively. If anything, measurement error would lead to an underestimated effect of shared work experience on reducing mortality rates.

4.2 Empirical Strategy II: Two-Way Fixed Effects Model

4.2.1 Identification

In this section, I consider an alternative empirical strategy that includes all patients, regardless of whether admitted through the ED. 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. Fixed effects of proceduralists and physicians 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. This identification strategy allows me to examine the effect of shared work experience among both emergency and non-emergency 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.

Yet 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 there could be multiple physicians associated with a patient during the hospital stay, it is difficult to observe the same exact group of physicians work together again. Therefore, instead of controlling for physician group fixed effects, I control for fixed effects of the *main physician*, i.e., the physician who provides the largest share of hospital visits to the patient during the inpatient stay.[26] I also control for weighted average characteristics of physicians other than the main physician.[27] 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 obervable characteristics). About

[26] I do not include main physician fixed effects in Empirical strategy I because including them would result in a smaller sample: patients treated by singleton main physicians (i.e., physicians with only one patient in the years of observation) will be excluded from the estimation. A larger sample would afford me the opportunity to detect treatment effects with less noise. In Panel B of Appendix Table A12, I control for main physician fixed effects for the ED patients as a robustness check.

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

60 percent of inpatient care to the patients in my sample is provided by the main physician. As a robustness check, I control for fixed effects of 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 86 percent of care to PCI and CABG patients.

The identifying assumptions in the two-way fixed effects model are:

Assumption 2.1 (Independence) *Conditional on proceduralist and main physician identities, observed characteristics of the non-main physicians, hospital-year, and time categories of the admission (month and day-of-the-week), patient potential outcomes are mean independent of shared work experience.*

Assumption 2.2 (Exclusion) *Conditional on proceduralist and main physician identities, observed characteristics of the non-main physicians, hospital-year, and time categories of the admission (month and day-of-the-week), physician unobserved characteristics that may affect patient outcomes are mean independent of shared work experience.*

Appendix Table A2 assesses Assumption 2.1 by reporting 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 controls listed in Assumption 2.1, patient observable characteristics that are predictive of health risks are similar across shared work experience. Further, similar to empirical strategy I, I test the robustness of my estimates to patient unobservables by including $C_{14}^{0} + 14 \times 13 + C_{14}^{14} = 184$ different sets of patient controls. Appendix Figure A4 shows that the estimates are remarkably stable across specifications. These results lend credence to Assumption 2.1.

For Assumption 2.2, I admittedly cannot rule out the possibility of violation. Yet controlling for main physician fixed effects and the use of physician characteristics that may affect patient treatment outcomes makes 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 fact, estimates from this two-way fixed effects model are very similar to the quasi-experimental estimates obtained from Empirical Strategy I. This pattern lends credibility to both Assumption 2.1 and Assumption 2.2.

4.2.2 Empirical Specification

The specification in this approach takes the following form:

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

where α is the coefficient of interest and measures how patient mortality rates change with shared work experience. Standard errors are clustered at the proceduralist level. $\boldsymbol{\theta}_{d(i)}$ includes both proceduralist fixed effects ($\theta_{k(i)}$) and main physician fixed effects ($\theta_{\hat{\jmath}(i)}$). $\bar{\mathbf{H}}_{\check{\jmath}(i)}$ is the weighted average characteristics of the physicians other than the main physician who treat the patient. 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 is provided by each physician to that patient.

4.2.3 Results

Figure 5 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 5 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 0.50 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.[28]

4.3 Robustness Checks

4.3.1 Ruling Out Alternative Explanations

In this section, I investigate the potential role of three 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"—i.e., doctors who frequently practice at a hospital may be (i) more familiar with procedures at the hospital, which may improve

[28] A 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 that discussed in Section 4.1.3, we may not interpret the estimates as, for example, an increase of 8.5 hospital visits reduces PCI patients' 30-day mortality by 0.5 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 Appendix Section A.1, I run a series of simulations to infer the standard deviation of shared work experience among the population.

care quality, and (ii) more likely to exhibit high shared work experience when practicing at the hospital. Appendix Table A3 shows that my estimates are robust in specifications that flexibly control for proceduralists' and physicians' patient volume or tenure at the hospital. Appendix Table A4 shows similar-magnitude returns to shared work experience when restricting the sample to patients treated by doctors who have been practicing at the hospital in the last two years (the same time window used for measuring shared work experience). These findings support the hypothesis 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 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 of the 4-digit ICD-10 code of the patient's primary diagnosis in the current hospital stay.[29] These codes provide detailed information on patient disease types—for example, ST elevation versus non-ST elevation myocardial infarction, which is a key determinant of heart attack severity. Appendix Table A5 shows that the results are stable when I control for 4-digit ICD-10 codes, in support of limited estimation bias due to current disease severity.

Third, an important 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 non-procedural medical management) if there is an available PCI doctor team with high shared work experience. Appendix Section A.2 discusses this possibility and shows that there is little evidence of procedure selection.

4.3.2 Additional Robustness Checks

Appendix Tables A6 and A7 measure shared work experience in multiple alternative ways, including in different time windows—the past year and the past three years; 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; as the shared work experience between the proceduralist and the first physician who treats the patient during the hospital stay; and as a function of a decay parameter that captures experience depreciation over time. Appendix Section A.3 describes the details and shows that the results are consistent.

[29] For years before the implementation of ICD-10, I convert ICD-9 to ICD-10 using crosswalks. For ICD-9 codes with multiple ICD-10 codes, I pick the lowest-value ICD-10 code. Results are robust to alternative rules—the highest or the median value.

Appendix Tables A8-A11 report additional robustness checks showing that the results are robust to controlling for doctors' individual work experience in alternative functional forms, are similar when considering mortality outcomes in a longer or shorter time window after the hospital 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.[30]

5 Mechanisms

Having established that patients treated by teams with more shared work experience achieve lower mortality rates, I next investigate the underlying mechanisms. I first show that returns to past collaboration experience are a central mechanism by ruling out a competing mechanism—proceduralist-physician matching—which is not specific to the effect of shared work experience. I then distinguish between two mechanisms that may generate the effect of shared work experience: (i) improved productivity; versus (ii) increased inputs. I find evidence consistent with improved productivity. Finally, I discuss possible mechanisms behind the productivity improvement.

5.1 Returns to Shared Work Experience versus Proceduralist-Physician Matching

A competing hypothesis that may explain the mortality improvements associated with shared work experience is proceduralist-physician matching: 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. This is in contrast to the central explanation that past collaboration experience improves current team performance. It is important to distinguish between the experience and the matching mechanism 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 team performance is fixed (regardless of shared work experience) and determined by the quality of match among team members. Frequent team switches, therefore, should be

[30] See, e.g., Verdier (2020) for a discussion of noise arising in fixed effects models with few observations per value of the variables that index fixed effects.

encouraged to improve the matching function between collaborators.[31]

Intuitively, the two competing mechanisms (i.e., experience and matching) that determine team performance can be written as:

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

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.

Yet institutional features suggest that proceduralist-physician matching may be unlikely in my study setting. First, most patients are treated by proceduralists and physicians who belong to different practice groups. For example, in the ED analysis sample, 73 and 89 percent of patients undergoing PCI and CABG are treated by proceduralists and physicians who belong to different practices, respectively.[32] For proceduralists and physicians from different practices, it is difficult to arrange shifts to work on the same patient. Second, in speaking with doctors, doctors pointed out that besides seeing patients, they are responsible for administration tasks and many of them 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. These institutional features could restrict the possibility of proceduralist-physician matching.

To empirically test the possibility of matching, I 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, similar to the issue discussed in the two-way fixed effects estimation, it is difficult to observe exactly the same group of physicians working together multiple times. For this reason, controlling for team fixed effects of 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.,

[31] These two views have a parallel in the literature on firm-specific human capital. The experience view is similar to the notion that a worker's productivity in a firm increases with her experience in the specific firm (Jovanovic 1979a). The match view is similar to the notion that a worker's productivity depends on the quality of match between her and the firm, regardless of her experience in the specific firm (Jovanovic 1979b).

[32] In the two-way fixed effects estimation sample, 69 and 89 percent PCI and CABG patients are treated by proceduralists and physicians from different practices, respectively. 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 physicians who work in the same practice as the proceduralist.

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.

Table 4 reports results from the proceduralist-main physician team fixed effects estimation. Sample sizes are smaller than those reported in Table 3 because singleton proceduralist-main physician teams (i.e., proceduralist-main physician teams that have only one observed patient) are removed from the analysis. 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 be 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. The coefficients on shared work experience are not statistically different between the two estimations, consistent with limited evidence of proceduralist-main physician matching.[33]

As another test of matching, I examine changes in explanatory power 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 fit the data (Card et al. 2013). Yet Table 4 shows that the team fixed effects model has a only minimally better fit (the adjusted R-squared change only minimally).

Finally, I test the matching explanation by restricting the sample to patients treated by proceduralists and physicians who belong to different practice groups.[34] As mentioned above, matching is less likely among doctors from different practices because coordinating shifts to work on the same patient is difficult. Focusing on this subset of patients reduces concerns about proceduralist-

[33]Table 4 reports the team fixed effects estimation results based on the the sample used in the two-way fixed effects analysis. For the results based on the ED patients, see Appendix Table A12.

[34]See Footnote 32 for how belonging to different practice groups is defined.

physician matching. The results are reported in Appendix Table A13, which show a similar effect of shared work experience on lowering patient 30-day mortality rates.

Taken together, it seems plausible that the documented effect of shared work experience is not driven by proceduralist-physician matching. They point to the alternative view that past experience working together improves current team performance. This indicates that the value of a team increases with the accumulation of shared work experience over the course of a collaboration, rather than being fixed over time as implied by search-and-matching models. Team-building through continued collaboration is an important ingredient of team production.

5.2 Improved Productivity versus Increased Inputs

Having established that proceduralist-physician matching is unlikely in my setting, I next examine two potential mechanisms through which shared work experience improves patient mortality outcomes: (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 in the specific firm (Jovanovic 1979a). Intuitively, through shared work experience, team members may gain skills and knowledge for 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 healthcare. A substantial number of medical studies have documented poor teamwork between doctors as a key contributor to low quality of care.[35] Under the improved productivity hypothesis, 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 indicates a higher probability of future interactions 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

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

willing to exert effort to preserve the relationship.[36] 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., Card et al. 2009; Doyle 2011; Doyle et al. 2015). Under the increased inputs explanation, 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:

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

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 (which is specified in Equation (6)), $a_{jk}(e)$ 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 $a_{jk}(e)$, while the increased inputs mechanism implies that team performance improves with shared work experience by raising $I_{jk}(e)$.

Understanding the relative importance of the improved productivity and the increased inputs mechanism is important since they have different welfare implications. The improved productivity hypothesis indicates welfare gains since we can achieve better outcomes without incurring higher costs, while the increased inputs view may imply a welfare loss if the cost of extra inputs outweighs the benefit of better team performance. 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 6.2, 4.4, and 14.0 percent reduction (compared to the mean) in length of hos-

[36] This intuition relates to relational contracting, i.e., the value of relationships can serve as an informal enforcement that increases coordinative behaviors among peers. See, e.g., MacLeod and Malcomson (1989), Baker et al. (2002), Levin (2003), and Halac (2012) for theoretical discussions. See, e.g., Jackson and Schneider (2011), Antras and Foley (2015), Macchiavello and Morjaria (2015), and Ghani and Teed (2018) for empirical evidence.

pital 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 4.4, 4.7, and 4.3 percent, respectively.[37, 38]

Appendix Table A15 shows that lower medical resource use during the hospital stay is not at the cost higher post-discharge healthcare use: there is no significantly positive correlation between shared work experience and the probability of discharge to skilled nursing or rehabilitation facilities, 30-day inpatient readmission rates, or number of outpatient visits in the 30 days after the hospital discharge. If anything, shared work experience seems to lower post-discharge healthcare use.

Taken together, these findings support the existence of improved team 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. In other words, past collaboration experience raises productivity: it enables team members to achieve better outcomes—with even fewer inputs.

5.3 Mechanism behind Improved Productivity

What drives the productivity increase with shared work experience? Kellogg (2011), in the setting of collaboration between firms, finds that repeated interactions facilitate *learning* about how to work with the specific collaborator; this creates collaborator-specific expertise which enhances firm productivity. This learning hypothesis also has a parallel in theoretical work[39] and was brought

[37] Table 5 has a smaller sample than Table 3. This is because patients 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 stay, 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 less shared work experience. This suggests that Table 5 still underestimates the effect of shared work experience on lowering patient medical resource use.

[38] Table 5 reports results based on the two-way fixed effects model. For results based on the ED analysis, see Appendix Table A14.

[39] Ellison and Holden (2013) models the development of rules in a setting where an agent repeatedly takes an action for a principal. Due to communication frictions, the principal cannot communicate perfectly the optimal state-contingent action to the agent unless the state has been experienced by the agent. The agent thus may not be able to take the optimal action in the beginning, but over time her performance improves as each period's experience allows the principal to convey the optimal action for that state. The agent can then take that optimal action when the same state arises again. As such, the agent's performance improves over time with the accumulation of experience working with the principal. Although it is not clear that there is a principal and an agent when it comes to the collaboration between proceduralists and physicians, Ellison and Holden (2013) provides an intuition about how worker performance may improve over the course of a collaboration.

up by doctors as a plausible mechanism in interviews.[40] 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 should raise the returns to shared work experience if fewer routines have been established for more complex tasks (Autor et al. 2003); second, belonging to the same organization may be correlated with a smaller productivity effect of shared work experience since organizations encompass specified rules for coordination among co-workers (Dessein et al. 2016) and may provide opportunities of informal interactions in addition to directly working together (formal interactions) to learn how to coordinate with one another. Section 6.2 tests these two heterogeneity patterns and finds evidence consistent with the prediction.

6 Heterogeneity in the Effect of Shared Work Experience

Given the existence and substantial magnitude of 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 qualitatively similar, this section focuses on the two-way fixed effects model to exploit its larger sample size to reduce noise.

6.1 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 et al. 2017). It is thus possible that an experienced doctor works well with any doctor regardless of their prior experience working together. In such a 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

[40] For example, doctors pointed out that past collaboration experience helps them learn how to better communicate with one another and learn each others' specific practice style.

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 practice 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:

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

where $E_i \times E(d(i);t(i))$ refers to the interaction between shared work experience—E_i, and proceduralists' or physicians' individual work experience—i.e., $E(k(i);t(i))$ or $E(J(i);t(i))$, both of which are included in $\mathbf{F}_i$. To facilitate interpretation, both $E(k(i);t(i))$ and $E(J(i);t(i))$ 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 lowers the effect of shared work experience on 30-day mortality rates by 0.27 percentage points among PCI patients. Table 6 also shows similar declines in the effect of shared work experience when physicians' individual work experience increases.[41]

A second finding in Table 6 is that, although the effect of shared work experience declines with proceduralists' and physicians' individual work experience, 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.

[41] A potential question is whether the observed substitution between shared and individual work experience is confounded by non-linear 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, Appendix Table A16 incorporates the non-linear 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.

6.2 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:

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

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

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 environments, following standard procedures may suffice. Consistent with this intuition, Columns 1-3 of Table 7 show that, for PCI, the effect of shared work experience is larger among patients with less common comorbidities,[42] 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. Appendix Table A17 divides the mortality reduction in each group of PCI patients by its mean mortality and similarly shows 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 compared 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. If organizations encompass tacit knowledge for how to work with each other (Dessein et al. 2016) or provide opportunities of informal interactions in addition to directly working together (formal interactions), past collaboration experience would be less important when doctors are from the same practice group.

[42] This is defined as 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.

7 Discussion and Conclusion

This study shows that team members' past collaboration creates team-specific human capital and raises team productivity. In the context of two common 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. A one standard deviation increase in proceduralist-physician shared work experience reduces patient 30-day mortality by 0.5-1 percentage points, or equivalently, 10-13 percent compared to the mean. Patient medical resource use also declines with shared work experience—even as survival improves. Together, these findings point to increased productivity with the accumulation of shared work experience. Further, I find that 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 could have implications for policies that aim to improve healthcare productivity. To put the effect magnitudes in perspective, it is instructive 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 that, in each hospital, (i) holds fixed the number of patient cases and the number of hospital visits associated with each case, (ii) reduces the number of unique physicians a proceduralist collaborates with by half[43]—a way to increase shared work experience by reducing the frequency of team switches, 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 0.4 percentage points—or equivalently, 8 percent of the mean mortality—for all patients undergoing PCI and CABG in my years of analysis (2010-2016). Appendix Section A.5 provides details of the simulation algorithm. To put the magnitude of this 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) adoption of new medical technologies. First, within my application of Medicare patients admitted to the hospital due to emergency conditions, Card

[43]This is equivalent to a decline of 0.5 standard deviations for both PCI and CABG, or a decline from an average of 120 unique physicians to 60 and from 99 to 44.5 over a two-year window for PCI and CABG, respectively.

et al. (2009) estimates that being covered by Medicare (relative 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 the returns to Medicare coverage. Second, the improvement in survival is about one-fifth of the magnitude of the survival gains attributed to the major breakthrough in heart attack treatment—primary angioplasty, which started being increasingly used the 1990s and has been estimated to reduce patient 30-day mortality by 38 percent over the relatively traditional 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 the productivity effects of these practices can be an effective way to increase adoption (Bloom et al. 2013; Gibbons and Henderson 2013). Another explanation, which is particularly relevant for healthcare, could be the fragmented organizational structure of healthcare 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 healthcare 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 an intensively-collaborated coworker is no longer available. Investigating the implications of such a trade-off remains a valuable subject for future research.

Nevertheless, these findings suggest two main takeaways. First, even holding medical technology and the pool of doctors fixed, we can achieve higher healthcare productivity—i.e., yield better patient survival with even fewer medical inputs—by reorganizing healthcare providers, which has been typically neglected. Second and more broadly for contexts outside healthcare, these findings show that the productivity (and value) of a team increases with the continuation of the collaborative relationship, instead of being only determined by team members' match quality and thus fixed over time. These results provide a proof of concept that team-building through continued collaboration is an important ingredient of productivity.

References

Agha, Leila, Keith Marzilli Ericson, Kimberley Geissler, and James Rebitzer, "Team formation and performance: Evidence from healthcare referral networks," *National Bureau of Economic Research*, 2018, *No. w24338*.

Alchian, Armen and Harold Demsetz, "Production, information costs, and economic organization," *American Economic Review*, 1972, *62* (5), 777–795.

Altonji, Joseph, Todd Elder, and Christopher Taber, "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of Political Economy*, 2005, *113* (1), 151–184.

Antras, Pol and Fritz Foley, "Poultry in motion: A study of international trade finance practices," *Journal of Political Economy*, 2015, *123* (4), 853–901.

Autor, David H, Frank Levy, and Richard J Murnane, "The skill content of recent technological change: An empirical exploration," *Quarterly journal of economics*, 2003, *118* (4), 1279–1333.

Baker, George, Robert Gibbons, and Kevin J Murphy, "Relational contracts and the theory of the firm," *Quarterly Journal of Economics*, 2002, *117* (1), 39–84.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul, "Social preferences and the response to incentives: Evidence from personnel data," *Quarterly Journal of Economics*, 2005, *120* (3), 917–962.

_ , _ , and _ , "Team incentives: Evidence from a firm level experiment," *Journal of the European Economic Association*, 2013, *11* (5), 1079–1114.

Bartel, Ann, Nancy Beaulieu, Ciaran Phibbs, and Patricia Stone, "Human capital and productivity in a team environment: Evidence from the healthcare sector," *American Economic Journal: Applied Economics*, 2014, *6* (2), 231–259.

Benjamin, Emelia J, Salim S Virani, Clifton W Callaway, Alanna M Chamberlain, Alexander R Chang, Susan Cheng, Stephanie E Chiuve, Mary Cushman, Francesca N Delling, Rajat Deo et al., "Heart disease and stroke statistics–2018 update: a report from the American Heart Association," *Circulation*, 2018, *137* (12), e67–e492.

Benkard, Lanier, "Learning and forgetting: The dynamics of aircraft production," *American Economic Review*, 2000, *90* (4), 1034–1054.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts, "Does management matter? Evidence from India," *Quarterly Journal of Economics*, 2013, *128* (1), 1–51.

Bonatti, Alessandro and Johannes Hörner, "Collaborating," *American Economic Review*, 2011, *101* (2), 632–663.

Card, David, Alessandra Fenizia, and David Silver, "The health effects of cesarean delivery for low-risk first births," *National Bureau of Economic Research*, 2018, *No. w24493.*

_ , Carlos Dobkin, and Nicole Maestas, "Does Medicare save lives?," *Quarterly Journal of Economics*, 2009, *124* (2), 597–636.

_ , Jörg Heining, and Patrick Kline, "Workplace heterogeneity and the rise of West German wage inequality," *Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Cebul, Randall D, James B Rebitzer, Lowell J Taylor, and Mark E Votruba, "Organizational fragmentation and care quality in the US healthcare system," *Journal of Economic Perspectives*, 2008, *22* (4), 93–113.

Centers for Disease Control and Prevention, "Cost of hospital discharges with common hospital operating room procedures in nonfederal community hospitals, by age and selected principal procedure: United States, selected years 2000-2013," 2015. Accessed November 17, 2019. `https://www.cdc.gov/nchs/data/hus/2015/096.pdf`.

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

_ , Matthew Gentzkow, and Chuan Yu, "Selection with skills: Evidence from radiologists," *NBER Working Paper*, 2019, *No. w26467.*

Chandra, Amitabh and Douglas Staiger, "Productivity spillovers in health care: Evidence from the treatment of heart attacks," *Journal of Political Economy*, 2007, *115* (1), 103–140.

Charles, Anthony, Shiara Ortiz-Pujols, Thomas Ricketts, Erin Fraher, Simon Neuwahl, Bruce Cairns, and George Sheldon, "The employed surgeon: A changing professional paradigm," *JAMA Surgery*, 2013, *148* (4), 323–328.

Christian, Caprice, Michael Gustafson, Emilie Roth, Thomas Sheridan, Tejal Gandhi, Kathleen Dwyer, Michael Zinner, and Meghan Dierks, "A prospective study of patient safety in the operating room," *Surgery*, 2006, *139* (2), 159–173.

Clemens, Jeffrey and Joshua Gottlieb, "Do physicians' financial incentives affect medical treatment and patient health?," *American Economic Review*, 2014, *104* (4), 1320–1349.

Currie, Janet and Bentley MacLeod, "Diagnosing expertise: Human capital, decision making, and performance among physicians," *Journal of Labor Economics*, 2017, *35* (1), 1–43.

Delarue, Anne, Geert Van Hootegem, Stephen Procter, and Mark Burridge, "Teamworking and organizational performance: A review of survey-based research," *International Journal of Management Reviews*, 2008, *10* (2), 127–148.

Deloitte, *Global Human Capital Trends: The New Organizational: Different by Design*, London: Deloitte University Press, 2016.

Dessein, Wouter, Andrea Galeotti, and Tano Santos, "Rational inattention and organizational focus," *American Economic Review*, 2016, *106* (6), 1522–1536.

Doyle, Joseph, "Returns to local-area health care spending: Evidence from health shocks to patients far from home," *American Economic Journal: Applied Economics*, 2011, *3* (3), 221–243.

_ , John Graves, Jonathan Gruber, and Samuel Kleiner, "Measuring returns to hospital care: Evidence from ambulance referral patterns," *Journal of Political Economy*, 2015, *123* (1), 170–214.

Ellison, Glenn and Richard Holden, "A theory of rule development," *The Journal of Law, Economics, & Organization*, 2013, *30* (4), 649–682.

Frakes, Michael, "The impact of medical liability standards on regional variations in physician behavior: Evidence from the adoption of national-standard rules," *American Economic Review*, 2013, *103* (1), 257–276.

Frasier, Lane, Sudha Pavuluri Quamme, Aimee Becker, Sara Booth, Adam Gutt, Douglas Wiegmann, and Caprice Greenberg, "Investigating teamwork in the operating room: Engaging stakeholders and setting the agenda," *JAMA Surgery*, 2017, *152* (1), 109–111.

Friebel, Guido, Matthias Heinz, Miriam Krüger, and Nikolay Zubanov, "Team incentives and performance: Evidence from a retail chain," *American Economic Review*, 2017, *107* (8), 2168–2203.

Gawande, Atul, Michael Zinner, David Studdert, and Troyen Brennan, "Analysis of errors reported by surgeons at three teaching hospitals," *Surgery*, 2003, *133* (6), 614–621.

Gaynor, Martin, James Rebitzer, and Lowell Taylor, "Physician incentives in health maintenance organizations," *Journal of Political Economy*, 2004, *112* (4), 915–931.

Ghani, Tarek and Tristan Teed, "Relationships on the rocks: Contract evolution in a market for ice," 2018. Accessed March 18, 2019. `https://drive.google.com/file/d/0B2zdXwAFImkSSEZydlFlYkJHTXc/view`.

Gibbons, Robert and Rebecca Henderson, "What do managers do? Exploring persistent performance differences among seemingly similar enterprises," in "Handbook of Organizational Economics," Princeton University Press, 2013, pp. 680–731.

Haggag, Kareem, Brian McManus, and Giovanni Paci, "Learning by driving: Productivity improvements by new york city taxi drivers," *American Economic Journal: Applied Economics*, 2017, *9* (1), 70–95.

Halac, Marina, "Relational contracts and the value of relationships," *American Economic Review*, 2012, *102* (2), 750–779.

Halm, Ethan, Clara Lee, and Mark Chassin, "Is volume related to outcome in health care? A systematic review and methodologic critique of the literature," *Annals of Internal Medicine*, 2002, *137* (6), 511–520.

Hamilton, Barton, Jack Nickerson, and Hideo Owan, "Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation," *Journal of Political Economy*, 2003, *111* (3), 465–497.

Hannan, Edward, Chuntao Wu, Thomas Ryan, Edward Bennett, Alfred T Culliford, Jeffrey Gold, Alan Hartman, O Wayne Isom, Robert Jones, Barbara McNeil, Eric Rose, and Valavanur Subramanian, "Do hospitals and surgeons with higher coronary artery bypass graft surgery volumes still have lower risk-adjusted mortality rates?," *Circulation*, 2003, *108* (7), 795–801.

Holmstrom, Bengt, "Moral hazard in teams," *The Bell Journal of Economics*, 1982, *13* (2), 324–340.

Huckman, Robert and Gary Pisano, "The firm specificity of individual performance: Evidence from cardiac surgery," *Management Science*, 2006, *52* (4), 473–488.

Jackson, Kirabo and Henry Schneider, "Do social connections reduce moral hazard? Evidence from the New York City taxi industry," *American Economic Journal: Applied Economics*, 2011, *3* (3), 244–267.

Jaravel, Xavier, Neviana Petkova, and Alex Bell, "Team-specific capital and innovation," *American Economic Review*, 2018, *108* (4-5), 1034–1073.

Johnson, Erin and Marit Rehavi, "Physicians treating physicians: Information and incentives in childbirth," *American Economic Journal: Economic Policy*, 2016, *8* (1), 115–141.

Jovanovic, Boyan, "Firm-specific capital and turnover," *Journal of Political Economy*, 1979, *87* (6), 1246–1260.

_ , "Job matching and the theory of turnover," *Journal of Plitical Economy*, 1979, *87* (5), 972–990.

Joynt, Karen E, Daniel M Blumenthal, E John Orav, Frederic S Resnic, and Ashish K Jha, "Association of public reporting for percutaneous coronary intervention with utilization and outcomes among Medicare beneficiaries with acute myocardial infarction," *JAMA*, 2012, *308* (14), 1460–1468.

Kandel, Eugene and Edward Lazear, "Peer pressure and partnerships," *Journal of Political Economy*, 1992, *100* (4), 801–817.

Kellogg, Ryan, "Learning by drilling: Interfirm learning and relationship persistence in the Texas oilpatch," *Quarterly Journal of Economics*, 2011, *126* (4), 1961–2004.

Kolstad, Jonathan, "Information and quality when motivation is intrinsic: Evidence from surgeon report cards," *American Economic Review*, 2013, *103* (7), 2875–2910.

Lafontaine, Francine and Kathryn Shaw, "Serial entrepreneurship: Learning by doing?," *Journal of Labor Economics*, 2016, *34* (S2), S217–S254.

Levin, Jonathan, "Relational incentive contracts," *American Economic Review*, 2003, *93* (3), 835–857.

Levitt, Steven, John List, and Chad Syverson, "Toward an understanding of learning by doing: Evidence from an automobile assembly plant," *Journal of Political Economy*, 2013, *121* (4), 643–681.

Macchiavello, Rocco and Ameet Morjaria, "The value of relationships: Evidence from a supply shock to Kenyan rose exports," *American Economic Review*, 2015, *105* (9), 2911–2945.

MacLeod, Bentley and James Malcomson, "Implicit contracts, incentive compatibility, and involuntary unemployment," *Econometrica*, 1989, *57* (2), 447–480.

Mas, Alexandre and Enrico Moretti, "Peers at work," *American Economic Review*, 2009, *99* (1), 112–145.

Mazzocco, Karen, Diana Petitti, Kenneth Fong, Doug Bonacum, John Brookey, Suzanne Graham, Robert Lasky, J Bryan Sexton, and Eric Thomas, "Surgical team behaviors and patient outcomes," *The American Journal of Surgery*, 2009, *197* (5), 678–685.

Menees, Daniel S, Eric D Peterson, Yongfei Wang, Jeptha P Curtis, John C Messenger, John S Rumsfeld, and Hitinder S Gurm, "Door-to-balloon time and mortality among patients undergoing primary PCI," *New England Journal of Medicine*, 2013, *369* (10), 901–909.

Molitor, David, "The evolution of physician practice styles: Evidence from cardiologist migration," *American Economic Journal: Economic Policy*, 2018, *10* (1), 326–356.

Myles, Paul S, Julian A Smith, Andrew Forbes, Brendan Silbert, Mohandas Jayarajah, Thomas Painter, D James Cooper, Silvana Marasco, John McNeil, Jean S Bussières et al., "Stopping vs. continuing aspirin before coronary artery surgery," *New England Journal of Medicine*, 2016, *374* (8), 728–737.

Newman, Mark, Bruce Ferguson, Jennifer White, Giuseppe Ambrosio, Joerg Koglin, Nancy Nussmeier, Ronald Pearl, Bertram Pitt, Andrew Wechsler, Richard Weisel, Tammy Reece, Armando Lira, and Robert Harrington, "Effect of adenosine-regulating agent acadesine on morbidity and mortality associated with coronary artery bypass grafting: the RED-CABG randomized controlled trial," *JAMA*, 2012, *308* (2), 157–164.

Ost, Ben, "How do teachers improve? The relative importance of specific and general human capital," *American Economic Journal: Applied Economics*, 2014, *6* (2), 127–151.

Oster, Emily, "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Ricciardi, Rocco, Beth A Virnig, James W Ogilvie, Peter S Dahlberg, Harry P Selker, and Nancy N Baxter, "Volume-outcome relationship for coronary artery bypass grafting in an era of decreasing volume," *Archives of Surgery*, 2008, *143* (4), 338–344.

Shaw, Kathryn and Edward Lazear, "Tenure and output," *Labour Economics*, 2008, *15* (4), 704–723.

Shroyer, Laurie, Brack Hattler, Todd Wagner, Joseph Collins, Janet Baltz, Jacquelyn Quin, Hossein Almassi, Elizabeth Kozora, Faisal Bakaeen, Joseph Cleveland Jr, Muath Bishawi, and Frederick Grover, "Five-year outcomes after on-pump and off-pump coronary-artery bypass," *New England Journal of Medicine*, 2017, *377* (7), 623–632.

Silver, David, "Haste or waste? Peer pressure and the distribution of marginal returns to health care," 2020. Accessed July 6, 2020. `https://www.dropbox.com/s/sn6jzo0vmz354nj/jmp.pdf?dl=0`.

Thiele, Holger, Ibrahim Akin, Marcus Sandri, Suzanne de Waha-Thiele, Roza Meyer-Saraei, Georg Fuernau, Ingo Eitel, Peter Nordbeck, Tobias Geisler, Ulf Landmesser et al., "One-year outcomes after PCI strategies in cardiogenic shock," *New England Journal of Medicine*, 2018, *379* (18), 1699–1710.

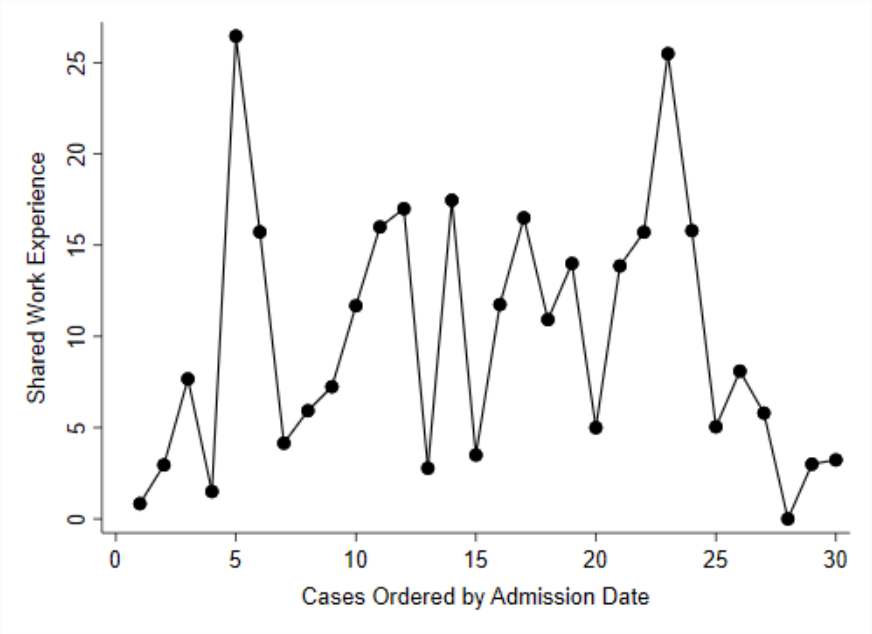
Thompson, Peter, "How much did the Liberty shipbuilders forget?," *Management Science*, 2007, *53* (6), 908–918.

Verdier, Valentin, "Estimation and inference for linear models with two-way fixed effects and sparsely matched data," *Review of Economics and Statistics*, 2020, *102* (1), 1–16.

Weaver, W Douglas, R John Simes, Amadeo Betriu, Cindy L Grines, Felix Zijlstra, Eulogio Garcia, Lilliana Grinfeld, Raymond J Gibbons, Expedito E Ribeiro, Marcus A DeWood et al., "Comparison of primary coronary angioplasty and intravenous thrombolytic therapy for acute myocardial infarction: A quantitative review," *JAMA*, 1997, *278* (23), 2093–2098.

Wennberg, David E, F Lee Lucas, Andrea E Siewers, Merle A Kellett, and David J Malenka, "Outcomes of percutaneous coronary interventions performed at centers without and with onsite coronary artery bypass graft surgery," *JAMA*, 2004, *292* (16), 1961–1968.

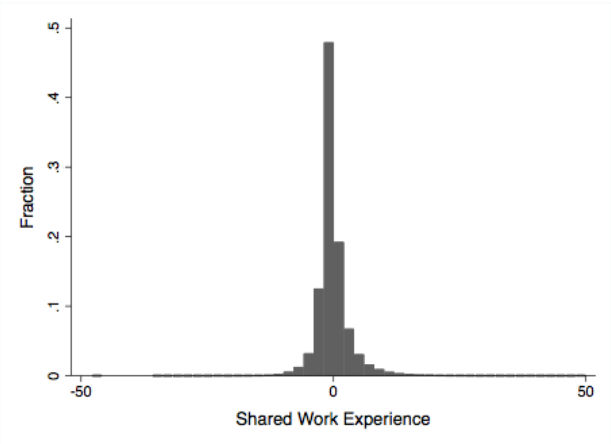
Figure 1: Within-Proceduralist Variation in Shared Work Experience: An Example



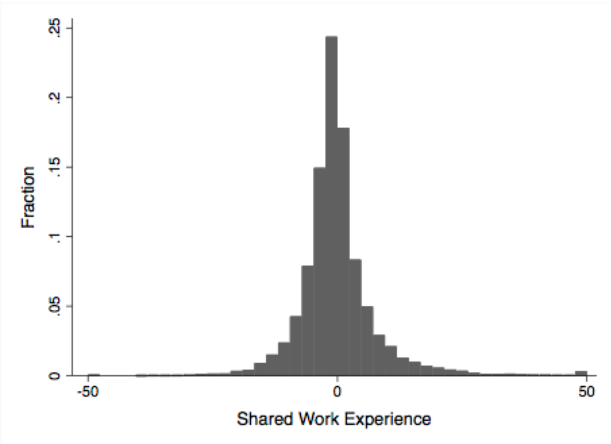
Notes: This figure shows variation in shared work experience across patients treated by an example proceduralist. To construct this figure, I first randomly pick a CABG proceduralist with 30 patient cases from the analysis sample. I then plot the shared work experience between the proceduralist and the physicians who treated the patient during the hospital stay for each of the observed ED patient cases treated by the proceduralist. Each dot in the figure represents a separate patient case. Cases are ordered by admission dates on the x-axis. Numbers on the x-axis are false IDs assigned to each case.

Figure 2: Distribution of Shared Work Experience

A. PCI



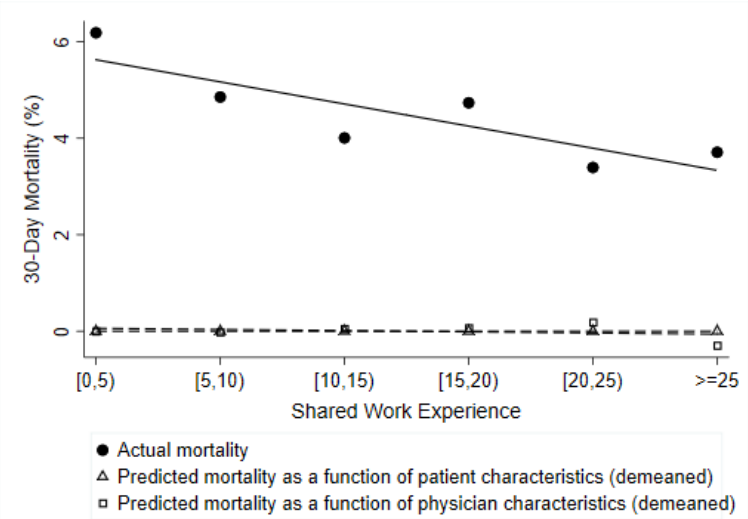
B. CABG



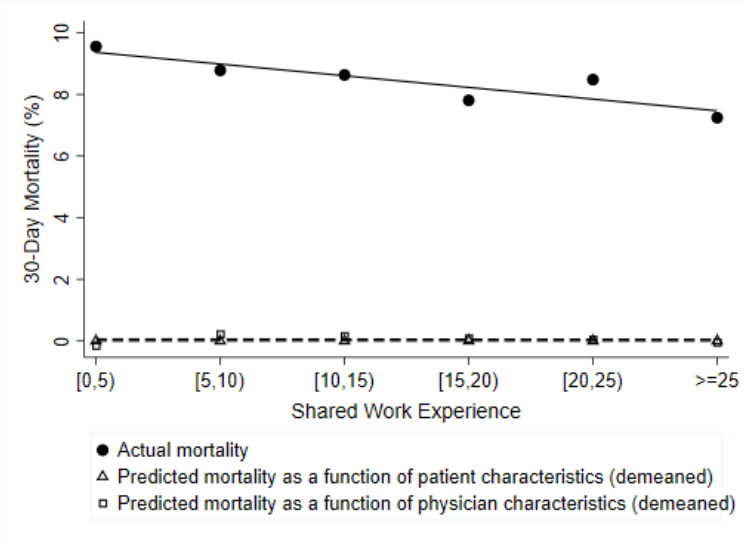
Notes: These figures show variation of shared work experience after residualizing by proceduralist identities for patients included in empirical strategy I (i.e., the ED analysis). Residualized shared work experience is winsorized at -50 and 50.

Figure 3: Actual and Predicted 30-Day Mortality versus Shared Work Experience: ED Patients

A. PCI



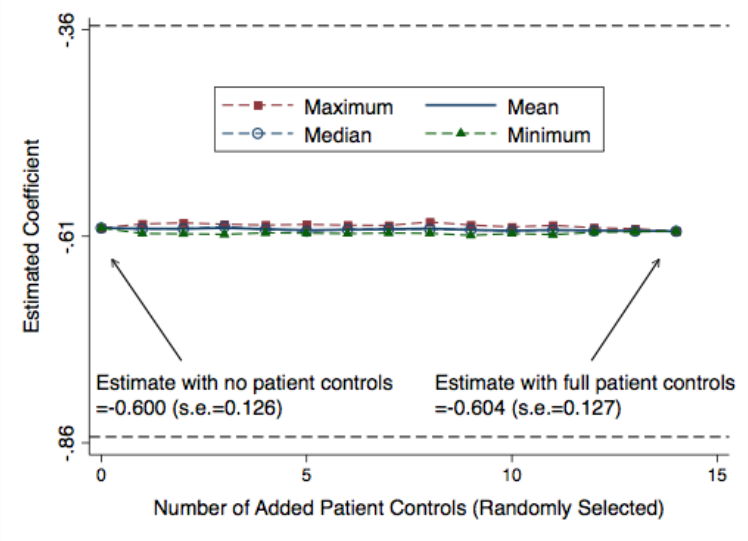
B. CABG



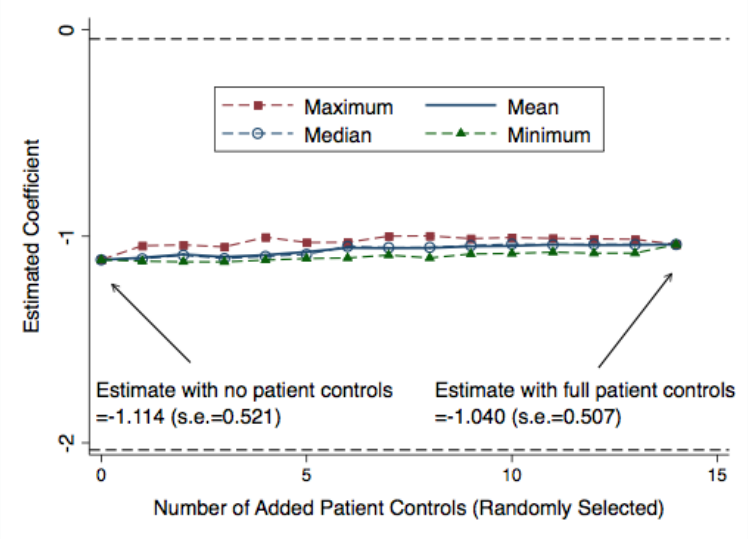
Notes: These figures plot actual 30-day mortality (in circles), predicted 30-day mortality as a function of patient characteristics (in triangles), and predicted 30-day mortality as a function of physician characteristics (in squares) for patients treated by proceduralist-physician teams with differing shared work experience. The sample includes all patients included in empirical strategy I (i.e., 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 ethnicity, 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 non-patient 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.

Figure 4: Sensitivity of Effect of Shared Work Experience on Patient 30-Day Mortality: ED Analysis

A. PCI



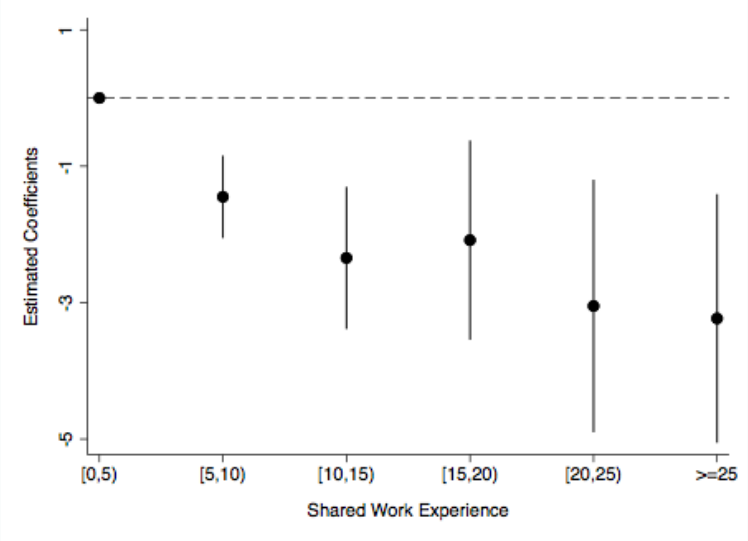
B. CABG



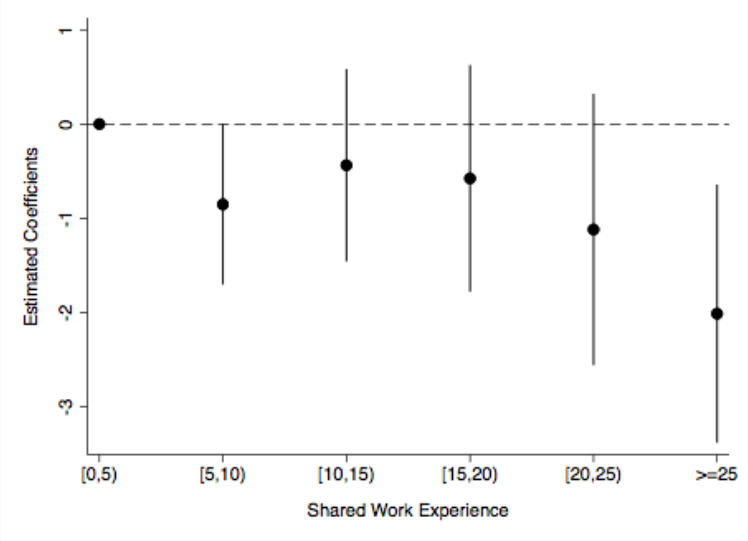
Notes: These figures plot the estimated effect of shared work experience on 30-day mortality with the inclusion of different sets of patient controls based on empirical strategy I (i.e., the ED analysis). Specifically, from the 14 patient demographic and comorbidity variables described in Section 4.1.2, I randomly select subsets of n covariates to include in the regression and collect the coefficients on shared work experience for each integer $n = 0, 1, ..., 14$. By definition, only $C_{14}^{0} = C_{14}^{14} = 1$ set of patient controls is available when $n = 0$ or $n = 14$. For $n = 1, 2, .., 13$, 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, median, and minimum of the estimated coefficients on shared work experience for each integer $n = 0, 1, ..., 14$. To provide a benchmark, I show in black dashed lines 95% confidence intervals of the coefficient estimates with the full set of patient controls.

Figure 5: Effects of Shared Work Experience on 30-Day Mortality: Two-Way Fixed Effects Model

A. PCI



B. CABG



Notes: These figures plot coefficients from regressing 30-day mortality on shared work experience based on empirical strategy II (i.e., the two-way fixed effects model). The specification is the same as Equation (5), except that shared work experience is categorized into groups. 95% 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 1: Balance in Patient Characteristics: ED Patients

	Shared work experience below mean	Shared work experience above mean	p-value
Panel A. PCI			
Age	76.09	76.12	0.44
	(6.28)	(6.55)	
Female	0.435	0.434	0.69
	(0.430)	(0.452)	
Black	0.077	0.077	0.85
	(0.209)	(0.223)	
Hispanic	0.016	0.015	0.38
	(0.100)	(0.107)	
Medicaid	0.168	0.165	0.35
	(0.307)	(0.325)	
Disabled	0.161	0.158	0.30
	(0.315)	(0.333)	
Number of Comorbidities	2.260	2.248	0.23
	(1.382)	(1.454)	
Predicted 30-day Mortality (%)	5.935	5.930	0.78
(by patient characteristics)	(2.525)	(2.660)	
Observations	60,297	24,592	
Panel B. CABG			
Age	74.44	74.48	0.64
	(4.84)	(5.13)	
Female	0.334	0.333	0.79
	(0.372)	(0.396)	
Black	0.065	0.062	0.31
	(0.186)	(0.189)	
Hispanic	0.015	0.016	0.37
	(0.089)	(0.092)	
Medicaid	0.145	0.140	0.28
	(0.263)	(0.282)	
Disabled	0.139	0.140	0.86
	(0.272)	(0.293)	
Number of Comorbidities	1.814	1.818	0.83
	(1.128)	(1.190)	
Predicted 30-day Mortality (%)	8.959	9.010	0.40
(by patient characteristics)	(3.687)	(3.909)	
Observations	11,917	5,753	

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 (i.e., the ED analysis). Standard deviations are reported in parentheses. Each characteristic is residualized with respect to the set of non-patient controls used empirical strategy I. Unconditional means of each characteristic are added back for ease of interpretation. Predicted 30-day mortality is predicted 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 ethnicity, 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.

Table 2: Shared Work Experience and 30-Day Mortality: ED Analysis

	(1)	(2)	(3)	(4)	(5)
Panel A. PCI					
Shared work experience	-0.778***	-0.979***	-0.889***	-0.600***	-0.604***
	(0.097)	(0.114)	(0.132)	(0.126)	(0.127)
Proceduralist FE	X	X	X	X	X
Hospital-year/Adm. time FE		X	X	X	X
Individual experience			X	X	X
Physician covariates				X	X
Patient characteristics					X
Mean dep. var.	5.93	5.93	5.93	5.93	5.93
S.D. dep. var.	23.63	23.63	23.63	23.63	23.63
Observations	84,889	84,889	84,889	84,889	84,889
Panel B. CABG					
Shared work experience	-1.124***	-1.522***	-1.473***	-1.114**	-1.040**
	(0.259)	(0.372)	(0.508)	(0.521)	(0.507)
Proceduralist FE	X	X	X	X	X
Hospital-year/Adm. time FE		X	X	X	X
Individual experience			X	X	X
Physician covariates				X	X
Patient characteristics					X
Mean dep. var.	8.98	8.98	8.98	8.98	8.98
S.D. dep. var.	28.58	28.58	28.58	28.58	28.58
Observations	17,670	17,670	17,670	17,670	17,670

Notes: This table reports coefficients from regressing patient 30-day mortality on shared work experience based on empirical strategy I (i.e., 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 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 4 adds weighted averages characteristics (years of practice, age, gender, rank of medical school attended, and specialty, see details under Equation (4)) of the physicians who treat the patient during the hospital stay. Column 5 adds patient covariates, including 5-year age bin fixed effects, gender, black race, Hispanic ethnicity, 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. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

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

	(1) PCI	(2) CABG
Shared work experience	-0.499**	-0.746***
	(0.223)	(0.255)
Full control	X	X
Mean dep. var.	5.07	5.85
S.D. dep. var.	21.94	23.47
Observations	91,862	49,673

Notes: This table reports coefficients from regressing patient 30-day mortality on shared work experience based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. 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 the physicians other than the main physician who treat the patient during the hospital stay, the proceduralist's and physicians' individual work experience, hospital-year fixed effects, fixed effects of patient admission month and day-of-the-week, and patient covariates specified under Table 2. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table 4: Within Proceduralist-Physician Team Estimation

	(1) PCI	(2) CABG
Panel A. Team fixed effects		
Shared work experience	-0.971***	-1.305***
	(0.228)	(0.341)
Full control	X	X
Mean dep. var.	4.31	5.41
S.D. dep. var.	20.31	22.62
Adj. R-squared	0.15	0.13
Obserations	46,172	34,193
Panel B. Separate proceduralist and physician fixed effects		
Shared work experience	-0.648***	-0.929***
	(0.234)	(0.331)
Full control	X	X
Mean dep. var.	4.31	5.41
S.D. dep. var.	20.31	22.62
Adj. R-squared	0.14	0.13
Observations	46,172	34,193

Notes: Panel A reports coefficients from regressing patient 30-day mortality on shared work experience based on the proceduralist-main physician team fixed effects model specified in Equation (7). Sample sizes are smaller than those reported in Table 3 because singleton proceduralist-main physician teams are dropped from the analysis. Panel B reports the results based on the two-way fixed effects model that replaces proceduralist-main physician team fixed effects with separate proceduralist and main physician fixed effects. For ease of comparison, I restrict the sample in Panel B to be the same as that used in Panel A. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

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

	PCI			CABG		
	(1) Length of stay	(2) Number tests exams	(3) Outlier payments	(4) Length of stay	(5) Number tests exams	(6) Outlier payments
Shared work experience	-0.258***	-0.316***	-0.007***	-0.451***	-0.794***	-0.006
	(0.075)	(0.116)	(0.002)	(0.081)	(0.137)	(0.004)
Full control	X	X	X	X	X	X
Mean dep. var.	4.17	7.25	0.05	10.33	16.80	0.14
S.D. dep. var.	4.30	6.36	0.22	6.81	11.75	0.35
Observations	88,051	88,051	88,051	46,865	46,865	46,865

Notes: This table reports coefficients from regressing patient medical resource use outcomes on shared work experience based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. 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. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

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

	(1) PCI	(2) CABG
Panel A. Heterogeneity by proceduralists' individual work experience		
Shared work experience*Proceduralist experience	0.271***	0.111
	(0.051)	(0.223)
Shared work experience	-1.050***	-0.845***
	(0.216)	(0.307)
Full control	X	X
Observations	91,862	49,673
Panel B. Heterogeneity by physicians' individual work experience		
Shared work experience*Physician experience	0.112***	0.104*
	(0.027)	(0.062)
Shared work experience	-1.055***	-1.020***
	(0.212)	(0.331)
Full control	X	X
Observations	91,862	49,673

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 and individual work experience (details in Equation (9)). For ease of interpretation, proceduralists' and physicians' 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. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)	(4)
Panel A. PCI				
Interaction	-0.460***	-0.579***	-0.272**	1.107***
	(0.177)	(0.192)	(0.115)	(0.208)
Shared work experience	-0.401*	-0.363*	-0.387*	-1.059***
	(0.211)	(0.203)	(0.211)	(0.231)
Interaction term	Age in top quartile	Predicted mortality in top quartile	Uncommon comorbidities	Same practice
Full control	X	X	X	X
Observations	91,862	91,862	91,862	91,862
Panel B. CABG				
Interaction	-0.626**	-0.200	-0.104	0.256
	(0.311)	(0.301)	(0.244)	(0.364)
Shared work experience	-0.642**	-0.699***	-0.719***	-0.783***
	(0.255)	(0.262)	(0.258)	(0.267)
Interaction term	Age in top quartile	Predicted mortality in top quartile	Uncommon comorbidities	Same practice
Full control	X	X	X	X
Observations	49,673	49,673	49,673	49,673

Notes: This table shows heterogeneity patterns in the effect of shared work experience on patient 30-day mortality. Each column represents a separate regression based on the two-way fixed effects model with an interaction term between shared work experience and the dummy specified in the third row of each panel (details in Equation (10)). The dummies in Columns 1-4 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. Each of the interacted dummies is also included in the corresponding regression. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

For Online Publication

Appendix

A.1 Interpretation of One Standard Deviation and Measurement Error in Shared Work Experience

Since my data is a 20 percent random sample of traditional Medicare patients, we can only observe shared work experience in the sample. In Appendix Figure A2, I run a series of simulations to estimate the value of one standard deviation in shared work experience among the population. To construct the figure, I first run a series of simulations that randomly draw subsamples (50 percent, 55 percent, 60 percent, ..., 95 percent) of patients from the 20 percent Medicare claims (e.g., 50 percent of the 20 percent claims is equal to 10 percent of traditional Medicare enrollees on the x-axis). To account for sampling error, I repeat 50 draws for each of the 10 subsample groups that range from 50 to 95 percent and calculate the standard deviation of shared work experience in each draw. I then plot in solid lines the mean standard deviation of shared work experience for each subsample group. Since the solid lines suggest a linear relationship between the y- and the x-axis variable, I run linear regressions of the y-axis variable on the x-axis variable to predict the standard deviation of shared work experience beyond the 20 percent sample. Assuming that half of PCI and CABG procedures are performed on patients outside traditional Medicare (see statistics reported in, for example, Ricciardi et al. 2008), the standard deviation of shared work experience is equal to 56 and 136 hospital visits for ED patients undergoing PCI and CABG, respectively, and equal to 100 and 185 visits for patients undergoing PCI and CABG in the two-way fixed effects analysis, respectively.

A related question is how measurement error in shared work experience due to a 20 percent random sample may affect my estimates. Although the sample is randomly drawn, measurement error in this setting may differ from classical measurement error if the size of the bias is proportional to the underlying true shared work experience. Appendix Figure A3 explores how measurement error may affect my estimates. Similar to Appendix Figure A2, I run a series of simulations that randomly draw subsamples (50 percent, 55 percent, 60 percent, ..., 95 percent) of patients from the 20 percent Medicare claims and repeat 50 draws for each of the 10 subsample groups. I then estimate the effect of shared work experience using each of the $50 \times 10 = 500$ randomly drawn subsamples. Appendix Figure A3 shows that, if anything, measurement error would lead to an

underestimated effect of shared work experience on reducing mortality rates.

A.2 Procedure Selection

Perhaps a question of interest is whether patients select into different procedures based on available doctor teams. For example, a patient may undergo PCI instead of CABG (or nonprocedural medical management) if there is an available PCI proceduralist-physician team with high shared work experience. In this case, patient characteristics would be systematically different across shared work experience. Yet it is reassuring that patient demographics and comorbidities are well balanced across shared work experience (Table 1 and Appendix Table A2), which mitigates the concern about selection into procedures. In addition, if there is selection, we would expect that the marginal patients selecting into the procedure due to a high shared work experience team are worse fits for the procedure. In this case, if anything, the selection issue would lead to an underestimated survival-improving effect of shared work experience.

As a further check, I restrict my sample to patients who have a high probability of undergoing PCI and CABG for PCI and CABG analysis, respectively. For example, since clinical guidelines recommend that patients older than 80 and patients with certain conditions not be treated with CABG, then regardless of the available doctor teams, these patients are likely to undergo an alternative instead of a CABG. I compute predicted possibilities of undergoing PCI or CABG from patient-level regressions of procedure indicators on patient characteristics (five-year age bin fixed effects, gender, black race, Hispanic ethnicity, 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). I then run my analysis using only patients with predicted possibilities in the top tercile of the sample. Appendix Table A18 shows a similar trend that shared work experience reduces patient mortality rates, although the estimates are less significant with the smaller samples. Sample sizes in Appendix Table A18 are smaller than one-third of the corresponding samples in Tables 2 and 3. This is because, to control for proceduralist and (or) main physician fixed effects, patients treated by proceduralists and (or) main physicians with only one observed patient in the top-tercile are dropped from the analysis.

A.3 Alternative Measures of Shared Work Experience

In Appendix Table A6, I consider alternative measures of shared work experience. Column 1 repeats the results from my main analysis. Columns 2 and 3 measure shared work experience by the number of hospital visits the physicians provided to the proceduralist's patients in the past year and in the past three years, respectively. Columns 4 and 5 defines shared work experience 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, respectively.[1] Column 6 defines shared work experience as that between the proceduralist and the first physician who treats the patient during the hospital stay. To facilitate comparison, none of the shared work experience measures is standardized by its standard deviation. Thus, the coefficients can be interpreted as how a one hospital visit increase in each of the measured shared work experience in the data influences patient 30-day mortality outcomes.

Across all these different measures of shared work experience, results are stable and suggest significant effects of shared work experience on reducing patient 30-day mortality rates. Similar to studies that suggest the effect of individual work experience decays with time (e.g., Benkard 2000; Thompson 2007), Columns 1-3 of Appendix Table A6 show that shared work experience accumulated in the distant past has a slightly smaller effect on patient mortality than does shared work experience accumulated more recently.

In Appendix Table A7, I define shared work experience as a function of a decay parameter that captures experience depreciation over time:

$$E_i = \sum_{j \in J(i)} \sigma_{ij} \sum_{t<t(i)} N_{j,k(i);t} \times e^{\delta(t-t(i))/365} \tag{11}$$

where $N_{j,k(i);t}$ is the number of hospital visits provided by physician j to proceduralist $k(i)$'s patients at day t. δ is the decay parameter. Appendix Table A7 reports the returns to shared work experience using different values of δ based on the range estimated in the literature (Benkard 2000; Kellogg 2011; Levitt et al. 2013; Ost 2014).

A.4 Other Health Professionals Caring for the Patient

Patients may be cared for by health professionals other than proceduralists and physicians—for example, nurses and physician assistants—during the hospital stay. While interactions between these

[1] In cases of multiple modes, I define it as the highest value of the modes.

health professionals and proceduralists/physicians are interesting, this paper abstracts from them and focuses on shared work experience between proceduralists and physicians, since (i) Medicare claims data allow me to track proceduralist-physician collaboration histories and (ii) proceduralists and physicians could be associated with larger welfare implications as it seems plausible that doctors play a larger role in deciding patient treatments.

A related question is whether the presence of these other health professionals may confound my analysis. Yet for such a confounding bias to exist, characteristics of these health professionals would need to be closely correlated with proceduralist-physician shared work experience. It seems reasonable to assume that such a correlation does not exist given that doctors and nurses/physician assistants have different scopes of tasks and different employment relationships with hospitals, making it difficult for them to systematically arrange the same work schedules. For example, anecdotal evidence suggests that nurses schedules are independent of doctor schedules outside surgical teams. Further, a possible empirical test is examining how the estimates change when adding other health professionals' characteristics as covariates. A significant change indicates potential estimation biases, while a robust estimate suggests the opposite. While I am not able to track the nurses who cared for the patient and only few analyzed patients received care from physician assistants during the hospital stay,[2] I can observe the anesthesiologist who worked in conjunction with the proceduralist for patients undergoing CABG. It is reassuring that controlling for anesthesiologist characteristics (age, gender, years of practice, and rank of medical school attended) only minimally affects my estimates: the coefficient on shared work experience changes slightly from -1.04 to -1.02 and from -0.75 to -0.74 in empirical strategy I and II, respectively.

A.5 Simulation Algorithm for Counterfactual Mortality Reduction

The algorithm for the counterfactual analysis in Section 7 is as follows:

1. In each hospital, I hold fixed the number of patient cases and the number of hospital visits associated with each case. By reducing the number of unique physicians a proceduralist collaborates with by half and evenly distributes patient care to each proceduralist-physician pair, the counterfactual shared work experience for patient case i, $\tilde{E}_i$, is calculated as:

$$\sum_{\tau=t(i)-730}^{\tau=t(i)-1} N_{\tau,h(i)} = \frac{\parallel P_{h(i),t(i)} \parallel}{2} \tilde{E}_i$$

[2] In the ED sample, only 5 and 13 percent of PCI and CABG patients, respectively, received care from physician assistants during the hospital stay. Among the two-way fixed effects sample, 5 and 10 percent of PCI and CABG patients, respectively, received care from physician assistants.

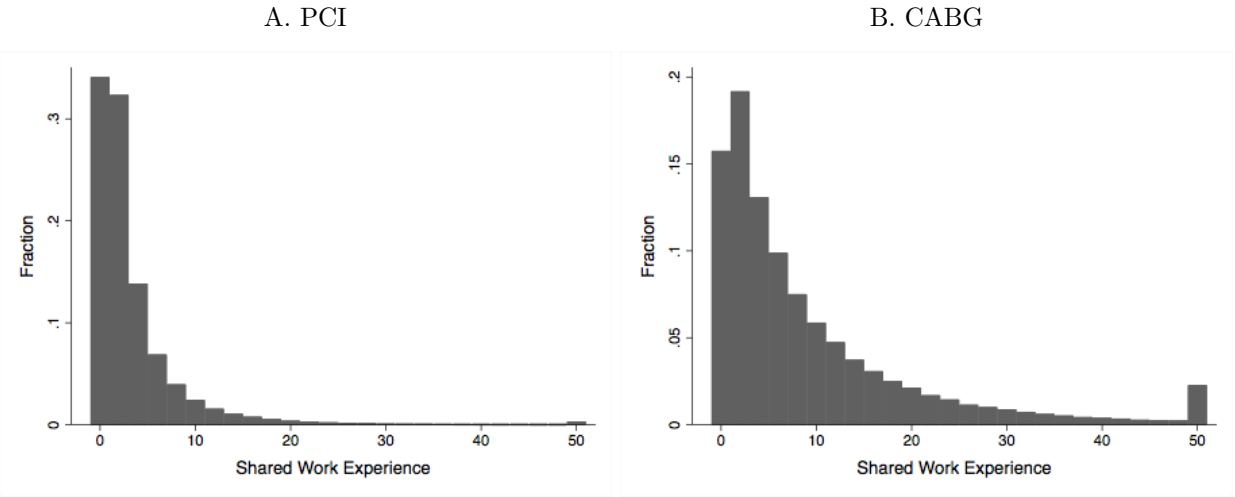
where $N_{\tau,h(i)}$ is the number of hospital visits provided to PCI and CABG patients in day τ at hospital $h(i)$ in the two years (i.e., 730 days) before the admission of i for i undergoing PCI and CABG, respectively. $\parallel P_{h(i),t(i)} \parallel$ is the number of unique proceduralist-physician pairs that have worked together on PCI and CABG patients at hospital $h(i)$ in $[t(i)-730,\ t(i)-1]$ for i undergoing PCI and CABG, respectively. I estimate $\tilde{E}_i$ separately for PCI and CABG for each hospital.

2. Assuming that reorganizing doctor teams acts solely through the effect of shared work experience, this hypothetical scenario would yield the following (mean) mortality decline for all patients undergoing procedure $p \in \{PCI,\ CABG\}$:

$$\Delta y = \parallel i \parallel^{-1} \sum_i \sum_p (\tilde{E}_i - E_i) \times \hat{\beta}_p \times I(p(i) = p)$$

where $\tilde{E}_i$ and E_i are, respectively, the counterfactual and actual shared work experience for patient case i. $\hat{\beta}_p$ is the estimated effect of shared work experience. In this analysis, I apply $\hat{\beta}_p$ reported in Table 3. $I(p(i) = p)$ is an indicator that equals one if the procedure the patient underwent is p.

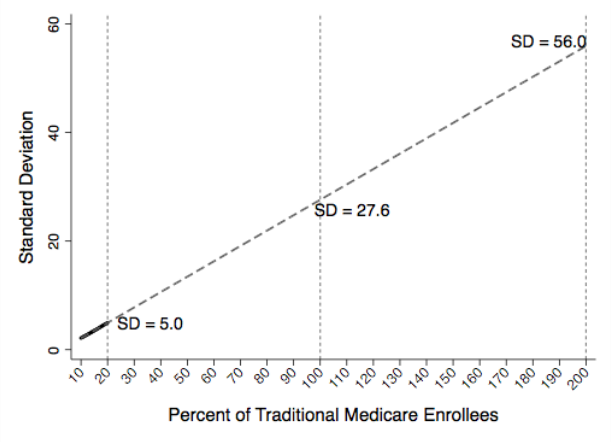
Figure A1: Distribution of Shared Work Experience



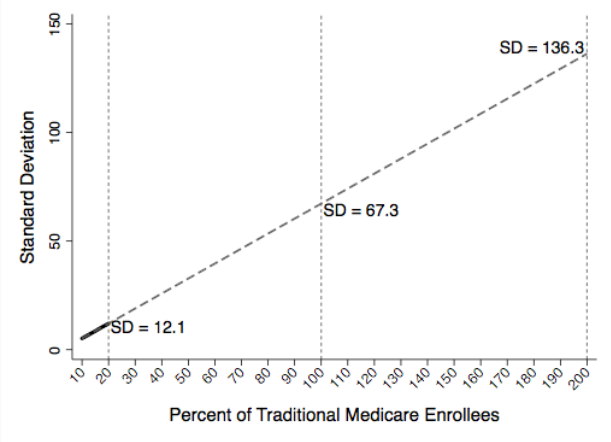
Notes: These figures plot distribution of shared work experience estimated based on Equation (2). The sample includes all PCI (Panel A) and CABG (Panel B) patients observed in the data. Shared work experience is winsorized at 50.

Figure A2: Standard Deviation of Shared Work Experience

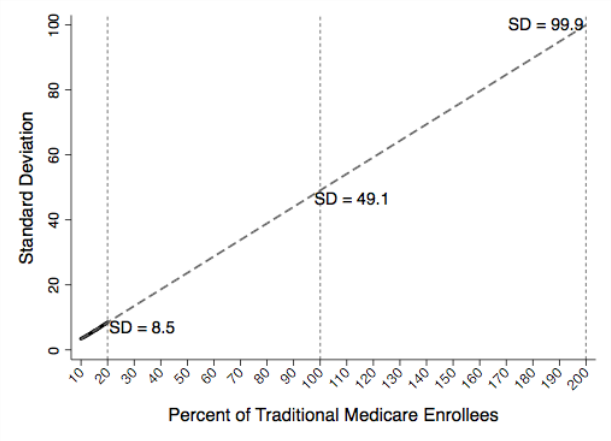
A. PCI, ED Sample



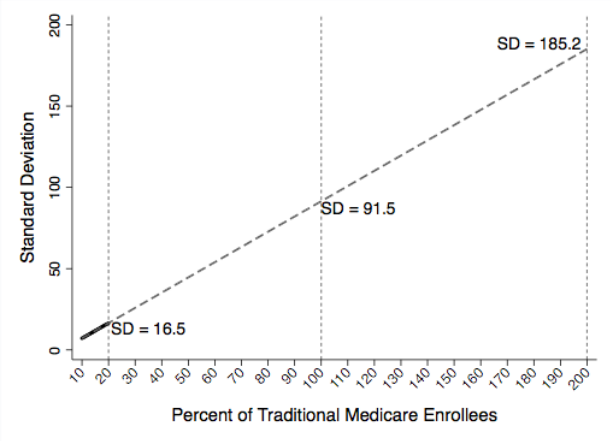
B. CABG, ED Sample



C. PCI, Two-Way Fixed Effects Sample



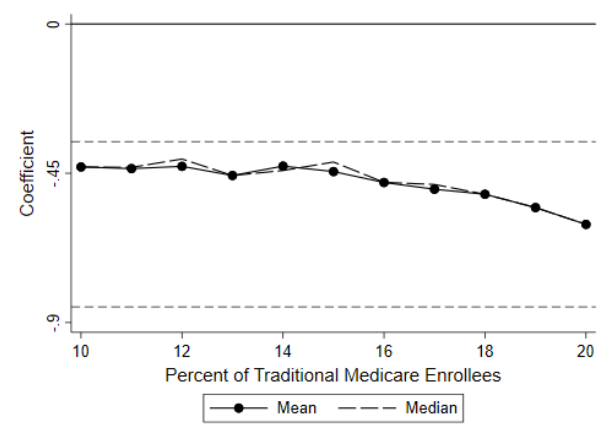
D. CABG, Two-Way Fixed Effects Sample



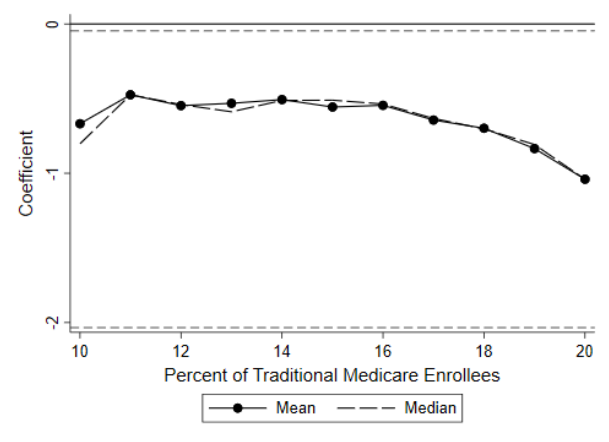
Notes: These figures infer the standard deviation of shared work experience when considering patients unobservable in Medicare data. To construct these figures, I first run a series of simulations that randomly draw subsamples (50 percent, 55 percent, 60 percent, ..., 95 percent) of patients from the 20 percent Medicare claims (e.g., 50 percent of the 20 percent claims is equal to 10 percent of traditional Medicare enrollees on the x-axis), and plot in solid lines the standard deviation of shared work experience based on each subsample. To account for sampling error, I repeat 50 random draws for each percentage subsample and report the mean standard deviation. Since the solid lines suggest a linear relationship between the y- and the x-axis variable, I run linear regressions of the y-axis variable on the x-axis variable to predict the standard deviation of shared work experience beyond the 20 percent sample (with the predicted values plotted in dashed lines). The adjusted R-squared of the regression is above 0.999 in all panels. The first, second, and third dotted vertical line in each panel marks the 20 percent traditional Medicare sample, the 100 percent traditional Medicare sample, and the population (assuming half of PCI and CABG procedures are performed on patients outside traditional Medicare, see similar statistics reported in, for example, Ricciardi et al. 2008). Panels A and B plot the simulation results for ED patients undergoing PCI and CABG, respectively (i.e., the sample analyzed in empirical strategy I). Panels C and D plot the simulation results for patients analyzed in the two-way fixed effects model (i.e., empirical strategy II) for PCI and CABG, respectively.

Figure A3: Exploring Measurement Error

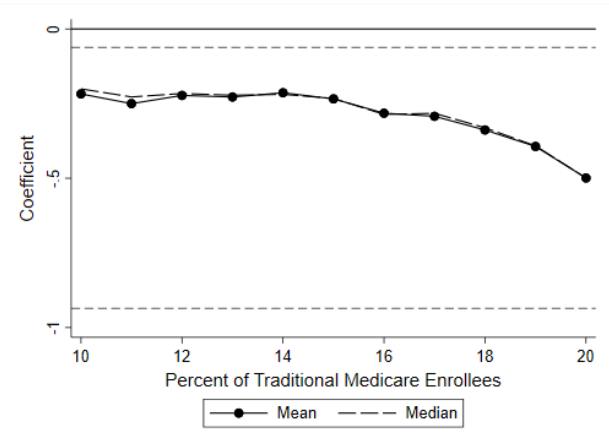
A. Empirical Strategy I, PCI



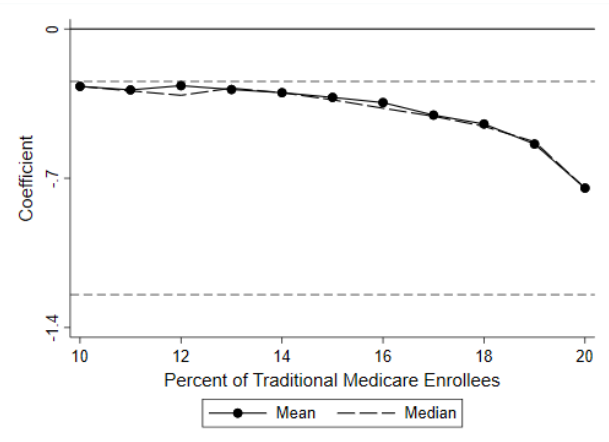
B. Empirical Strategy I, CABG



C. Empirical Strategy II, PCI



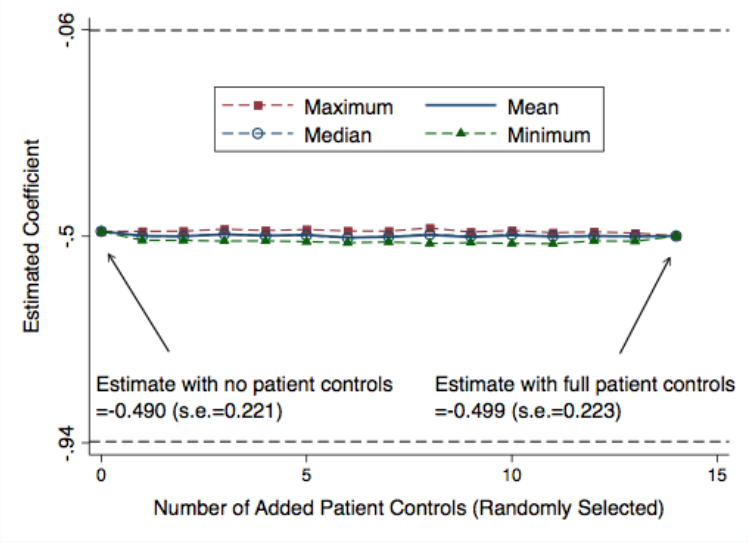
D. Empirical Strategy II, CABG



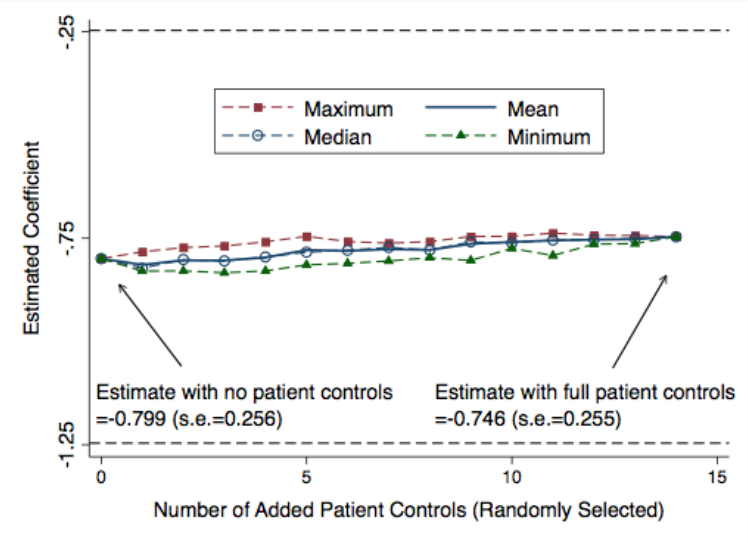
Notes: These figures explore the impact of measurement error on my estimates. To construct these figures, I run a series of simulations that randomly draw subsamples (50 percent, 55 percent, 60 percent, ..., 95 percent) of patients from the 20 percent Medicare claims (e.g., 50 percent of the 20 percent claims is equal to 10 percent of traditional Medicare enrollees on the x-axis). I then estimate the effect of shared work experience on patient 30-day mortality. To account for sampling error, I repeat 50 random draws for each of the 10 different percentage subsamples that range from 50 percent to 95 percent. Therefore, each panel summarizes $10 \times 50 = 500$ different regression specifications. The solid and long dashed line connects the mean and median of the estimated coefficients on shared work experience for each subsample, respectively; the short dashed lines plot the 95% confidence interval of the coefficient on shared work experience based on the 20 percent Medicare claims. Panels A and B plot the simulation results based on empirical strategy I for PCI and CABG, respectively. Panels C and D plot the simulation results based on empirical strategy II for PCI and CABG, respectively.

Figure A4: Sensitivity of Effect of Shared Work Experience on Patient 30-Day Mortality: Two-Way Fixed Effects Model

A. PCI



B. CABG



Notes: These figures plot the estimated effect of shared work experience on patient 30-day mortality with the inclusion of different sets of patient controls based on empirical strategy II (i.e., the two-way fixed effects model). Specifically, from the 14 patient demographic and comorbidity variables described in Section 4.1.2, I randomly select subsets of n covariates to include in the regression and collect the coefficients on shared work experience for each integer $n = 0, 1, ..., 14$. By definition, only $C_{14}^{0} = C_{14}^{14} = 1$ set of patient controls is available when $n = 0$ or $n = 14$. For $n = 1, 2, .., 13$, 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, median, and minimum of the estimated coefficients on shared work experience for each integer $n = 0, 1, ..., 14$. To provide a benchmark, I show in black dashed lines 95% confidence intervals of the coefficient estimates with the full set of patient controls.

Table A1: Sample Construction

	PCI		CABG	
	N	%	N	%
Panel A. ED analysis sample				
January 1, 2010 - December 1, 2016, all patients[a]	196,744	100.0	104,976	100.0
Hospital visits in the first two days of admission and the last two days before discharge	156,273	79.4	76,663	73.0
Between 65 and 100 years old	131,807	67.0	67,649	64.4
Admitted through the ED	90,219	45.9	20,286	19.3
Treated by proceduralists with at least two patients in the years of observation	84,889	43.1	17,670	16.8
Panel B. Two-way fixed effects sample				
January 1, 2010 - December 1, 2016, all patients[a]	196,744	100.0	104,976	100.0
Hospital visits in the first two days of admission and the last two days before discharge	156,273	79.4	76,663	73.0
Between 65 and 100 years old	131,807	67.0	67,649	64.4
Treated by proceduralists with at least two patients in the years of observation	125,534	63.8	66,087	63.0
Treated by main physicians with at least two patients in the years of observation	91,862	46.7	49,673	47.3

Notes: This table reports changes in sample size when applying each of the listed sample restrictions.

[a] Since I measure doctors' shared work experience based on collaboration in the past two years and my data start at 2008, my empirical regression restricts the sample to patients admitted to the hospital in 2010 or after to allow for an at least two-year look-back window for measuring doctors' shared work experience. To measure patient 30-day mortality outcomes, I also restrict the sample to patients discharged from the hospital in December 1, 2016 or before, to allow for a 30-day observation window after the hospital discharge (my data track patient mortality outcomes until December 31, 2016).

Table A2: Balance in Patient Characteristics: Two-Way Fixed Effects Sample

	PCI			CABG		
	Shared experience below mean	Shared experience above mean	p-value	Shared experience below mean	Shared experience above mean	p-value
Age	76.06	76.04	0.69	74.49	74.44	0.35
	(4.97)	(5.67)		(4.44)	(5.03)	
Female	0.427	0.423	0.14	0.314	0.310	0.27)
	(0.347)	(0.397)		(0.344)	(0.397)	
Black	0.073	0.072	0.52	0.051	0.050	0.89
	(0.164)	(0.190)		(0.157)	(0.172)	
Hispanic	0.015	0.015	0.66	0.011	0.011	0.98
	(0.076)	(0.095)		(0.072)	(0.081)	
Medicaid	0.164	0.163	0.52	0.110	0.108	0.45
	(0.243)	(0.283)		(0.217)	(0.255)	
Disabled	0.161	0.159	0.52	0.120	0.119	0.58
	(0.255)	(0.294)		(0.239)	(0.276)	
Number of Comorbidities	2.291	2.290	0.90	1.869	1.859	0.33
	(1.093)	(1.248)		(1.019)	(1.165)	
Predicted 30-day Mortality (%)	5.074	5.070	0.79	5.861	5.822	0.15
(by patient characteristics)	(1.838)	(2.103)		(2.756)	(3.158)	
Observations	66,183	25,679		33,223	16,450	

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 for patients included in empirical strategy II (i.e., the two-way fixed effects model). Standard deviations are reported in parentheses. Each characteristic is residualized with respect to proceduralist fixed effects, main physician fixed effects, average characteristics of other physicians treating the patient, and other controls included in Equation (5), except for patient demographics and comorbidities. Unconditional means of each characteristic are added back for ease of interpretation. Predicted 30-day mortality is predicted based on logistic regressions of patient actual 30-day mortality outcomes on patient demographics and comorbidities specified under Table 2. p-values of t-tests for the equivalence of means between the two subgroups are shown in the last column.

Table A3: Controlling for Hospital-Specific Experience

	PCI				CABG			
	(1) Linear	(2) Linear spline	(3) Cubic spline	(4) Tenure	(5) Linear	(6) Linear spline	(7) Cubic spline	(8) Tenure
Panel A. ED analysis								
Shared work experience	-0.591***	-0.565***	-0.563***	-0.589***	-0.939*	-0.914*	-0.917*	-0.983*
	(0.126)	(0.126)	(0.126)	(0.127)	(0.512)	(0.515)	(0.515)	(0.511)
Full control	X	X	X	X	X	X	X	X
Mean dep. var.	5.93	5.93	5.93	5.93	8.98	8.98	8.98	8.98
S.D. dep. var.	23.63	23.63	23.63	23.63	28.58	28.58	28.58	28.58
Observations	84,889	84,889	84,889	84,889	17,670	17,670	17,670	17,670
Panel B. Two-way fixed effects model								
Shared work experience	-0.485**	-0.471**	-0.468**	-0.489**	-0.676***	-0.624**	-0.619**	-0.724***
	(0.219)	(0.221)	(0.220)	(0.224)	(0.257)	(0.257)	(0.257)	(0.256)
Full control	X	X	X	X	X	X	X	X
Mean dep. var.	5.07	5.07	5.07	5.07	5.85	5.85	5.85	5.85
S.D. dep. var.	21.94	21.94	21.94	21.94	23.47	23.47	23.47	23.47
Observations	91,862	91,862	91,862	91,862	49,673	49,673	49,673	49,673

Notes: This table shows results that control for proceduralists' and physicians' patient volume/tenure at the hospital to which the patient is admitted. The outcome variable is patient 30-day mortality. Patient volume and tenure are measured, respectively, as the number of patient cases the doctor has treated and the number of years the doctor has practiced at the hospital in the two years prior to the admission of the current patient (i.e., the same time window as that used for measuring shared work experience). Columns 1 and 5 control for patient volume linearly. Columns 2 and 6 and Columns 3 and 7 control for patient volume as linear and cubic splines, respectively. Columns 4 and 8 control for tenure. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A4: Sample Restricted to Patients Treated by Doctors Continuously Practicing at the Hospital

	(1) PCI	(2) CABG
Panel A. ED analysis		
Shared work experience	-0.644***	-0.909
	(0.149)	(0.619)
Full control	X	X
Mean dep. var.	5.83	8.59
S.D. dep. var.	23.43	28.02
Observations	56,787	11,575
Panel B. Two-way fixed effects model		
Shared work experience	-0.436*	-0.646**
	(0.254)	(0.289)
Full control	X	X
Mean dep. var.	4.74	5.51
S.D. dep. var.	21.25	22.82
Observations	57,105	34,217

Notes: This table shows the effect of shared work experience on patient 30-day mortality. The sample is restricted to patients treated by proceduralists and physicians who have been practicing at the hospital to which the patient is admitted in the two years prior to the admission. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A5: Controlling for Severity of Current Condition

	(1) PCI	(2) CABG
Panel A. ED analysis		
Shared work experience	-0.475***	-1.010**
	(0.124)	(0.504)
Full control	X	X
Mean dep. var.	5.93	8.98
S.D. dep. var.	23.63	28.58
Observations	84,889	17,670
Panel B. Two-way fixed effects model		
Shared work experience	-0.415**	-0.735***
	(0.205)	(0.251)
Full control	X	X
Mean dep. var.	5.07	5.85
S.D. dep. var.	21.94	23.47
Observations	91,862	49,673

Notes: This table shows effects of shared work experience on 30-day mortality when controlling for 4-digit ICD-10 code of the primary diagnosis of the current hospital stay. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A6: Alternative Measures of Shared Work Experience I

	PCI						CABG					
	(1) Past two years	(2) Past year	(3) Past three years	(4) Median	(5) Mode	(6) First physician	(7) Past two years	(8) Past year	(9) Past three years	(10) Median	(11) Mode	(12) First physician
Panel A. ED analysis												
Shared work experience	-0.121***	-0.129***	-0.093***	-0.136***	-0.099***	-0.058***	-0.086**	-0.105	-0.017	-0.081**	-0.053**	-0.076**
	(0.026)	(0.038)	(0.023)	(0.022)	(0.018)	(0.022)	(0.042)	(0.064)	(0.033)	(0.032)	(0.021)	(0.032)
Full control	X	X	X	X	X	X	X	X	X	X	X	X
Mean dep. var.	5.93	5.93	5.83	5.93	5.93	5.93	8.98	8.98	8.91	8.98	8.98	8.98
S.D. dep. var.	23.63	23.63	23.43	23.63	23.63	23.63	28.58	28.58	28.49	28.58	28.58	28.58
Observations	84,889	84,889	66,630	84,889	84,889	84,889	17,670	17,670	14,463	17,670	17,670	17,670
Panel B. Two-way fixed effects model												
Shared work experience	-0.059**	-0.075**	-0.031	-0.076***	-0.077***	-0.042**	-0.045***	-0.063**	-0.041***	-0.042***	-0.026**	-0.024**
	(0.026)	(0.034)	(0.032)	(0.024)	(0.020)	(0.019)	(0.015)	(0.025)	(0.013)	(0.014)	(0.011)	(0.012)
Full control	X	X	X	X	X	X	X	X	X	X	X	X
Mean dep. var.	5.07	5.07	4.98	5.07	5.07	5.07	5.85	5.85	5.71	5.85	5.85	5.85
S.D. dep. var.	21.94	21.94	21.76	21.94	21.94	21.94	23.47	23.47	23.20	23.47	23.47	23.47
Observations	91,862	91,862	65,993	91,862	91,862	91,862	49,673	49,673	39,468	49,673	49,673	49,673

Notes: This table shows estimation results based on alternative measures of shared work experience. For ease of comparison, none of the shared work experience measures is scaled in units of standard deviations. The outcome variable is patient 30-day mortality. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Column 1 replicates the results from Table 2 and Table 3 for ease of comparison and measures shared work experience of a proceduralist-physician team based on collaboration in the past two years (yet different from Table 2 and Table 3, shared work experience in this table is *not* scaled in units of standard deviation). Column 2 and Column 3 measure shared work experience in the past year and the past three years, respectively. Columns 4 and 5 define shared work experience as the median and mode of the shared work experience between the proceduralist and each of the physicians who treat the patient during the hospital stay, respectively. Column 6 defines shared work experience as that between the proceduralist and the first physician who treats the patient during the hospital stay. The same measures of shared work experience are used in Columns 7-12 for CABG. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A7: Alternative Measures of Shared Work Experience II

	PCI					CABG				
	(1) δ=1	(2) δ=1.5	(3) δ=2	(4) δ=2.5	(5) δ=3	(6) δ=1	(7) δ=1.5	(8) δ=2	(9) δ=2.5	(10) δ=3
Panel A. ED analysis										
Shared work experience	-0.202***	-0.218***	-0.216***	-0.213***	-0.210**	-0.071	-0.135	-0.127	-0.116	-0.105
	(0.056)	(0.059)	(0.068)	(0.076)	(0.084)	(0.088)	(0.102)	(0.120)	(0.135)	(0.150)
Full control	X	X	X	X	X	X	X	X	X	X
Mean dep. var.	5.83	5.93	5.93	5.93	5.93	8.91	8.98	8.98	8.98	8.98
S.D. dep. var.	23.43	23.63	23.63	23.63	23.63	28.49	28.58	28.58	28.58	28.58
Observations	66,630	84,889	84,889	84,889	84,889	14,463	17,670	17,670	17,670	17,670
Panel B. Two-way fixed effects model										
Shared work experience	-0.122*	-0.131**	-0.133**	-0.130**	-0.125*	-0.142***	-0.145***	-0.162***	-0.176***	-0.186***
	(0.068)	(0.053)	(0.060)	(0.066)	(0.071)	(0.037)	(0.041)	(0.049)	(0.055)	(0.060)
Full control	X	X	X	X	X	X	X	X	X	X
Mean dep. var.	4.98	5.07	5.07	5.07	5.07	5.71	5.85	5.85	5.85	5.85
S.D. dep. var.	21.76	21.94	21.94	21.94	21.94	23.20	23.47	23.47	23.47	23.47
Observations	65,993	91,862	91,862	91,862	91,862	39,468	49,673	49,673	49,673	49,673

Notes: This table measures shared work experience as a function of a decay parameter (δ) that captures experience depreciation over times (see details in Appendix Section A.3). For ease of comparison, shared work experience is *not* scaled in units of standard deviations. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A8: Alternative Functional Forms of Doctors' Individual Work Experience

	PCI				CABG			
	(1) Quadratic	(2) Fixed effects	(3) Linear spline	(4) Cubic spline	(5) Quadratic	(6) Fixed effects	(7) Linear spline	(8) Cubic spline
Panel A. ED analysis								
Shared work experience	-0.558***	-0.617***	-0.594***	-0.586***	-0.927*	-1.031*	-0.954*	-0.935*
	(0.127)	(0.132)	(0.126)	(0.125)	(0.514)	(0.550)	(0.509)	(0.509)
Full control	X	X	X	X	X	X	X	X
Mean dep. var.	5.93	5.94	5.93	5.93	8.98	9.00	8.98	8.98
S.D. dep. var.	23.63	23.63	23.63	23.63	28.58	28.62	28.58	28.58
Observations	84,889	84,804	84,889	84,889	17,670	17,597	17,670	17,670
Panel B. Two-way fixed effects model								
Shared work experience	-0.384**	-0.488**	-0.477**	-0.453**	-0.702***	-0.771***	-0.699***	-0.695***
	(0.181)	(0.206)	(0.207)	(0.199)	(0.251)	(0.277)	(0.251)	(0.249)
Full control	X	X	X	X	X	X	X	X
Mean dep. var.	5.07	5.08	5.07	5.07	5.85	5.85	5.85	5.85
S.D. dep. var.	21.94	21.96	21.94	21.94	23.47	23.47	23.47	23.47
Observations	91,862	91,729	91,862	91,862	49,673	49,600	49,673	49,673

Notes: This table examines the robustness of my estimation results to controlling for proceduralists' and physicians' individual work experience in alternative functional forms. The outcome variable is patient 30-day mortality. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Columns 1 and 5 control for individual work experience in a quadratic form; Columns 2 and 6 control for individual work experience in fixed effects; Columns 3 and 7 control for linear splines of individual work experience; Columns 4 and 8 control for cubic splines of individual work experience. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A9: Alternative Measurement Windows of Patient Mortality

	PCI			CABG		
	(1) Two weeks	(2) 30-day	(3) 60-day	(4) Two weeks	(5) 30-day	(6) 60-day
Panel A. ED analysis						
Shared work experience	-0.520***	-0.604***	-0.574***	-0.731	-1.040**	-0.721
	(0.112)	(0.127)	(0.141)	(0.457)	(0.507)	(0.532)
Full control	X	X	X	X	X	X
Mean dep. var.	5.00	5.93	7.33	7.88	8.98	10.45
S.D. dep. var.	21.79	23.63	26.06	26.95	28.58	30.59
Observations	84,889	84,889	84,463	17,670	17,670	17,431
Panel B. Two-way fixed effects model						
Shared work experience	-0.352*	-0.499**	-0.467*	-0.636***	-0.746***	-1.162***
	(0.189)	(0.223)	(0.261)	(0.241)	(0.255)	(0.287)
Full control	X	X	X	X	X	X
Mean dep. var.	4.18	5.07	6.33	5.05	5.85	6.88
S.D. dep. var.	20.02	21.94	24.34	21.90	23.47	25.31
Observations	91,862	91,862	91,356	49,673	49,673	49,014

Notes: This table shows estimation results based on alternative measurement windows of patient mortality. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). The outcome variables in Columns 1-3 (4-6) are, respectively, whether the patient died within two weeks, 30 days, and 60 days after the hospital discharge. Sample size varies slightly across columns because only patients with the relevant observation windows are included in the analysis. For example, to observe 60-day mortality outcomes, patients need to be discharged from the hospital at least 60 days before the end of the data observation period. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A10: Alternative Levels of Standard Error Clustering

	PCI			CABG		
	(1) Proceduralist	(2) Hospital	(3) Hospital-year	(4) Proceduralist	(5) Hospital	(6) Hospital-year
Panel A. ED analysis						
Shared work experience	-0.604***	-0.604***	-0.604***	-1.040**	-1.040**	-1.040**
	(0.127)	(0.123)	(0.121)	(0.507)	(0.517)	(0.473)
Full control	X	X	X	X	X	X
Mean dep. var.	5.93	5.93	5.93	8.98	8.98	8.98
S.D. dep. var.	23.63	23.63	23.63	28.58	28.58	28.58
Observations	84,889	84,889	84,889	17,670	17,670	17,670
Panel B. Two-way fixed effects model						
Shared work experience	-0.499**	-0.499**	-0.499***	-0.746***	-0.746***	-0.746***
	(0.223)	(0.198)	(0.175)	(0.255)	(0.274)	(0.260)
Full control	X	X	X	X	X	X
Mean dep. var.	5.07	5.07	5.07	5.85	5.85	5.85
S.D. dep. var.	21.94	21.94	21.94	23.47	23.47	23.47
Observations	91,862	91,862	91,862	49,673	49,673	49,673

Notes: This table examines the robustness of my estimates to alternative levels of standard error clustering. The outcome variable is patient 30-day mortality. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Columns 1 and 3 repeat my main analysis and cluster standard errors by proceduralist; Columns 2 and 4 cluster standard errors by hospital; and Columns 3 and 6 cluster standard errors by hospital-year. Shared work experience is scaled in units of standard deviations. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A11: Robustness to Excluding Patients Treated by Proceduralist/Physicians with Few Patients

	(1) PCI	(2) CABG
Panel A. ED analysis		
Shared work experience	-0.595***	-0.751
	(0.128)	(0.524)
Full control	X	X
Mean dep. var.	5.87	8.55
S.D. dep. var.	23.50	27.96
Observations	78,674	15,260
Panel B. Two-way fixed effects model		
Shared work experience	-0.459**	-0.846***
	(0.218)	(0.250)
Full control	X	X
Mean dep. var.	4.69	5.44
S.D. dep. var.	21.15	22.67
Observations	65,191	38,479

Notes: Panel A examines the robustness of my estimates to excluding patients treated by proceduralists with less than five patients in the data (about the 10th percentile of the ED sample) for empirical strategy I (i.e., the ED analysis, which controls for proceduralist fixed effects). Panel B examines the robustness of my estimates to excluding patients treated by proceduralists with less than five patients (about the 5th percentile of the sample) or main physicians with less than four patients (about the 40th percentile of the sample) for empirical strategy II (i.e., the two-way fixed effects model, which controls for both proceduralist and main physician fixed effects). Shared work experience is scaled in units of standard deviations. Standard errors are clustered at the the proceduralist level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A12: Within Proceduralist-Physician Team Estimation: ED Analysis

	(1) PCI	(2) CABG
Panel A. Team fixed effects		
Shared work experience	-0.959***	-1.430
	(0.291)	(1.345)
Full control	X	X
Mean dep. var.	5.03	7.29
S.D. dep. var.	21.86	26.01
Adj. R-squared	0.12	0.07
Observations	21,435	3,290
Panel B. Separate proceduralist and physician fixed effects		
Shared work experience	-0.763**	-1.589
	(0.336)	(1.584)
Full control	X	X
Mean dep. var.	5.03	7.29
S.D. dep. var.	21.86	26.01
Adj. R-squared	0.12	0.07
Observations	21,435	3,290

Notes: This table reports results based on patients analyzed in empirical strategy I (i.e., the ED analysis). Panel A reports coefficients from regressing patient 30-day mortality on shared work experience, controlling for proceduralist-main physician team fixed effects and the full set of controls used in Table 2 except proceduralist fixed effects. The main physician is defined as the physician who provides the largest share of hospital visits to the patient during the hospital stay. Sample sizes are smaller than those reported in Table 2 because patients treated by singleton proceduralist-main physician teams are dropped from the analysis. Panel B reports results from the same regression used in Panel A, but replaces proceduralist-main physician team fixed effects with separate proceduralist and main physician fixed effects. For ease of comparison, I restrict the sample in Panel B to be the same as that used in Panel A. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A13: Patients Treated by Proceduralists and Physicians from Different Practices

	(1) PCI	(2) CABG
Panel A. ED analysis		
Shared work experience	-0.654***	-1.212**
	(0.161)	(0.523)
Full control	X	X
Mean dep. var.	6.75	8.86
S.D. dep. var.	25.09	28.41
Observations	62,212	15,763
Panel B. Two-way fixed effects model		
Shared work experience	-0.874***	-0.872***
	(0.295)	(0.291)
Full control	X	X
Mean dep. var.	6.07	5.91
S.D. dep. var.	23.88	23.59
Observations	57,347	42,977

Notes: This table examines the effect of shared work experience on 30-day mortality among patients treated by proceduralists and physicians from different practices. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A14: Shared Work Experience and Medical Resource Use: ED Analysis

	PCI			CABG		
	(1) Length of stay	(2) Number tests exams	(3) Outlier payments	(4) Length of stay	(5) Number tests exams	(6) Outlier payments
Shared work experience	-0.169***	-0.239***	-0.004***	-0.165	-0.472**	-0.001
	(0.026)	(0.035)	(0.001)	(0.135)	(0.231)	(0.006)
Full control	X	X	X	X	X	X
Mean dep. var.	4.48	7.74	0.06	12.76	20.39	0.20
S.D. dep. var.	4.42	6.33	0.23	7.58	12.58	0.40
Observations	81,615	81,615	81,615	16,240	16,240	16,240

Notes: This table reports coefficients from regressing patient medical resource use outcomes on shared work experience based on empirical strategy I (i.e., the ED analysis). Shared work experience is scaled in units of standard deviations. 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. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A15: Shared Work Experience and Post-Discharge Medical Resource Use

	PCI			CABG		
	(1)	(2)	(3)	(4)	(5)	(6)
	SNF Rehab.	30-Day Readmission	30-day outpatient visits	SNF Rehab.	30-Day Readmission	30-day outpatient visits
Panel A. ED analysis						
Shared work experience	-0.006***	0.000	-0.012	-0.003	-0.004	0.023
	(0.002)	(0.002)	(0.009)	(0.008)	(0.007)	(0.027)
Full control	X	X	X	X	X	X
Mean dep. var.	0.10	0.12	1.95	0.35	0.09	1.65
S.D. dep. var.	0.30	0.33	1.50	0.48	0.29	1.42
Observations	81,615	79,563	79,563	16,240	15,689	15,689
Panel B. Two-way fixed effects model						
Shared work experience	-0.003	-0.003	-0.011	-0.011**	0.001	0.032
	(0.003)	(0.003)	(0.013)	(0.005)	(0.004)	(0.019)
Full control	X	X	X	X	X	X
Mean dep. var.	0.09	0.12	1.92	0.29	0.09	1.72
S.D. dep. var.	0.29	0.33	1.49	0.45	0.29	1.42
Observations	88,051	85,465	85,465	46,865	45,753	45,753

Notes: This table reports coefficients from regressing patient post-discharge medical resource use outcomes on shared work experience. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. The dependent variables in Columns 1-3 are, respectively, whether the patient is discharged to skilled nursing or rehabilitation facilities, whether the patient is rehospitalized within 30 days after the discharge, and number of physician and ED visits in the 30 days after the discharge. Columns 4-6 repeat the same set of dependent variables. To observe a full length of 30 days, Columns 2-3 and 5-6 restrict the sample to patients who are alive until 30 days after the discharge. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A16: Substitution between Individual and Shared Work Experience

	PCI			CABG		
	(1) Baseline	(2) Linear spline	(3) Cubic spline	(4) Baseline	(5) Linear spline	(6) Cubic spline
Panel A. Heterogeneity by proceduralists' individual work experience						
Shared work experience*Proceduralist experience	0.271***	0.106	0.122*	0.111	0.116	0.125
	(0.051)	(0.067)	(0.065)	(0.223)	(0.244)	(0.244)
Full control	X	X	X	X	X	X
Mean dep. var.	5.07	5.07	5.07	5.85	5.85	5.85
S.D. dep. var.	21.94	21.94	21.94	23.47	23.47	23.47
Observations	91,862	91,862	91,862	49,673	49,673	49,673
Panel B. Heterogeneity by physicians' individual work experience						
Shared work experience*Physician experience	0.112***	0.078**	0.080***	0.104*	0.147*	0.153*
	(0.027)	(0.031)	(0.030)	(0.062)	(0.085)	(0.080)
Full control	X	X	X	X	X	X
Mean dep. var.	5.07	5.07	5.07	5.85	5.85	5.85
S.D. dep. var.	21.94	21.94	21.94	23.47	23.47	23.47
Observations	91,862	91,862	91,862	49,673	49,673	49,673

Notes: This table reports heterogeneity in the effect of shared work experience on 30-day mortality by doctors' individual work experience. Columns 1 and 4 repeat the results in Table 6. Columns 2 and 5 control for shared work experience as linear splines. Columns 3 and 6 control for shared work experience as restricted cubic splines. Shared work experience is scaled in units of standard deviations. Individual work experience is demeaned and scaled in units of standard deviation. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A17: Heterogeneity in Effects of Shared Work Experience

	PCI		CABG	
	Coefficient	% Effect	Coefficient	% Effect
Panel A. Age in top quartile				
Yes	-0.861***	-11.19	-1.268***	-14.83
	(0.296)		(0.374)	
No	-0.401*	-9.54	-0.642**	-12.68
	(0.211)		(0.255)	
Panel B. Predicted mortality in top quartile				
Yes	-0.942***	-10.80	-0.899***	-7.99
	(0.305)		(0.347)	
No	-0.363*	-9.40	-0.699***	-17.27
	(0.203)		(0.262)	
Panel C. With uncommon comorbidities				
Yes	-0.659***	-10.19	-0.823**	-11.12
	(0.252)		(0.323)	
No	-0.387*	-9.37	-0.719***	-14.04
	(0.211)		(0.258)	
Panel D. Proceduralist/Physicians different practices				
Yes	-1.059***	-17.21	-0.783***	-13.12
	(0.231)		(0.267)	
No	0.048	1.79	-0.527	-10.74
	(0.188)		(0.378)	

Notes: This table reports heterogeneity in the effect of shared work experience on patient 30-day mortality. Each panel of Columns 1 and 3 represents a separate regression for PCI and CABG, respectively. Columns 1 and 3 report α_1 and α_2 from the following specification:

$$y_i = \alpha_1 E_i \times 1(g_i = 1) + \alpha_2 E_i \times 1(g_i = 0) + \alpha_3 g_i + \theta_{d(i)} + \bar{\mathbf{H}}_{j(i)}\lambda + \mathbf{T}_i\eta + \mathbf{F}_i\gamma + \mathbf{X}_i\beta + \varepsilon_i \quad (12)$$

where g_i is a dummy that takes a value of one for patients with age in the top quartile, with predicted mortality in the top quartile, with uncommon comorbidities, and treated by a proceduralist and physicians from different practices in Panels A, B, C and D, respectively. Columns 2 and 4 report percentage impacts by dividing the coefficient by the mean 30-day mortality rate of each group. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A18: Patients with High Probability of Undergoing PCI and CABG

	(1) PCI	(2) CABG
Panel A. ED analysis		
Shared work experience	-1.039***	-1.043
	(0.308)	(1.138)
Full control	X	X
Mean dep. var.	8.78	4.80
S.D. dep. var.	28.29	21.38
Observations	23,737	3,686
Panel B. Two-way fixed effects model		
Shared work experience	-0.571	-0.862*
	(0.544)	(0.443)
Full control	X	X
Mean dep. var.	6.88	2.21
S.D. dep. var.	25.31	14.69
Observations	15,190	9,785

Notes: This table reports the effect of shared work experience on 30-day mortality based on patients with high probabilities of undergoing PCI and CABG in Column 1 and Column 2, respectively (see details in Appendix Section A.2). Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). The sample size in Panel A, Column 1 is smaller than that in Panel B, Column 1. This is because Panel B further controls for main physician fixed effects and thus drops patients treated by main physicians who have only observed patient in the sample. Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Table A19: Non-Linear Returns to Shared Work Experience

	(1) PCI	(2) CABG
Panel A. ED analysis		
Shared work experience	-1.028***	-1.367*
	(0.162)	(0.705)
[Shared work experience]^2	0.052***	0.047
	(0.010)	(0.072)
Full control	X	X
Mean dep. var.	5.93	8.98
S.D. dep. var.	23.63	28.58
Observations	84,889	17,670
Panel B. Two-way fixed effects model		
Shared work experience	-1.302***	-1.063***
	(0.239)	(0.346)
[Shared work experience]^2	0.088***	0.048*
	(0.017)	(0.027)
Full control	X	X
Mean dep. var.	5.07	5.85
S.D. dep. var.	21.94	23.47
Observations	91,862	49,673

Notes: This table examines non-linear effects of shared work experience on patient 30-day mortality by adding a quadratic term of shared work experience to the estimation. Panel A reports estimates based on empirical strategy I (i.e., the ED analysis). Panel B reports estimates based on empirical strategy II (i.e., the two-way fixed effects model). Shared work experience is scaled in units of standard deviations. Standard errors clustered at the proceduralist level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.