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ABSTRACT

Learning-by-Doing and Productivity Growth among High-Skilled Workers: Evidence from the Treatment of Heart Attacks*

Learning-by-doing is a fundamental concept in economics but a challenging one to document in high-skilled settings due to non-random assignment of workers to tasks and lacking performance measures. Our paper overcomes these challenges in the context of heart attack treatments in Sweden, where we exploit quasirandom assignment of physicians to patients. We document long learning curves, where physicians keep learning over the first 1000 treatments performed, affecting both proficiency and decision-making skills. These learning effects translate into effects on patient health, but only over the first 150 treatments performed, corresponding to one year of experience. Learning rates are higher for physicians who have worked with more experienced colleagues and who have gained more experience in treating complicated cases. Experienced physicians are more responsive to patient characteristics when deciding on treatments and experience from more recent heart attack treatments is more valuable than experience from more distant ones, suggesting that human capital depreciates. We also show that productivity growth keeps pace with wage growth over the first four years of the career but flattens out thereafter. Our results provide rare evidence on the existence of prolonged learning curves in high-skilled tasks and support the notion that learning-by-doing can be a powerful mechanism for productivity growth.

JEL Classification: I11, I12, I18, L11

Keywords: operation volume, learning-by-doing, survival, causal effect

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1 Introduction

Learning-by-doing is believed to be a major source of economic growth, human capital, and comparative advantage (Arrow, 1962; Lucas, 1988; Romer, 1990; Yang and Borland, 1991). Lucas (1988), for instance, used the concept in his growth theory to explain increasing returns to human capital. The extent of learning is also important for the understanding of labor markets and wage dynamics. If performance increases with experience, it supports a human-capital based interpretation of upward-sloping experience-wage profiles (Becker, 1964). If learning is limited, such profiles would instead have to be explained by other theories, such as contract-based theories or matching models, with important policy implications (Jovanovic, 1979; Lazear and Moore, 1984).[1] Learning-by-doing has also been of particular interest to health economists, as medical technologies often require substantial practice to master and since learning effects have important implications for productivity growth in the health care sector.

Despite its fundamental importance in economics, documenting learning-by-doing at the individual level has proven challenging. While a large literature has documented empirical patterns consistent with learning, a key challenge is that selection bias prevents a causal interpretation of the results. In many contexts, there is non-random assignments of workers to tasks, where more experienced workers typically take on more challenging job tasks. Another challenge is "dynamic selection, where more productive workers are more likely to stay on the job, producing a spurious relationship between experience and performance. On top of this, high-quality data on performance is often lacking and researchers have to rely on measures such as unit costs, quantity, and wages (Thompson, 2001).[2] This also makes it difficult to disentangle the specific mechanisms behind learning and what type of skills that improve.

Our paper overcomes these challenges in the context of heart attack treatments in Sweden and provides rare evidence on individual learning-by-doing in a high-skilled white-collar occupation. First, the setting allows us to break the commonly observed sorting of more experienced workers to more difficult tasks by focusing on heart attack treatments performed during on-call shifts (nights, holidays and weekends). During these shifts, only one physician is present and no systematic assignment of physicians to patients can take place. Second, we use rich data on performance, measured through

[1] Delayed compensation schemes, intended to discourage shirking, imply a discrepancy between the wage and the the worker's marginal product, where workers are paid below their productivity during the first few years of their contract but above their productivity in later stages of their career. Human capital-based and contract-based theories thus have different implications for firms incentives to hire older workers (see e.g. Hutchens, 1986)

[2] Wages may fail to capture productivity for many reasons, such as the presence of wage-deferring contracts, monopsonies, and efficiency wages (Ost, 2014).

physician speediness, use of medical inputs, decision-making, and on patient outcomes, which we relate to the physicians' accumulated experience. Third, by focusing on complex heart attack treatments, we study a high-skilled setting which offers plenty of opportunities for learning, as the task is non-trivial and non-standardized and involves a range of decisions to be taken under time pressure.[3] Fourth, dynamic selection effects are limited in our setting and the data at hand allows us to test for any such effects by following physicians over time as they accumulate experience.

Our data covers linked physician-patient data on all Percutaneous Coronary Interventions (PCIs) performed on heart attack patients in Sweden between 2004 and 2013. This is a particularly relevant setting, since cardiovascular disease is the leading cause of death globally and, each year, more than 30,000 Swedes and about 1 million Americans suffer from a heart attack.[4] We follow physicians from their first ever PCI and use their accumulated number of PCIs as our measure of physician experience. The data also includes detailed information on patients medical background, which we use to test whether physician experience is unrelated to characteristics of the patients they treat during on-call time.

We show that learning-by-doing in PCI treatments occurs continually over many years. In terms of proficiency, the physicians get 21 percent faster in performing a PCI between their first and 1000th PCI. This is a substantial productivity improvement, corresponding to a 3-minute reduction in the time to identify blockages in the arteries and to perform the medical procedures. Learning is fastest over the first 600 cases, slows down thereafter, and stops after 1000 PCIs. We obtain similar results for other measures of proficiency, such as the adoption of more advanced technology that requires greater manual skills, and the rate of complications during treatment.

The learning process for medical decision-making follows a similar pattern, where the invasiveness of the chosen medical procedures increases over the first 1000 PCIs and then stabilizes. We show that the more invasive, and more time-consuming, treatments by experienced physicians reflect more appropriate treatments of patients with multiple blocked arteries. More experienced physicians are also more responsive to patient characteristics when taking their decisions and this pattern is particularly pronounced in the treatment of high-risk patients.

We demonstrate that the learning effects translate into effects on patient health, but only among high-risk patients and only over the first 150 PCIs performed. The learning curve is steep, where the risk of having another heart attack or dying within one year

[3] Becoming a PCI operator requires both a specialist degree in cardiology and specialized PCI training.

[4] Source: CDC http://www.cdc.gov/NCHS/data/nvsr/nvsr58/nvsr58_19.pdf.

decreases by 40 percent. This result adds to the discussion on the amount of training needed before physicians should be performing PCIs on heart attack treatments on their own.

Accounting for sorting of physicians to patients is crucial for our results. We observe a strong positive correlation between physician experience and predicted patient risk during day-time shifts, suggesting that hospitals assign more experienced physicians to more complicated cases. This correlation vanishes when we use data from on-call shifts, providing us with the quasi-experimental variation in physician assignment needed to identify learning-by-doing effects. We also show that experience is unrelated to the number of patients treated during night shifts, assuring that our estimates are not affected by selective referral of patients during the shifts, and that early-career patient outcomes are unrelated to whether a physician stays on the job in the future, ruling out dynamic selection effects. In addition, our estimates are robust to the inclusion of physician fixed effects.

Besides documenting learning, our results also give additional insights into particular learning mechanisms. An attractive feature of our data is that we can study how learning differs across tasks that vary in complexity. Treating high-risk patients is arguably more difficult than treating low-risk patients and our results suggest that physicians indeed learn more from treating difficult cases.

Our data also allows us to whether the skills of physicians depreciate over time or if the knowledge "sticks". We show that experience from more recent PCIs is more valuable than experience from more distant ones when it comes to proficiency but not for decision-making. This suggests that fine-tuned manual skills depreciate over time, whereas more intellectual skills stick. Our results also highlight the role of peers in the learning process: learning rates are substantially higher for physicians who have worked with more experienced colleagues. This suggests that productivity growth is enhanced by placing inexperienced workers with experienced ones in occupations where tasks are non-standardized and learning curves are long.

Finally, we find that productivity growth in PCI treatments keeps pace with wage growth over the first four years of the physicians' careers. Productivity growth then fades out, while wage growth continues. This suggests that a human capital mechanism may explain upward-sloping experience-wage profiles in the beginning of the physicians' careers, while other mechanisms better explain long-run wage growth.

Our paper contributes to several literatures. At a general level, it adds to the literature on upward-sloping experience-wage profiles. Using performance-ratings as a measure of productivity, several papers show that wages increase much more than productivity, casting doubt on human capital-based interpretations of upward-sloping experience-wage profiles (Medoff and Abraham, 1980, 1981; Flabbi and Ichino, 2001). The assignment of workers to tasks is not necessarily independent of worker experience in these papers, however, and to account for such potential non-random assignment, some studies instead focus on standardized job tasks, where performance is easy to measure and where all workers perform more or less the same task (Shaw and Lazear, 2008; Haggag et al., 2017). While these studies can rule out systematic sorting of workers to tasks, it comes at the price of studying standardized tasks, where the learning curves are typically short and steep, such as windshield installation and taxi driving.[5] We contribute to this literature by estimating learning curves in a setting where white-collar workers are quasi-randomly assigned to an advanced task, which involves both fine-tuned manual skills and decision-making skills. Our results support the notion that learning-by-doing can be a powerful mechanism for productivity growth in high-skilled occupations.

Our paper also adds to the understanding of labor markets characterized by large supply-side variation in practice styles, decision-making, and resource use, such as healthcare (e.g., Skinner, 2011; Finkelstein et al., 2016; Currie and MacLeod, 2017; Cutler et al., 2019). We show that learning-by-doing may be an important factor in explaining such variation across physicians and hospitals. We also add to the literature that highlights the role of peers for physicians' practice styles and productivity by showing that physicians learn faster when working with more experienced colleagues (e.g., Chandra and Staiger, 2007; Epstein and Nicholson, 2009; Doyle et al., 2010; Chan, 2016; Molitor, 2018; Chan, 2020). In addition, our paper relates to the small literature that uses linked physician-patient data and runs physician fixed effects regressions to study learning-by-doing in health care (Huesch, 2009; Contreras et al., 2011).[6] We contribute to this literature by using a design that explicitly accounts for the systematic assignment of physicians to patients and, in contrast to these papers, showing the presence of prolonged learning curves. This is of interest to policy-makers and patients,

[5]A related literature in education economics relies on value-added or teacher fixed effects models to estimate the effect of teacher experience on student outcomes. This literature generally finds small, short-lived, but positive effects of teacher experience, see for instance Rockoff (2004), Hanushek et al. (2005), Rivkin et al. (2005), Jackson (2013, 2014), and Ost (2014). Particular challenges for the literature on teacher experience are potential student sorting and sorting of teachers to classes based on experience, see the discussions in e.g. Rothstein (2010), Angrist et al. (2016), and Chetty et al. (2017).

[6]Huesch (2009) found no evidence of learning-by-doing in coronary artery bypass graft operations, using patient mortality and morbidity as outcomes. Contreras et al. (2011) studied outcomes after refractive eye surgeries and also found no evidence of learning-by-doing. While physician fixed effect regressions solve some endogeneity issues, they cannot account for time-varying experience-based allocation of physicians to patients.

who like to know at what levels of experience physicians can be expected to perform at acceptable levels.[7]

Finally, our papers relates to the literature on organizational learning. A number of studies exploit rich data on production processes within firms, allowing for detailed studies on learning mechanisms.[8] In a health care setting, a large medical literature relates cumulative experience at the hospital level to patient outcomes in a variety of settings, often finding a positive relationship.[9] We complement this literature by showing that learning-by-doing at the individual level may be an important mechanism behind organizational learning.

We proceed as follows. Section 2 gives some institutional background on heart attack treatments and discusses learning-by-doing mechanisms. Section 3 presents our data and Section 4 introduces our empirical design. Section 5 presents our main results and Section 6 examines learning mechanisms. In Section 7 we compare productivity growth and wage growth. Section 8 concludes.

2 Background

2.1 Heart attacks and institutional context

We study learning-by-doing in the treatment of patients suffering from myocardial infarctions (often referred to as heart attacks), which are caused by the build-up of cholesterol inside the artery, leading to a reduced or blocked blood flow. We focus on the most common treatment of heart attacks: percutaneous coronary interventions, referred to as PCIs (Socialstyrelsen, 2015). A PCI is a nonsurgical technique where the physician accesses the heart through a catheter, with the aim to restore the blood flow through the blocked arteries. To identify the blocked arteries, contrast medium and X-ray are used to examine how the blood flows through the arteries. The blocked artery is then pushed open by inflating a balloon in the artery. To ensure that the artery

[7] In many countries, minimum operation volume standards have been implemented, without much supporting scientific evidence, in order to ensure medical quality, see Birkmeyer et al. (2002) for a discussion.

[8] See for instance Hatch and Mowery (1998), Benkard (2000), Thompson (2001), Das et al. (2013), Levitt et al. (2013) and Hendel and Spiegel (2014). Lack of evidence about the underlying individual mechanisms that generate organizational learning has been frequently noted in this literature, see Lapre et al. (2000) and Argote (2013).

[9] For an overview of the literature, see Halm et al. (2002). A few papers use a quasi-experimental approach to study the effect of volume changes at the hospital level on patient outcomes, see, for example Gaynor et al. (2005) and Avdic et al. (2019).

remains open, a tube-shaped metal device, called stent, is inserted into the artery.[10]

In Sweden, PCIs are performed by medical teams at specialized PCI centers, situated at publicly owned hospitals.[11] PCI physicians are paid a fixed, individually negiotiated, monthly salary and face no financial incentives to provide certain types of care.[12] The team consists of a cardiologist (PCI-operator), a nurse that assists the physician, and assistant nurses that provide additional support. The tasks performed by each member of the team are well-defined, where the cardiologist performs and decides upon all diagnostic and treatment procedures during the PCI. While the composition of the team is similar during day-time and on-call hours, an important difference is that more than one cardiologist may be present at the PCI-center during day-time hours, meaning that more complicated cases can be allocated to more experienced cardiologists and that inexperienced cardiologists can obtain guidance. During on-call hours, however, there is only one cardiologist present, who has to handle all patients that arrive.

During the time period we study (2004-2013), there was no formal PCI-training in Sweden and physicians who obtained a specialist degree in cardiology obtained their PCI training through a two-year apprentice program, where knowledge was obtained by observing and working together with experienced cardiologists. The physicians were only allowed to perform PCIs on their own after having completed the program.

2.2 Learning-by-doing in PCI treatments

There are several mechanisms through which learning can affect the outcomes of PCIs. One is through decision-making, where the physician decides on how many coronary artery segments of the heart to treat and the number of stents to insert. These decisions are taken under high time pressure and can have important consequences for the patient's health.

Besides decision-making, learning can also affect proficiency and the quality of the

[10]Alternative treatments include pharmacological thrombolysis and Coronary Artery Bypass Grafting (CABG) surgery. In Sweden, pharmacological thrombolysis, which consists of giving the patient drugs which actively breaks down the blood clots that block the artery, is only performed in cases where a PCI could not be performed within a certain time limit from the onset of the heart attack (due to long travel distances, for instance). CABG surgery is performed in less than 1 percent of cases, typically when multiple arteries are blocked (Socialstyrelsen, 2015).

[11]Each or the 21 county councils in Sweden decide on the mechanisms for paying hospitals, but typically a mix of global budgets and DRGs is used to reimburse hospitals, while performance-based payments only consistute a minor part. For an overview, see https://www.commonwealthfund.org/international-health-policy-center/countries/sweden.

[12]Evidence that financial incentives can affect treatment decisions in heart attack treatments has been obtained in the US (Coey, 2015).

performance. Medical inputs, such as balloons and stents, are placed inside the heart using a catheter. If these are not optimally placed, the likelihood of another heart attack and ultimately mortality can be affected. It is also important that the physician acts fast in identifying the blocked arteries using contrast medium and X-ray. The physician also has to decide where to insert the catheter, either in the thigh or in the arm, where the choice partly depends on the proficiency of the physician. Since the experience of the physician may be important both for decisions about technology and for the quality of the performance, we will study measures of both proficiency and decision-making in our empirical analyses. We further discuss our measures of proficiency and decision-making, and their interpretation, in the following section.

3 Data

Our main data source is the Swedish Coronary Angiography and Angioplasty Register (SCAAR), which is a national database that covers all PCIs performed in Sweden.[13] The register links physicians to patients and includes detailed information on all medical procedures performed during the PCIs. We are able to follow physicians over time, so that we can construct a detailed history of all patients that they treated. For administrative and evaluation reasons, the register also includes information on whether the PCI was conducted during on-call time, which typically starts at 16:30 on weekdays and ends 07:30 the following day. Holidays and weekends are also defined as on-call time. This information is used to construct our on-call time indicator. We use data for the period 2004–2013, since information on on-call time is only available from 2004 and onwards, and select physicians who did their first PCI in 2004 or later.

The SCAAR register is part of the SWEDEHEART register, which provides information on various health outcomes and demographics for all heart patients in Sweden. With this information, we can construct health histories for each patient, following the approach in previous medical studies on PCIs (see, e.g., Hambraeus et al., 2016). In our regressions, we control for pre-determined characteristics, such as the patients' age, BMI, gender, previous heart attacks and PCIs, and information on diabetes, hypertension, and smoking (see Panels B–C of Table 1 for a full list). We also use these variables to establish that the experience of physicians is unrelated to pre-determined characteristics of the patients treated during on-call shifts, i.e. that our identification strategy is valid.

[13]The register is developed and administered by the Uppsala Clinical Research Center (UCR) and sponsored by the Swedish Health Authorities, and is thus independent of commercial funding.

We restrict our analyses to STEMI heart attacks (ST elevation myocardial infarction), which are the most serious type of heart attacks, where one or several of the arteries are completely blocked. STEMIs are, therefore, sometimes referred to as massive heart attacks. One key aspect of STEMIs is that they are more easily detected using a ECG, which is normally performed already in the ambulance. Since STEMIs are severe types of heart attacks, and since they are often detected using a ECG in the ambulance, most STEMI patients are directly transferred to the closest PCI-center, meaning that there is limited discretion in the decision where to send the STEMI patients.

To capture the various dimensions of learning-by-doing we study several outcomes related to physician proficiency, physician decision making, and patient health. To measure physician proficiency, we use outcome measures routinely used in the medical literature. One of the most common measures of proficiency is fluoroscopy time (X-ray time).[14] Fluoroscopy is a type of medical imaging showing a continuous X-ray image on a monitor. During the fluoroscopy procedure, an X-ray beam is passed through the body and the image is transmitted to a monitor so that the movement of an instrument or contrast agent ("X-ray dye") through the body can be seen in detail. Fluoroscopy time describes how efficiently (in time) this procedure is performed (see, e.g., Hess et al., 2014; Jensen et al., 2012). This is an important measure when measuring proficiency in PCI treatments, since fluoroscopy is used throughout the PCI treatment, both during the initial examination of the blood flow and when different procedure during the PCI.[15] If any difficulties arise during the PCI, because of a mistake made by the physician, this may result in longer fluoroscopy time. Shorter fluoroscopy time thus indicates a more successful PCI, less X-ray exposure, and a higher level of physician proficiency.[16] Moreover, greater physician experience has been shown to be negatively associated with

[14] In a study on learning curves in PCI treatments, Jensen et al. (2012) write that: "Fluoroscopy time seems to be the best metric to determine coronary angiography performance level and might therefore be a good proficiency measure during training."

[15] One example is when the balloons and the stents are placed into the arteries. This requires a high level of technical skills as the physician needs to use the X-ray image to guide the catheter through the artery into the heart and place the catheter exactly at the right place in the blood vessel. Fluoroscopy time is a more relevant measure of physician proficiency than the total time of the PCI, since the latter is partly determined by tasks largely unrelated to physician proficiency, such as cleaning and shaving the catheter insertion site, placing electrodes on the chest, injecting local anaesthesia, and putting a bandage in place over the puncture site. In Section 5.3, we show that there is no correlation between experience and time from patient hospital admission to start of the PCI.

[16] It is also important to minimize fluoroscopy time since it can result in relatively high radiation doses for complex and time-consuming procedures, such as placing stents. The risks associated with fluoroscopy includes radiation-induced cancers and radiation-induces injuries to the skin and underlying tissues (source: https://www.fda.gov/radiation-emitting-products/medical-X-ray-imaging/fluoroscopy).

fluoroscopy time (see, e.g., Jensen et al., 2012).

Our second measure of physician proficiency is an indicator of using the radial technique (insertion of the catheter in the arm instead of the thigh), which has been found to reduce complications, but is considered to be more complicated (Ferrante et al., 2016). Since more skillful physicians are more inclined to use the more complex radial technique, this offers another measure of physician proficiency.[17]

We also use the detailed information on the medical procedures performed to examine physician decision-making in terms of the level of invasiveness of the procedures. Our first measure is the number of treated coronary artery segments, reflecting the physician's decision on whether to treat several segments or only the segment where the blood flow is reduced the most. Our second measure concerns the insertion of stents during the PCI. Stents are metal nets that are placed and left within the artery to keep it open and to prevent future heart attacks. As outcome measure, we use the total stent length, which varies both due to the length of each stent and due to the number of stents inserted.

The decision about how many segments to treat, and how many stents to insert, partly reflects whether the patient suffers from a single-vessel or multi-vessel disease. In the latter case, significant narrowings are observed in several vessels and the physician needs to decide whether to treat all the narrowings or focus on the most affected coronary artery. Several randomized trials and meta-analyses found that complete revascularization, where multiple narrowed arteries are treated, was associated with lower mortality in STEMI patients with multivessel disease compared to single-artery treatment (Bravo et al., 2017). For patients with multi-vessel disease, a larger number of segments treated and stents inserted may therefore reflect a "better" treatment. In our analyses, we will further look into this by using indicators of multi-vessel disease and multi-vessel PCI treatment.

To study patient health outcomes, we use two measures. The first is an indicator of having another heart attack or dying within one year after the PCI. The second is an indicator for any complications arising during the PCI. The most common complications are bleeding in the area where the catheter is inserted, other types of bleeding, perforation, arrythmia and haemadynamic complications, whereas a less common complication is stent loss (Swedeheart, 2020).

Our explanatory variable of main interest is physician experience. We define it as the accumulated number of PCIs, i.e. the number of previously performed PCIs. In

[17] In a meta-anlysis of randomized trials, Ferrante et al. (2016) concluded that radial access reduces major bleeding and patient complications, but that inadequate training and experience might prevent the use of the radial technique (Gilchrist, 2015).

additional analyses, we explore other measures of experience, such as experience from treating high-risk patients and experience from working together with more experienced PCI physicians during day-time hours. Since experience may correlate with other physician attributes, such as age and gender, we also run models where we control for such attributes.

Figure 1 describes the relationship between experience in terms of the number of PCIs performed and experience in terms of years since the first PCI. Physicians perform about 80 PCIs on average during their first year and about 130 PCIs per year in subsequent years. Figure 2 describes the yearly variation in the number of PCIs across hospitals (PCI centers) and physicians. It shows that many hospitals perform around 500 PCIs per year and that a few hospitals perform more than 1000 PCIs per year. Many physicians perform around 100 PCIs per year, but some physicians perform more than 200 PCIs per year and, thus, acquire their experience within a more narrow time window. This shows that experience in terms of the number of procedures performed captures experience more accurately than experience measured by time.

Table 1 provides sample statistics. In total, we have information on 82,559 PCIs performed by 110 physicians across 28 PCI centers in Sweden. The sample with STEMI infarctions includes 16,419 PCIs, of which 8,565 occur during on-call time. The table also provides descriptive statistics for all background characteristics and all outcomes used in the analysis.

4 Empirical strategy

4.1 As-if random allocation during on-call time

To estimate the effect of experience on performance, and thus measure learning-by-doing, our empirical design aims to break the systematic allocation of patients to physicians. We therefore next study the patient allocation process and how it varies between day-time and on-call shifts. We start by relating the experience of the physicians to the pre-determined health of the patients that they treat during day-time shifts. Here, we expect sorting to take place, since there are normally several physicians around and since high-risk patients can be allocated to more experienced physicians. We then redo this exercise on data from on-call shifts, where we expect no systematic sorting of physicians to patients, since there is only one physician around.[18]

[18]Our data shows that during day-time shifts, 1.6 physicians per center perform at least one PCI, on average. As expected, the corresponding number for on-call time shifts is 1.

To study sorting, we construct a measure of patient health risk by using the predetermined health characteristics to predict the 1-year mortality rate for each patient.[19] We then correlate this measure of patient risk with the experience of the physician. Panel A of Figure 3(a) shows this correlation for PCIs performed during day-time shifts, when more than one physician is around. The dots show average experience by patient risk (bins) and the solid line shows the estimated quadratic relationship between the two variables.[20] As expected, we find a strong relationship between physician experience and patient risk. This pattern is consistent with the results from previous studies on the allocation of physicians and suggests that experienced physicians are more likely to take on high-risk patients (see, e.g., Glance et al., 2008; Hess et al., 2014).

During on-call time, defined as weekends, holidays, early mornings, and late nights, there is only one physician on call, but sorting could still take place if certain types of physicians are more often scheduled to work during certain weekends and holidays where more individuals suffer from heart attacks. Conditional on hospital, year, month, and weekday effects, however, any such sorting should be accounted for. This is also confirmed by Figure 3(b), which shows no correlation between patient risk and physician experience during on-call time. By using data from on-call shifts, we are thus able to generate the as-if random allocation of physicians to patients needed to study the effect of experience on performance.

4.2 Econometric model

Our main econometric model uses a flexible specification, where experience is measured through a set of dummy variables, and can be written as:

$$\begin{aligned} Y_{ihymw} = \lambda_h + \nu_y + \delta_m + \mu_w + \psi X_i + \gamma_1 \mathrm{E}(251-500) + \gamma_2 \mathrm{E}(501-1000) \\ + \gamma_3 \mathrm{E}(1000+) + \varepsilon_{ihymw}, \end{aligned} \tag{1}$$

where Y denotes outcomes of the physician or patient i at hospital h, in year y, in month m, on weekday w. The effect of experience, E is measured through dummy variables indicating cumulated experience in bins: 251–500, 251–500, 501-100, and 1000+ PCIs performed. The omitted reference category is experience below 250 cases. The model controls for hospital fixed effects λ_h, which is the same as PCI center fixed effects as

[19]Specifically, we estimate a logit regression using the observed characteristics described in Table 1, and use the estimates from this model to predict the individual risk.

[20]We show residual plots after taking out PCI center and calendar time fixed effects (year, month, weekday), since we are interested in the sorting of physicians within hospitals. For ease of comparison, we have added the variable mean to the residuals.

each hospital have one PCI center at most. This allows us to focus on the allocation of patients and physicians within hospitals, thus controlling for any sorting of patients and physicians across hospitals. We also includes year- and month fixed effects (ν_y and δ_m) to control for seasonal variations in patient health, and weekday fixed effects (μ_w) to account for within-week variation. We also include a set of individual patient characteristics (X_i) that are believed to be risk factors for heart disease (Hambraeus et al., 2016)[21]

In additional analayses, we also estimate a "traditional" learning model that uses a power law specification. This specification assumes that $Y = AE^{\beta}$ describes the relationship between "productivity" and experience, Taking logs, the model can be written as:

$$\ln(Y_{ihymw}) = \lambda_h + \nu_y + \delta_m + \mu_w + \psi X_i + \beta \ln(E) + \epsilon_{ihymw}, \tag{2}$$

where β is the learning rate. Levitt et al. (2013) and Haggag et al. (2017) use similar models to study how experience impacts the average number of defective operations per car produced and earnings among taxi drivers, respectively. We use the model for our non-binary outcomes, both as check of our baseline model and to facilitate comparison with previous studies.

The models above are used to study proficiency, decision-making and patient health. To shed further light on how experience affects decision-making, we also investigate whether experienced physicians to a greater extent adjust their decisions to the characteristics of the patient. For this purpose, we first run regressions on our invasiveness measures (number of treated segments and total stent length) as functions of the patient characteristics used in in Panels B-C of Table 1. We then use the predicted values from these regressions as measures of the "appropriate" level of invasiveness for each patient. Finally, we interact these appropriateness measures, $f(x)$, with experience and study impacts on decision making, i.e. the level of invasiveness, using the following model:

$$\begin{aligned} Y_{ihymw} = &\lambda_h + \nu_y + \delta_m + \mu_w + \psi X_i + \gamma_1 \mathrm{E}(251-500) + \gamma_2 \mathrm{E}(501-1000) + \gamma_3 \mathrm{E}(1000+) + \\ &\phi_1 f(x)\mathrm{E}(251-500) + \phi_2 f(x)\mathrm{E}(501-1000) + \phi_3 f(x)\mathrm{E}(1000+) + \varepsilon_{ihymw}. \end{aligned} \tag{3}$$

[21]The risk factors include indicators for diabetes, insulin treated diabetes, hypertension, lipid lowering medicine, previous heart attack, previous coronary artery bypass surgery, previous PCI, male patient, age 60-69, age 70-79, age 80+, smoker, BMI over 25, normal atheromatous, 1-vessel disease, 2-vessel disease, 3-vessel disease, and main stem vessel disease (see Panels B-C of Table 1).

For interpretation reasons, $f(x)$ is mean-adjusted, so that the γ parameters measure the impact of experience on level of invasiveness for patients with average "appropriate" level of invasiveness. We define this as aggressiveness. The interaction parameters, ϕ, reflect to what extent experienced physicians perform more invasive procedures on patients with a higher "appropriate" level of invasiveness, which would imply a stronger mapping between patient characteristics and treatment decisions. We define this as responsiveness.

4.3 Some additional randomization tests

Figure 3 revealed a strong correlation between patient risk and physician experience during day-time hours, but no correlation during on-call time. We next present regression randomization tests that confirm these patterns. Table 2 reports estimates of the relationship between physician experience, measured as the accumulated number of previous PCIs, and predicted patient mortality risk (controlling for hospital, year, month and weekday fixed effects). As suggested by Figure 3, the estimate in column 1 shows that predicted risk is positively associated with the cumulated experience of the physician during day-time hours. Column 2 shows results where we restrict the day-time sample to only include STEMI cases. Again, we obtain a strong correlation between patient risk and physician experience but, as expected, this correlation becomes small and insignificant during on-call time (Column 3).[22] Altogether, these analyses show that the assignment of patients to physicians during on-call time appears as good as random.

5 Main results

5.1 Physician proficiency and decision making

We start our empirical analysis by studying how learning affects physician proficiency. Figure 4(a) illustrates the relationship between fluoroscopy time and physician experience, using data on PCIs performed during on-call shifts and adjusting for hospital and time (year, month and weekday) fixed effects, and the patient risk factors. The dots show the average residual outcome by physician experience (bins) and the line is

[22] We have also run our main model in equation (1) but using the predicted mortality/infarction rate, as well as other predicted health indicators, as outcomes. Again, we find no significant correlations between physician experience and pre-determined patient characteristics (see Table A-1).

a fitted quadratic relationship between fluoroscopy time and experience.[23] The figure reveals a distinct learning pattern where more experienced physicians perform the PCIs faster, as revealed by a reduction in fluoroscopy time. The learning process starts early on, is fastest over the first 600 PCIs, and then slows down. After the first 1000 PCIs, no additional learning appears to take place.[24] Figure 4(b) shows a similar learning pattern for our other proficiency measure; use of the radial puncture technique. Again, learning increases with experience up until about 1000 cases, after which no additional learning takes place.

The patterns in the figures are confirmed by the regression estimates in Columns 1–2 of Table 3. The estimates of the effect of experience on fluoroscopy time, using 0–250 PCIs as baseline category, are all significant and large. Moreover, the differences between physicians with 251–500 experience, and 500–1000 and 1000+ experience is significant at the 5% and the 1% levels, respectively (the difference between 500–1000 and 1000+ is significant at the 10% level). Physicians having performed more than 1000 PCIs are on average 3 minutes faster than physicians having performed at most 250 PCIs, corresponding to a 21 percent reduction. The estimates for the radial puncture technique are positive and sizable, suggesting that physicians gradually learn to use the technique, but do not reach statistical significance.

The results suggest that experience over the first 1000 PCIs matters the most for physician proficiency. For a physician performing 130 PCIs per year, this corresponds to 7-8 years of experience (see Figure 1). For a physician performing 250 PCIs per year, it corresponds to about 4 years of experience. Such long learning curves, that account for the selection of workers to tasks, have rarely been documented in the literature before. Haggag et al. (2017) found that learning only occurs over the first couple of months among New York taxi drivers. Similarly short learning curves were also reported by Shaw and Lazear (2008), where learning only takes place during the first eight months on the job among workers who install windshields at a car factory. These results contrast with our long learning curves, which likely reflects that PCI treatments constitute more complex tasks, with higher levels of worker discretion. This is also one of the unique contributions of our paper; to document learning-by-doing in a high-skilled occupation. The presence of such long learning curves have important implications for productivity growth in high-skill sectors in the economy.

[23]The risk factors include the variables in Panels B–C of Table 1. For ease of comparison we have added the variable mean to the residuals.

[24]After around 1200 PCIs, fluoroscopy time starts to increase again, reflecting that physicians start to provide more invasive treatments, which by construction leads to longer fluoroscopy time (as more X-ray is used when placing the balloons and stents). If we control for the invasiveness of the treatment, the increase in fluoroscopy time after 1200 PCIs disappears.

We next estimate the power law specification in equation (2) to compare our estimates to those obtained in previous studies that estimate traditional learning models, such as Levitt et al. (2013). Our estimate in Column 1 of Table A-2 in the appendix indicates a learning rate, β, of -0.11 for fluoroscopy time. This estimate implies a sizable reduction of fluoroscopy time by 7.3% ($2^{-0.11}$=0.927) for each doubling of experience.[25] But, this is still a substantially lower learning rate, implying a longer learning curve, than the one estimated by Levitt et al. (2013), who find a learning rate of -0.3, implying that the car defect rate falls by 18.8% for each doubling of experience.

With our measure of fluoroscopy time, we can also construct indicators of mishaps during the PCI treatment. If complications arise during the PCI treatment, the fluoroscopy time may increase rapidly, since X-rays are used during the entire PCI procedure, also when trying to correct for mishaps. To measure complications, we therefore relate the expected time of each PCI to the actual fluoroscopy time.[26] We define a mishap as PCIs where the actual time is more than 1.5 times the expected time. The estimates in Column 3 of Table 3 show that experienced physicians are much less likely to experience a mishap. The rate of mishaps among physicians having performed more than 1000 PCI's, for instance, is halved.

We next consider the effect of experience on decision-making, measured through stent length and the number of treated coronary artery segments (level of invasiveness). Figure 4(c) shows that stent length is unaffected by experience during the first 600 PCIs performed but starts to increase thereafter. The corresponding regression estimates in Column 4 of Table 3 show a similar pattern: stent length does not change over the first 500 PCIs but increases thereafter. None of the estimates reach statistical significance, however.

Figure 4(d) shows that the relationship between experience and the number of treated segments follows a similar pattern to that of the profiency measures. The number of treated segments increases over the first 1000 PCIs, after which no further learning takes place. The regression estimates in Column 5 of Table 3 show that these patterns are statistically significant. Physicians having performed more than 1000 PCIs treat 8 percent more segments on average, compared to physicians having performed 250 PCIs at most. When we run the power law specification, the estimate in Column 2 of Table A-2 implies that the number of treated segments increases by 1.7% ($2^{0.025}$=1.017)

[25] This is similar to the estimates from the dummy specification in Table 3, which indicate that doubling experience from 251–500 to 501–1000 cases decreases fluoroscopy time by 0.85 minutes, or by 6.6%.

[26] We predict the expected time based on the number of procedures that are performed during the PCI. We use information on the number of treated segments, the number of stents used, the length of the stents used, and whether the puncture technique was used.

for each doubling of experience.

The greater number of treated segments by experienced physicians could reflect a more appropriate treatment response to patients with multi-vessel disease, as discussed in Section 3. The results in columns 2 and 3 of Table 4 supports this interpretation, as the effect of experience on the number of treated segments is obtained for patients with multi-vessel disease, but not for patients with single-vessel disease. In line with these results, columns 5 and 6 show that more experienced physicians are also more likely to conduct a multi-vessel PCI on multi-vessel patients, whereas no such effect is (unsurprisingly) found for single-vessel patients. More experienced physicians are thus more likely to choose a more invasive treatment strategy in exactly the situations where the medical evidence discussed in Section 3 suggests that such a strategy is warranted.

To further investigate if more experienced physicians take better decisions, we can investigate whether more experienced physicians to a greater extent *adjust* their decisions to the characteristics of the patient. More experienced physicians may have learned what works best for different types of patients, which could be reflected in a stronger mapping between patient characteristics and treatment decisions. The results in Table 5 ("responsiveness") show that this is indeed the case for the number of treated segments, reflected in positive interaction terms between experience and the predicted number of treated segments, where the predicted number is meant to reflect the "appropriate" level of invasivenes, as described in Section 4.2. More experienced physicians are also more responsive in terms of the number of stents, but these estimates are insignificant. In sum, while more experienced physicians on average are more aggressive in their treatments, when needed, they also to a greater extent adjust their treatment decisions to the characteristics of the patients.

5.2 Patient health

We next examine if the effects on physician proficiency and decision-making translate into effects on patient health, our measure of output *quality*. Figures 4(e–f) suggest no effects of experience on patient health (mortality/infarctions and complications). These patterns are confirmed by the regression estimates in Columns 6–7 of Table 3, where the estimates are statistically insignificant.

Figures 4(e-f) and Table 3 focus on experience up to 1500 PCIs, but a number of medical studies on learning curves for PCIs suggest that patient health outcomes are mainly affected by learning effects in the very early phase of the physician's career. Ball et al. (2011), for instance, find that experience from 50 PCIs is enough to achieve outcomes comparable to those of experienced physicians. Similar findings are reported in a nationwide U.S study by Hess et al. (2014), who also document learning effects up to 50 cases. Although both these studies use observed characteristics to adjust for selection, and therefore cannot establish causality, they provide some suggestive evidence that learning effects on patient health may occur mainly at low levels of experience.

For this reason, we zoom in on learning over the first 250 PCIs and split our sample by patient risk, since experience may be more important for treatment of high-risk patients. We use the same measure of patient risk as above, i.e. we use the observed characteristics described in Table 1 to predict the 1-year mortality rate for each patient using a logit model. Based on these patient risk measures, we estimate separate learning curves for patients above and below the median risk. Figure 5(a-b) reveals learning effects for mortality/infarctions, but only among high-risk patients and only over the initial 150 PCIs. The effect is large, however, where the risk of death or having another infarction decreases by about 40 percent from the 1st to 150th PCI. The fact that experience matters at low levels of experience are confirmed by the results in Table A-3, where we instead use log experience as explanatory variable, and find significant learning effects over the first 100 cases (Column 2), i.e. the range where Figure 5(a-b) showed a clear negative slope. Column 1 shows a negative slope also over the first 250 cases, but the estimate is insignificant.

Figure 5(c-d) shows the corresponding results for complications, where a tendency to a learning pattern is observed in the treatment of high-risk patients. This pattern is to a large extent driven by particularly poor performance by the least experienced group of physicians, however, and is in line with the higher mortality/infarction rate observed in the patients treated by these physicians. Table A-3 shows that the differences in complications by experience are not significant, however.

The results provide some evidence that the scope for learning is greater when it comes to treating high-risk patients, in terms of patient health outcomes. The learning process is still quite rapid, however, and after the first 150 PCIs, the physicians achieve patient outcomes comparable to those of more experienced physicians.

5.3 Some robustness checks

Before examining the mechanisms behind the estimated learning effects we examine some potential threats to the internal validity of the estimates. One threat would be if physicians at the hospital's emergency room redirect (high-risk) patients with a heart attack to another PCI center if an inexperienced physician is on call. A similar threat would be if the ambulance personnel systematically send high-risk patients to hospitals where an experienced physician is on call. Since we focus on heart attacks, where speediness is key, these are somewhat unlikely scenarios, but with the data at hand we are able to investigate them.

In the case of selective referral by the physicians at the emergency room, we would expect a correlation between the average *number* of PCIs performed during on-call shifts and physician experience, where less experienced physicians perform fewer PCIs. As shown in Figure 6(a), however, both inexperienced and experienced physicians perform 1.2 PCIs per on-call shift on average.

In the case of selective referral by the ambulance personnel, we would expect a correlation between treatment response times and physician experience. To study this, we use data on the timing of the first symptom, the first ECG (hospital or ambulance), time of admission to the hospital, and the time when the PCI starts. Figure 6(b) shows that the average time from the first symptom to the PCI is around 240 minutes for both experienced and less experienced physicians. Figure 6(c-d) shows that, on average, it takes less than 120 minutes from the first ECG until the PCI starts and less than 60 minutes from hospital admission to the PCI. The response times are similar between experienced and less experienced physicians.[27] These patterns confirm that that heart attack patients are quickly redirected to the nearest PCI center, leaving little room for different types of selective referral behavior.

Another threat is that experience may affect the allocation of physicians to more or less attractive on-call shifts. Although we include week-day fixed effects in our main model, we can also include clock-hour fixed effects as a robustness check. This does not affect our estimates (Column 2 of Table 6).[28]

A related threat to the interpretation of the learning effects would be if less experienced physicians are subject to more stressful work conditions, with many and frequent on-call time shifts. Additionally, operators with lots of experience may be more likely to have treated patients in the recent past, meaning that the estimates pick up the effects of both ackumulated and recent experience. Column 3 shows that our results are unaffected when we control for the number of days since the last on-call time shift, however. We further investigate the role of recent experience in section 6.3 below, where we adress learning and forgetting.

A common threat to the estimation of learning curves is "dynamic selection", where the composition of workers changes with experience. In our context, dynamic selection

[27]These patterns are confirmed by the regression estimates in Table A-4 in the appendix, where we use our main model with experience in bins and correlate them with the number of PCIs and the different measures of response times (only one out of 12 estimates is significant at the 5-percent level).

[28]Table 6 reports robustness analyses for our three main outcomes and Table A-5 in the appendix reports similar analyses for the other three outcomes.

would occur if physicians who perform poorly in the beginning of their career stop performing PCIs, either because they choose another specialty or because the hospitals quit their positions. This would create a selection effect, where the least skilled physicians never get to perform a large number of PCIs, giving rise to a spurious correlation between experience and performance. We can explore this possibility by quantifying early performance in the first two years and relating this to the number of PCIs performed later in the career (during years 3 and 4). Table A-6 in the appendix shows no significant correlation between early performance (average mortality/infarction rate and average fluoroscopy time) and the future number of PCIs, however.

We can also examine "dynamic selection" by including physician fixed effects in the regressions, thereby exploiting within-physician variation in experience. The estimates for fluoroscopy time in Column 4 of Table 6 are similar to our main estimates, reported in Column 1. The estimates for invasiveness become attenuated when we add fixed effects but the results are qualitatively similar (Panel B).[29] Note that with random assignment of physicians to patients, and in the absence of dynamic selection effects, there is little gain from adding physician fixed effects to the regressions, as it greatly restricts the variation in the data and increases the attenuation bias from classical measurement error.

Even though our empirical design breaks the systematic allocation of physicians to patients by using on-call time data, our estimates reflect the effect of experience and everything else that is correlated with experience, net of patient and hospital characteristics. Since it is a priori not obvious which particular physician attributes that may correlate with experience, we use the available information in our data: the gender of the physician, an indicator for having obtained the physician degree outside Sweden, and the time since the first PCI.[30] Controlling for these physician attributes hardly changes our estimates at all (Column 6, Table 6). Note also that the regressions with physician fixed effects control for all physician characteristics that remain constant over time, such as underlying ability, birth year, and educational background.

Finally, in our main analyses, we adjust for the patient risk factors in Panels B and C of Table 1. Excluding these risk factors leaves our estimates unaffected, which is expected as the allocation of patients to physicians is as good as random during on-call time (Column 7, Table 6)

[29] An alternative approach to study dynamic selection effects is to restrict our analysis to physicians for whom we observe at least the first 1000 PCIs, i.e. physicians who continue performing PCIs. When we do so, the coefficients remain similar, but the effects become insignificant because of the much smaller sample size (Column 5, Table 6).

[30] The physicians' age is not observed in our data and we instead use a variable that is highly correlated with age as a proxy: time since the first PCI.

6 Mechanisms

6.1 Learning and complexity

We now turn to the underlying mechanisms behind our estimated learning effects. An attractive, and unusual, feature of our data is that we can study how learning differs across tasks that vary in complexity. Treating high-risk patients is arguably more difficult than treating low-risk patients, and our results can thus shed light on how the context of tasks affects learning. To examine if physicians learn more from treating high-risk cases, we extend our baseline model with variables indicating experience from high-risk cases. These high-risk cases are also included in our variable that measures accumulated experience and, thus, if physicians learn equally well from treating these high-risk cases as from low-risk cases, these additional variables should not affect proficiency and decision-making.

The results in Column 1 of Table 7 show that experience from 500+ high-risk cases is associated with a significant increase in proficiency, over and above the effect of total accumulated experience. The magnitude is substantial, where more experience from treating high-risk cases leads to an additional 2.4 minutes reduction in flouroscopy time. We find no significant effect for decision making, in terms of the level of invasiveness, although the sign of the estimate is consistent with increased invasiveness as experience from treating high-risk cases increases (Column 5). We conclude that experience from more complex tasks leads to additional learning effects but that these additional learning effects seem to be most important for worker proficiency and less important for worker decision making.[31]

6.2 Learning spillovers

We next shed additional light on the underlying mechanism by considering the role of peers. While a number of studies show the existence of peer effects on worker performance both in healthcare settings (e.g., Chandra and Staiger, 2007; Epstein and Nicholson, 2009) and other settings (see, e.g. Mas and Moretti, 2009; Falk and Ichino, 2006; De Grip and Sauermann, 2012), there is little evidence on how individual learning is affected by peer experience. Such knowledge is of importance in understanding the optimal allocation of workers to teams and how to allocate new workers to colleagues.

[31] We find no significant effects of experience from treating high-risk cases on proficiency in terms of using the radial technique, or on decision-making in terms of total stent length (Table A-7). We do find a significant negative effect on patient mortality, however, in line with the results for fluoroscopy time, but no effects on other health outcomes (Table A-8).

We first consider whether experience gained from working together with more experienced colleagues leads to more rapid learning. For this, we use variation in the mix of physicians at the PCI center on given days and distinguish between days working with experienced and non-experienced colleagues.[32] Our hypotheses are that physicians are able to learn from each other, through communication and observation, and that physicians learn more from experienced colleagues. We therefore include both total experience from treating PCIs, and experience from PCIs during days where an experienced PCI physician was present, in the regressions in Table 7. We define experienced colleagues as those having performed 1000 or more PCIs (Column 2) or 2000 or more PCIs (Column 3). In both cases, we find that performing PCIs with an experienced physician present leads to faster improvements in proficiency and by comparing the estimates in Column 2 and 3, it appears that this pattern is stronger when having experience from working with very experienced (2000+) colleagues.

The presence of learning spillovers in a healthcare context, where physicians learn about new technology and procedures from each other, appears plausible. At Swedish PCI labs, cardiologists are typically permanently employed and interact both professionally and socially at the workplace. Less experienced cardiologists may thus improve their manual skills by observing more experienced peers perform PCIs. Interestingly, we find no evidence of peer learning when it comes to decision-making (Columns 6 and 7, Table 7), however. This suggests that having experienced peers play a greater role for getting up to speed when performing PCIs but play less of a role for decision-making in PCIs.[33] To understand this finding, it is useful to consider the relationship between manual skills and decision-making when performing PCIs. An important decision concerns the number of artery segments to treat, where treating more segments is more time-consuming but also more beneficial in the presence of multi-vessel disease, as discussed in Section 3. Less experienced cardiologists may not yet have developed the speed necessary to perform time-consuming multiple-vessel PCIs, which would also explain why they would be less affected by decisions that more experienced cardiologists take.

[32]We define days working with experienced colleagues as days when an experienced physician performs at least one PCI. This does not capture the rare cases when experienced PCI physicians are present at the PCI lab without performing any PCIs themselves, since we cannot observe these cases in the data.

[33]We have also examined if learning curves are steeper for physicians at university hospitals, who may have even more skilled colleagues and who face a more research-oriented environment, but found no evidence suggesting so.

6.3 Learning and forgetting

An important question in the learning literature is whether skills gained through learning-by-doing depreciate over time. If depreciation rates are high, the costs of unemployment and labor market detachment are amplified. Several studies have found evidence of "'forgetting"' at both the individual and organizational level (Benkard, 2000; Hockenberry and Helmchen, 2014; Facchini Palma, 2020). In our context, it is important to understand whether physicians tend to forget some of their acquired skills or if the knowledge "sticks", once learned. In the former case, it would be important to keep performing the task frequently. We therefore next test whether an increase in the number of PCI treatments performed recently has an effect over and above the effect of total number of PCI treatments performed. With our data, we are also able to test which type of skills that tend to depreciate the most; manual skills or decision-making skills.

To test for forgetting, we add measures of the number of PCI treatments performed *in last year* to our regressions. We create two additional dummy variables, where the first one indicates having performed 100–250 PCIs last year and the second one having performed more than 250 PCIs. The results in Columns 4 and 8 of Table 7 show that an increase in recent PCI experience is associated with a substantial increase in proficiency, in terms of fluoroscopy time, but has no effect on decision-making, in terms of the number of treated segments. The effect is only found for those having performed more than 250 PCIs last year and the magnitude suggests that this group increase their speed by a sizable 2.6 minutes. The results suggests that fine-tuned manual skills depreciate over time whereas decision-making skills do not. Overall, this points to the importance of keeping up the practice when it comes to advanced manual skills and shows that forgetting is an important phenomenon at the individual level.[34,35]

[34] Tables A-7 and A-8 in the appendix show no effects on other measures of proficiency and decision-making or on patient outcomes. The latter result contrasts with those of Hockenberry and Helmchen (2014) who found that temporary breaks negatively affect physicians' performance in coronary artery bypass treatments, measured by patient outcomes.

[35] An alternative explanation is that less proficient physicians schedule fewer shifts, so that we observe less proficiency when there is less recent shifts and thus less recent experience. When we correlate the number of shifts per month with the physician's proficiency (average fluoroscopy time) in the preceding month, we find a small negative correlation, suggesting that endogenous scheduling cannot explain the observed forgetting pattern.

7 Wages, experience and performance

Conventional human capital theory explains upward-sloping experience-wage profiles by the accumulation of human capital partly acquired through learning-by-doing. To distinguish such an explanation from other ones, such as a deferred compensation mechanism, we next relate wage profiles to observed learning patterns. If the human capital story is correct, we expect a tight connection between wage and productivity profiles. But if wages increase faster than productivity, this would be inconsistent with human capital theory but consistent with the theory of deferred compensation as an incentive mechanism.[36]

To create wage profiles, we use data on (full-time adjusted) monthly wages on all cardiologists in Sweden from Statistics Sweden's annual study on wages (Strukturlönestatistiken). Note that there is substantial variation in the wages of cardiologists in Sweden, despite being employed in the public sector. Cardiologists in Sweden receive a monthly salary that is to be individually negotiated annually and when we run a wage regression with only age dummies as controls, age only explains 9 percent of the variation.

Since we are unable to link the physicians in our data to the wage data in Statistics Sweden's annual study on wages, we use individual-level wage data from the latter database on all cardiologists in Sweden, and select those who finished specialized cardiology training. We study their wage profiles starting three years after they obtain their specialist degree, since it normally takes around 2 years to finish PCI training.[37,38] Panel A of Figure 7 relates the indexed wage profile to the indexed productivity profile for proficiency, measured through fluoroscopy time. Productivity growth is rapid over the first two years and about twice as steep as wage growth. Between the second and fourth years, productivity growth slows down, while wage growth accelerates and exceeds productivity growth. After four years of employment, the wage and proficiency patterns diverge. While wages continue to increase, productivity growth flattens out.

Panel B of Figure 7 shows a similar divergence between wages and proficiency patterns already after two years when we use adoption of the radial technology as our

[36]Cardiologists with PCI training may also perform other tasks, such as academic research and leadership, that affect wages. Yet, PCI treatments are without doubt one of their most important tasks.

[37]The wage profiles look similar if we instead choose 2 or 4 years after specialized cardiology training, se Figure A-1.

[38]We use data on those graduating with a special degree in cardiology from 2002 and onward, since it normally takes two years of additional practical training before conducting PCI treatments on one's own. An individual who graduated 2002 with a special degree in cardiology will thus not start practicing on his or her own until 2004, at earliest, when our study period starts.

measure of proficiency. Panel B also relates wage profiles to our two measures of decision making. Here, we see changes in decision making after two years of employment, when the number of stents and treated segments starts to increase, but the increase is less prominent than the corresponding one for wages.

The results suggest that different mechanisms behind upward-sloping wage profiles may be in place at different phases of the career, for high-skill tasks such as PCI treatments. The finding that productivity growth flattens out after four years, while wages keep increasing, suggests that the human capital story may be right in the beginning of the career, whereas other mechanisms better explain long-run patterns. If these results generalize, they help understanding why older workers are often found to be discriminated on the labor market: the gap between productivity and wage growth widens by tenure.

8 Conclusions

This paper provides new evidence on learning-by-doing and productivity growth in a high-skill task. In the context of heart attack treatments, we estimate individual (causal) learning curves by relating physician experience to measures of physician proficiency, physician decision making, and patient outcomes.

Our results show the presence of prolonged learning curves in the treatment of heart attacks. Using proficiency measures commonly used in the medical literature, and accounting for systematic sorting of physicians to patients, we demonstrate a strong link between experience, measured as the accumulated number of procedures, and proficiency. We show that physicians get 21 percent faster in performing their PCIs between their first and 1000th PCI. We find similar results for other measures of proficiency, such as the adoption of more advanced technology that requires greater manual skills.

Greater experience also affects physician decision-making. Experienced physicians are more likely to choose more invasive treatments and the pattern is similar to that observed for proficiency. Our results suggest that the more invasive treatments by experienced physicians reflect more appropriate treatments of patients with multiple blocked arteries. In addition, we find that experienced physicians are more responsive to patient characteristics when taking their decisions.

The learning effects translate into effects on patient health, but only among high-risk patients and only over the first 150 PCIs performed. The effects are large, where the risk of having another heart attack or dying within one year decreases by 40 percent when assigned a physician who has performed at least 150 PCIs. Our results also highlight the role of peers in the learning process. We show the importance of gaining experience from working with experienced colleagues, as learning rates are substantially higher for workers who do so. This suggests that it is crucial for productivity growth to place inexperienced workers with experienced ones in occupations where tasks are high-skilled and non-standardized.

We also show that physicians learn more from the treatment of high-risk patients, suggesting that the learning rate is higher for more complex tasks. Moreover, we show that the productivity growth in PCI treatments follows wage growth for the first 4 years of the cardiologists' careers. After that, wages keep increasing while productivity growth flattens out.

We contribute to the learning-by-doing literature in several ways. We document learning in advanced tasks, using a context where we are able account for selection effects by breaking the commonly observed systematic assignment of workers to tasks. The previous literature has often focused on standardized tasks, where all workers perform more or less the same task, to account for such selection effects, at the price of studying tasks that are less representative of jobs in advanced economies (eg. Shaw and Lazear (2008); Haggag et al. (2017). Our results show that the learning curves for high-skill tasks like PCI treatments are much longer than those observed for many of the less complex tasks considered in the previous literature. We also contribute by using detailed measures of output quality, decision-making, and resource use. Often, the learning literature has focused on unit-cost or quantity-based productivity measures, preventing insights on *how* workers learn and in what dimensions (Thompson, 2001). In sectors such as healthcare, quality-based output measures such as patient outcomes are of obvious importance and policy relevance.

Our results also informs the debate about the mechanisms behind upward-sloping experience-wage profiles. Improvements in performance by experience would support human-capital based interpretations of such profiles. We show that this interpretation is valid for the first 4 years of cardiologists' careers, but not thereafter. This suggests that the gap between productivity and wages increases over the career, in line with the common finding that older workers have greater difficulties finding new jobs.

Our long learning curves contrast with some of the shorter ones estimated for PCI treatment in medical studies. This may reflect the lack of quasi-random assignment in these studies, where higher-risk patients and more complicated cases are often found to be allocated to more experienced physicians (Glance et al., 2008; Hess et al., 2014). Such sorting would push against finding long learning curves and previous medical studies have reported case-loads as low as 15-50 cases for overcoming the PCI learning curve (Hess et al., 2014; Khialani et al., 2018; Jayanti et al., 2021).

Finally, our results have policy implications for the treatment of heart attacks. First, since our results suggest extensive learning during the early phase of the career, policy-makers may want to investigate opportunities to speed up the learning process, which could generate substantial productivity gains. Second, since having performed more than 150 PCIs is crucial for patient outcomes among high-risk patients, policy-makers may want to consider options to improve performance during this early phase, such as performing night-shift PCIs under the supervision of a more experienced colleague. Third, performance is improved by having gained experience working with more experienced colleagues during day shifts and it may therefore be possible to speed up the learning process by improving the mix of young and experienced cardiologist. Finally, our results highlights the importance of performing advanced tasks like PCIs regularly in order for skills not to depreciate over time and the potential benefits of concentrating PCI treatments to larger units where cardiologists specialize in PCIs.

We acknowledge that our results reflect learning-by-doing in one particular task - the treatment of heart attacks. While we share this external validity concern with most other papers in the learning literature, who typically focus on particular tasks, we believe that our results offer some insight in the process of learning in advanced tasks, where both fine-tuned manual skills and fast decision-making are needed. Our results support the notion that learning-by-doing can be a powerful engine for productivity growth in high-skilled occupations.

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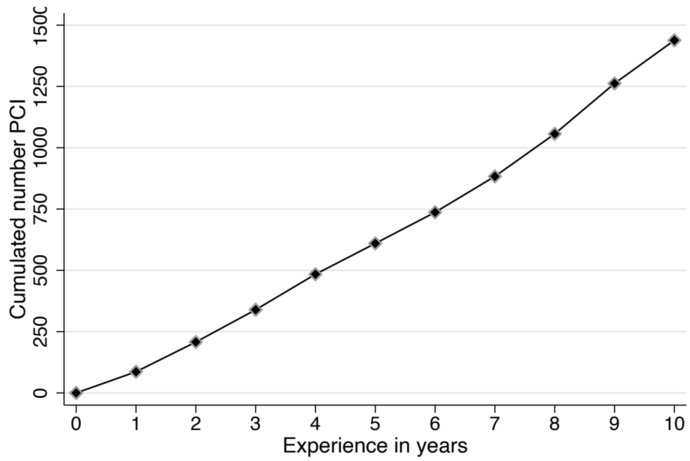
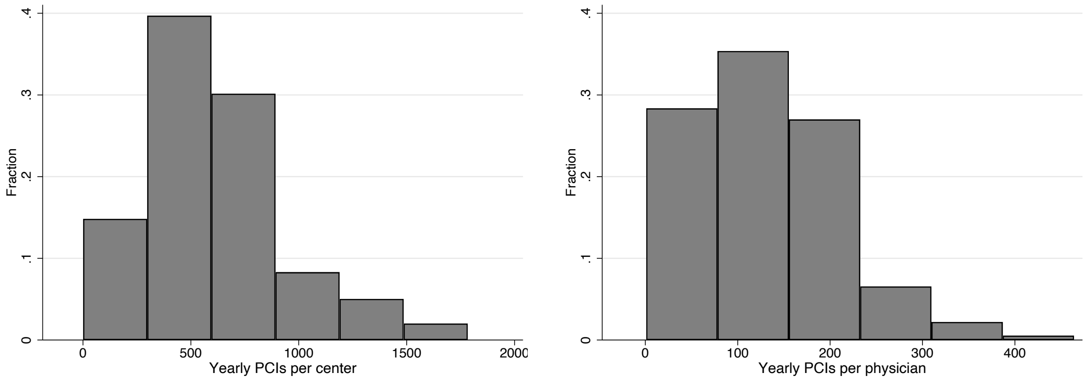
Table and Figures

Figure 1: Operator experience vs. tenure in years.



Note: Operator experience is the cumulated number of previous PCIs and tenure is years since the first PCI.

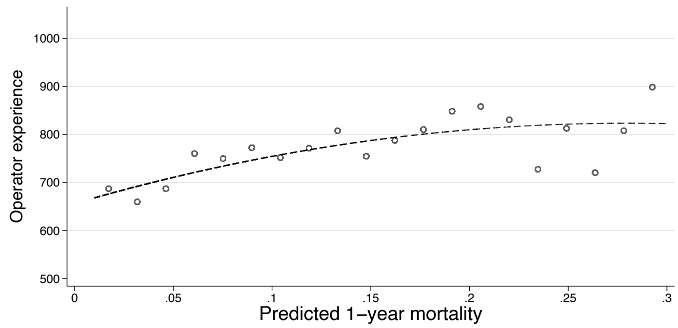
Figure 2: Histogram yearly number of PCIs per hospital and physician.



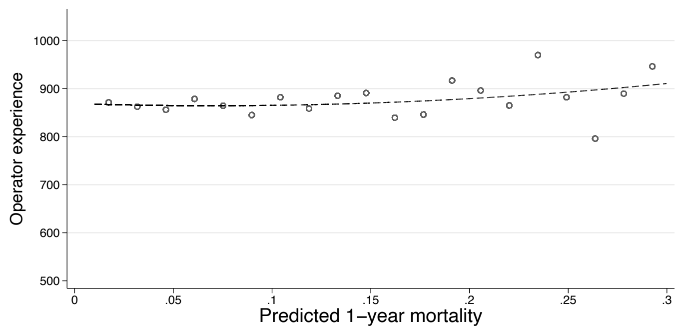
(a) Hospitals (b) Physicians

Note: Data for PCIs in Sweden 2004-2013.

Figure 3: Allocation of physicians during day-time hours and on-call time. Operator experience vs. predicted 1-year mortality



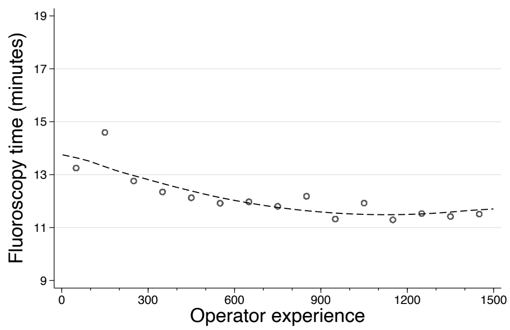
(a) Day-time hours



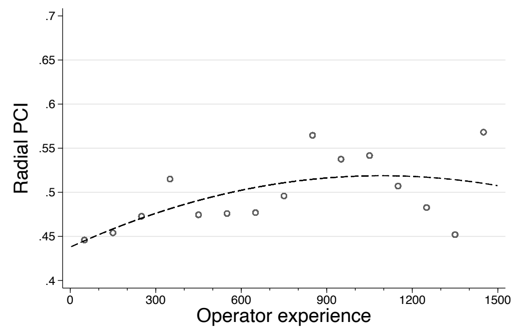
(b) On-call time

Note: PCIs in Sweden during 2004-2013. Mortality is predicted using the patient risk factors in Panels B–C of Table 1. Dots are averages in bins after adjusting for hospital and time fixed effects (year, month, weekday). The lines are fitted quadratic regression lines. Experience is the number of previous PCIs.

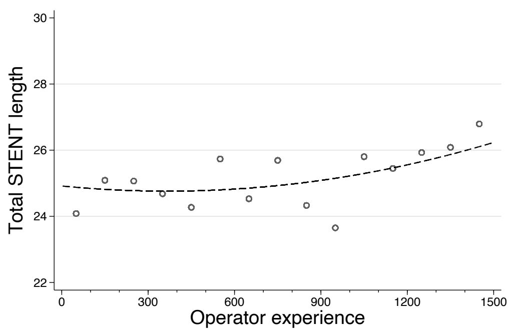
Figure 4: Physician experience, proficiency, decision making and patient health.



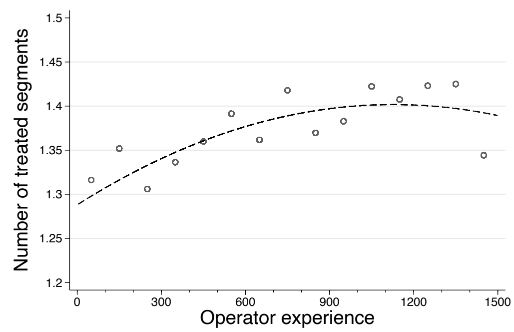
(a) Proficiency: Fluoroscopy time



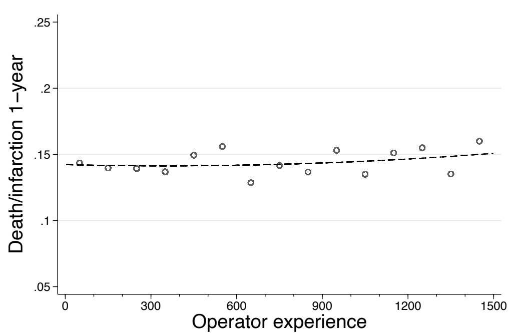
(b) Proficiency: Radial technique



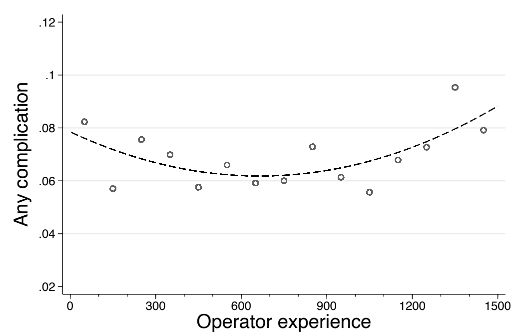
(c) Invasiveness: Total stent length



(d) Invasiveness: Treated segments



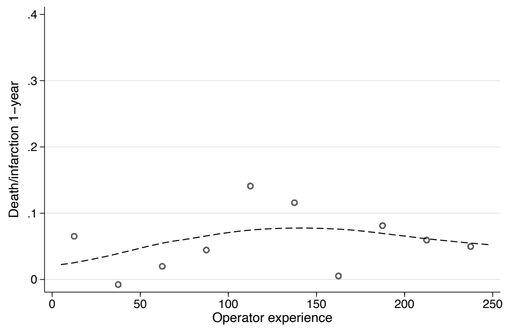
(e) Patient health: Mortality/Infarction



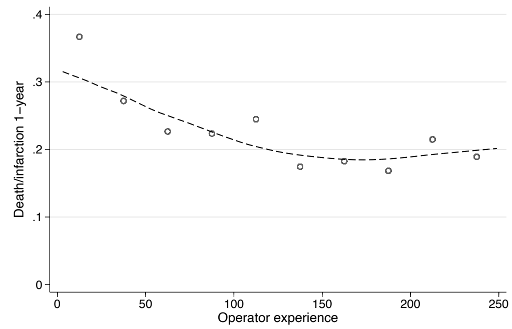
(f) Patient health: Complications

Note: STEMI PCIs in Sweden during 2004-2013. Outcome variables defined in Section 3. Dots are averages in bins adjusted for hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Lines are fitted quadratic regression lines.

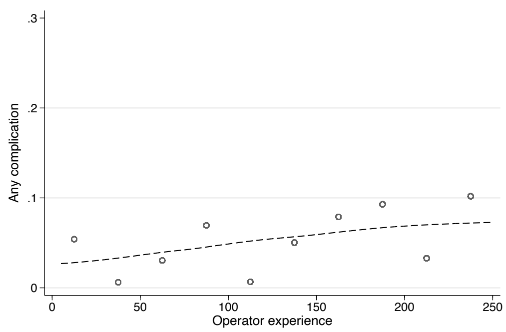
Figure 5: Low level of experience, patient health and patient risk.



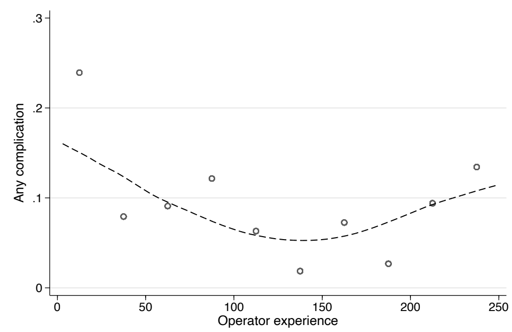
(a) Mortality/Infarction: Low risk group



(b) Mortality/Infarction: High risk group



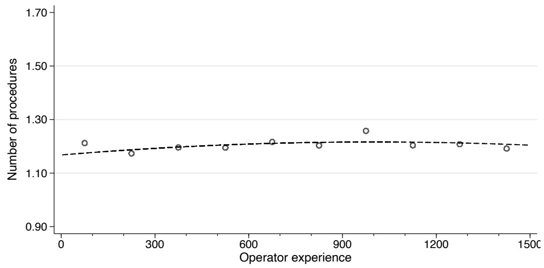
(c) Any complication: Low risk group



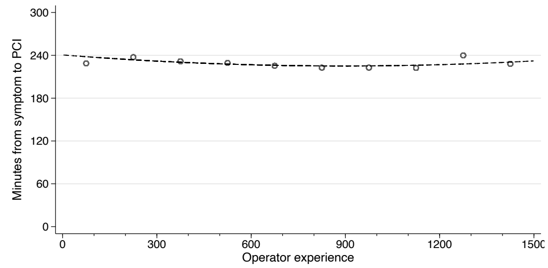
(d) Any complication: High risk group

Note: STEMI PCIs in Sweden during 2004-2013. In a-b the outcome is mortality or infarction within 1-year and in c-d an indicator of any complication arising during the PCI. Dots are averages in bins, adjusted for hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Lines are fitted local polynomial regression lines.

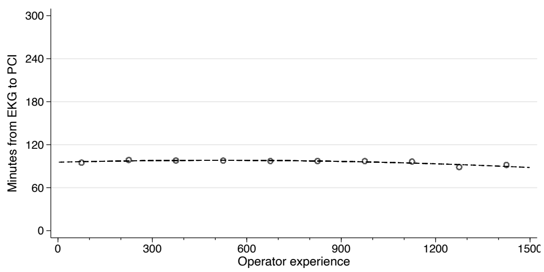
Figure 6: Operator experience, number of procedures per on-call shift and treatment response times



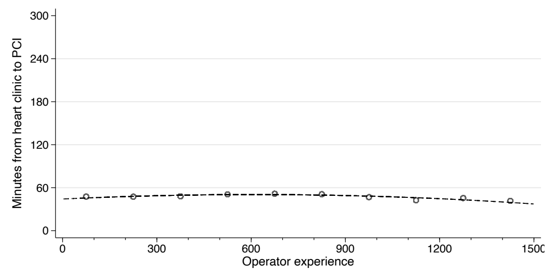
(a) Number of PCIs per work-shift



(b) Time from symptom to PCI



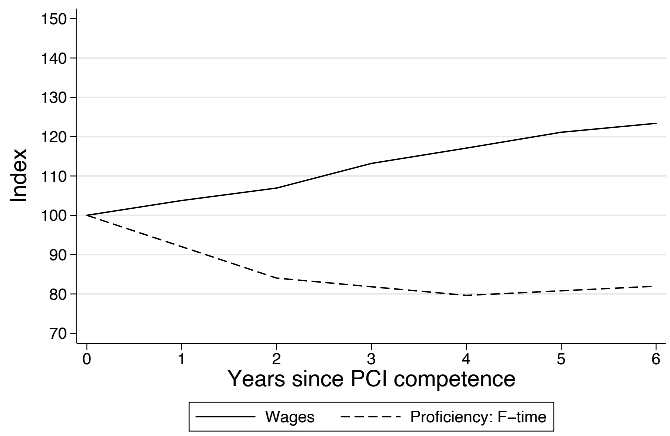
(c) Time from ECG to PCI



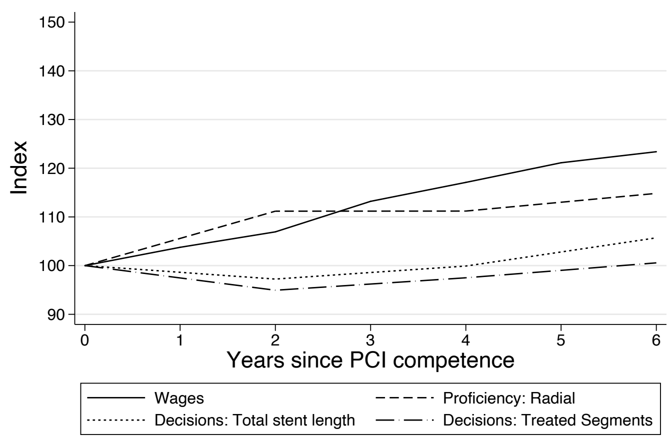
(d) Time from admission to PCI

Note: STEMI PCIs in Sweden during 2004-2013. Dots are averages in bins adjusted for hospital and time (year, month, weekday) fixed effects. The line are quadratic regression lines. Response times are in minutes and measure time to the PCI starts from: (b) the first recorded symptom PCI starts, (c) from the first ECG (hospital or ambulance), (d) from time of admission to the hospital.

Figure 7: Experience-wages-performance profiles for the physicians



(a) Proficiency: Fluoroscopy time



(b) Other measures

Note: Indexed tenure-wage profiles based on yearly wage rates from Statistics Sweden (see Section 7). The patient outcomes are indexed monthly averages by tenure in months, adjusting for hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1.

Table 1: Descriptive statistics for the analyses samples

	All PCIs		STEMI heart attacks	
	All	On-call time	All	On-call time
	(1)	(2)	(3)	(4)
	Panel A: Number of procedures			
# Patients	82,559	12,914	16,419	8,565
# Physicians	110	105	109	98
# Centers	28	28	28	24
	Panel B: Pre-PCI patient characteristics			
Male patient	72.7	72.0	72.2	71.9
Age -59	25.4	29.5	27.9	29.9
Age 60-69	32.8	30.5	30.0	30.2
Age 70-79	29.1	24.8	25.2	23.8
Age 80+	12.7	15.2	16.8	16.1
Smoker	54.0	53.4	51.1	52.7
BMI over 25	77.2	76.7	77.1	77.4
Diabetes	20.0	15.6	13.8	13.7
Insulin treated diabetes	8.8	6.8	5.7	5.6
Hypertension	74.2	75.5	79.9	74.4
Lipid lowering medicine	75.9	69.5	70.5	65.3
Previous heart attack	54.0	50.6	51.6	47.1
Previous CABG	10.5	6.8	4.8	4.9
Previous PCI	28.2	16.3	12.6	11.9
	Panel C: Angiographic findings			
Normal atheromatous	4.6	2.1	1.1	1.2
1-vessel disease	45.2	46.2	48.4	48.0
2-vessel disease	28.1	28.5	28.2	28.5
3-vessel disease	16.9	18.2	17.4	17.6
Main stem vessel disease	4.8	4.8	4.6	4.5
	Panel D: Type of heart disease			
STEMI heart attack	19.9	66.3	100.0	100.0
NSTEMI heart attack	35.7	23.3	0.0	0.0
Stabile angina	26.5	0.6	0.0	0.0
Unstable angina	13.6	6.8	0.0	0.0
Other	4.3	2.9	0.0	0.0
	Panel E: Outcomes			
Proficiency: Fluoroscopy time (minutes)	15.0	13.1	12.8	12.4
Proficiency: Radial technique	0.47	0.49	0.40	0.46
Invasiveness: Total stent length (mm)	22.9	24.4	24.5	24.6
Invasiveness: Treated segments	1.47	1.40	1.35	1.36
Patient health: Mortality/Infarction (1-year)	0.09	0.14	0.14	0.14
Patient health: Complications	0.06	0.07	0.07	0.07

Notes: PCIs in Sweden during 2004–2013. Variables in Panels A-C in percent. Fluoroscopy time in minutes. Complications is an indicator for any complication.

Table 2: Allocation of physicians during day-time hours and on-call time. Operator experience and predicted 1-year mortality

	Dependent variable: Physician experience		
	Day-time hours		On-call time
	All	STEMI	STEMI
	(1)	(2)	(3)
Predicted mortality rate	166***	151**	28.8
	(44.5)	(67.3)	(46.2)
Mean experience:	548.5	546.9	632.1
Mean predicted-mortality:	0.044	0.100	0.093
Observations	69,662	12,160	8,565
R2	0.32	0.39	0.31

Notes: PCIs in Sweden during 2004-2013. Experience is the number of previous PCIs. Mortality is predicted using the patient risk factors in Panels B–C of Table 1. (1) Includes all PCIs. (2) STEMI PCIs. (3) Restricts the sample to STEMI PCIs during on-call time. All models include hospital and time fixed effects (year, month, weekday). Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 3: Estimates for proficiency, decision-making and patient health

	Proficiency			Decision making		Patient health	
	Fluoroscopy time (minutes)	Radial technique	Mishaps	Total stent length	Treated segments	Mortality or Infarction	Any complication
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Experience 251–500	-1.52**	0.044	-0.057**	-0.0090	0.020	0.0067	-0.011
	(0.68)	(0.027)	(0.023)	(0.74)	(0.021)	(0.011)	(0.0089)
Experience 501–1000	-2.31***	0.053	-0.084***	0.53	0.081**	0.0051	-0.011
	(0.66)	(0.033)	(0.021)	(0.72)	(0.033)	(0.013)	(0.012)
Experience 1000+	-3.01***	0.042	-0.11***	1.82	0.11*	0.0067	-0.0031
	(0.73)	(0.029)	(0.023)	(1.22)	(0.056)	(0.011)	(0.015)
Observations	8,193	8,565	8,193	8,565	8,565	8,565	8,565
Mean:	14.2	0.32	0.22	23.7	1.33	0.14	0.078

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Experience is the number of previous PCIs. Outcome variables defined in Section 3. A mishap is defined as fluoroscopy time greater than 1.5 times the expected time (see Section 5.1). The bottow row shows mean outcomes for the omitted reference category (1–250 cases). All models include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 4: Learning, decision-making and multi-vessel diseases

	Treated segments			Multi-vessel PCI		
	All	Single-vessel disease	Multi-vessel disease	All	Single-vessel disease	Multi-vessel disease
	(1)	(2)	(3)	(4)	(5)	(6)
Experience 251–500	0.020	-0.012	0.048*	0.011	-0.0031	0.022
	(0.021)	(0.023)	(0.027)	(0.0079)	(0.0044)	(0.014)
Experience 501–1000	0.081**	0.025	0.13***	0.018**	-0.0032	0.036*
	(0.033)	(0.032)	(0.044)	(0.0085)	(0.0046)	(0.017)
Experience 1000+	0.11*	0.042	0.17**	0.027*	-0.0046	0.054*
	(0.056)	(0.049)	(0.071)	(0.013)	(0.0051)	(0.026)
Observations	8,565	4,220	4,345	8,565	4,220	4,345
Mean:	1.33	1.25	1.39	0.059	0.011	0.097

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Outcome variables defined in Section 3. The bottom row shows mean outcomes for the omitted reference category (1–250 cases). All models include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 5: Learning and decisions making measured by invasiveness and responsiveness

	Treated segments (1)	Total stent length (2)
Aggressiveness		
Experience 251–500	0.017	-0.36
	(0.021)	(0.65)
Experience 501–1000	0.079**	0.16
	(0.033)	(0.57)
Experience 1000+	0.11*	1.15
	(0.056)	(1.04)
Responsiveness		
f(x)*Experience 251–500	0.25*	0.21
	(0.13)	(0.22)
f(x)*Experience 501–1000	0.45***	0.27
	(0.15)	(0.20)
f(x)*Experience 1000+	0.51**	0.22
	(0.21)	(0.25)
Observations	8,565	8,558
Mean:	1.33	0.059

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Experience is the number of previous PCIs, and f(x) is the predicted total stent length and number of treated segments, respectively. The predictions are based on the risk factors in Table 1 and mean-adjusted. Outcome variables defined in Section 3. The bottom row shows mean outcomes for the omitted reference category (1–250 cases). All models include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 6: Robustness analyses.

	Main	Time of the day	Time since last on-call shift	Physician FE	Physicians who continue	Physician attributes	No patient risk factors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Proficiency, Fluoroscopy time							
Experience 251–500	-1.52**	-1.53**	-1.48**	-1.66**	-1.48	-1.76**	-1.58**
	(0.68)	(0.68)	(0.69)	(0.72)	(0.97)	(0.83)	(0.71)
Experience 501–1000	-2.31***	-2.32***	-2.26***	-2.13***	-2.34	-2.61**	-2.43***
	(0.66)	(0.66)	(0.67)	(0.68)	(1.47)	(1.00)	(0.66)
Experience 1000+	-3.01***	-3.01***	-2.95***	-2.53***	-2.87	-3.46**	-2.99***
	(0.73)	(0.75)	(0.74)	(0.68)	(2.24)	(1.24)	(0.81)
Panel B: Invasiveness, Treated segments							
Experience 251–500	0.020	0.019	0.020	0.023	0.052	0.0015	0.013
	(0.021)	(0.026)	(0.021)	(0.022)	(0.032)	(0.023)	(0.021)
Experience 501–1000	0.081**	0.082**	0.081**	0.035	0.038	0.026	0.073**
	(0.033)	(0.036)	(0.033)	(0.034)	(0.061)	(0.062)	(0.032)
Experience 1000+	0.11*	0.12*	0.11*	0.046	0.065	0.028	0.11*
	(0.056)	(0.058)	(0.056)	(0.071)	(0.10)	(0.10)	(0.055)
Panel C: Patient health, Mortality/Infarction							
Experience 251–500	0.0067	0.014	0.0060	0.020**	0.019	0.0083	0.0082
	(0.011)	(0.014)	(0.011)	(0.0094)	(0.016)	(0.0095)	(0.015)
Experience 501–1000	0.0051	0.0083	0.0044	0.027	0.015	0.010	0.0059
	(0.013)	(0.015)	(0.013)	(0.016)	(0.020)	(0.019)	(0.013)
Experience 1000+	0.0067	0.0075	0.0058	0.036	0.027	0.014	0.013
	(0.011)	(0.012)	(0.011)	(0.030)	(0.017)	(0.020)	(0.014)

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Outcome variables defined in Section 3. Experience is the number of previous PCIs. (1) Main specification. (2) Adjusts for hour of the day fixed effects. (3) Adjusts for days since last on-call time work-shift. (4) Adjusts for physician fixed effects. (5) Restricts the sample to physicians who are observed to perform 1000+ PCIs during the sampling period. (6) Adjusts for other observable physician attributes (gender, an indicator for having a physician degree outside Sweden and time (months) since the first PCI as proxy for age). (7) Excludes the patient risk factors included in the main specification. All models include hospital and time (year, month, weekday) fixed effects. (1)-(6) include the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

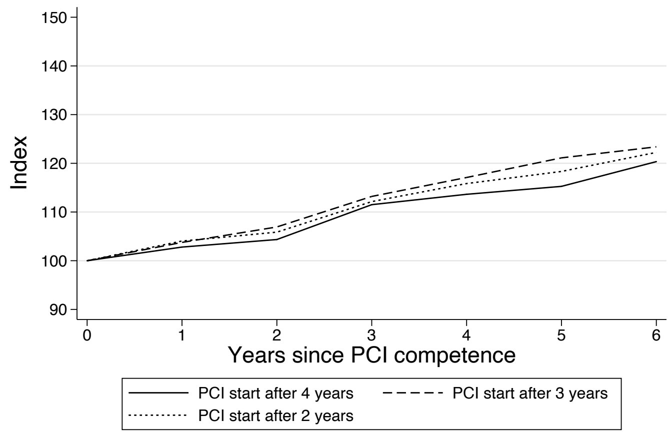
Table 7: Learning mechanisms: different experience, different environment and forgetting

	Proficiency: Fluoroscopy time				*Invasiveness: Treated segments*			
	High-risk-case exp.	Shifts w. 1000+ exp. physician	Shifts w. 2000+ exp. physician	Learning and forgetting	STEMI exp.	Shifts w. 1000+ exp. physician	Shifts w. 2000+ exp. physician	Learning and forgetting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience 251–500	-1.52**	-1.47**	-1.51**	-1.14**	0.017	0.017	0.018	0.022
	(0.73)	(0.69)	(0.71)	(0.53)	(0.021)	(0.021)	(0.021)	(0.021)
Experience 501–1000	-2.19***	-2.28***	-2.34***	-1.76***	0.079**	0.073**	0.075**	0.081**
	(0.70)	(0.57)	(0.64)	(0.50)	(0.033)	(0.032)	(0.031)	(0.032)
Experience 1000+	-2.75**	-2.35***	-3.29***	-2.33***	0.13**	0.13**	0.13**	0.14**
	(1.20)	(0.65)	(0.97)	(0.60)	(0.062)	(0.055)	(0.049)	(0.053)
High-risk-case-experience 251–500	-0.68				-0.0091			
	(0.54)				(0.032)			
High-risk-case-experience 500+	-2.44**				0.090			
	(0.89)				(0.13)			
Experience w. 1000+ physician 251–500		-1.50**				0.017		
		(0.62)				(0.041)		
Experience w. 1000+ physician 500+		-2.99***				-0.016		
		(0.93)				(0.055)		
Experience w. 2000+ physician 251–500			-2.05***				-0.035	
			(0.51)				(0.054)	
Experience w. 2000+ physician 500+			-4.67***				-0.078**	
			(0.63)				(0.028)	
Experience last year 100–250				-0.53				-0.016
				(0.52)				(0.017)
Experience last year 250+				-2.57***				-0.019
				(0.83)				(0.030)

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Outcome variables defined in Section 3. Experience is the number of previous PCIs. Besides total experience (1) and (5) examine experience from high-risk PCIs, (2-3) and (6-7) experience from PCIs during work-shifts with a physician with 1000+ or 2000+ PCI experience, and (4) and (8) experience in the last year before the current PCI. All models also include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Appendix: Additional figures and tables

Figure A-1: Robustness analyses on the wage profiles of the physicians



Note: Indexed wage profiles based on yearly wage rates from Statistics Sweden (see Section 7). Robustness analyses measuring wages from 2, 3 and 4 years after completed specialist training (ST).

Table A-1: Operator experience and patient health before the PCI

	Predicted 1-year mortality	Predicted 1-year mortality/infarction	Previous infarction	Previous PCI
	(1)	(2)	(3)	(4)
Experience 251–500	-0.0014	-0.0021	0.051	-0.015
	(0.0045)	(0.0056)	(0.098)	(0.024)
Experience 501–1000	-0.0033	-0.0041	0.075	-0.012
	(0.0050)	(0.0053)	(0.12)	(0.018)
Experience 1000+	0.0011	0.0017	0.13	-0.0033
	(0.0068)	(0.0075)	(0.18)	(0.015)
Observations	8,565	8,565	8,565	8,565
Mean:	0.087	0.14	0.49	0.13

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Experience is the number of previous PCIs. Predicted 1-year mortality and predicted 1-year mortality/infarction are predicted using the patient risk factors in Panels B–C of Table 1. Previous infarction and previous PCI are indicators for these previous health conditions. The bottow row shows mean outcomes for the omitted reference category (1–250 cases). All models include hospital and time fixed effects (year, month, weekday). Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-2: Power law specification for experience

	log(Fluoroscopy time) (1)	log(Treated segments) (2)
log(experience)	-0.11***	0.025**
	(0.018)	(0.012)
Observations	8,193	8,558

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Experience is the number of previous PCIs. Outcome variables defined in Section 3. All models include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C in Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-3: Estimates of log physician experience on patient health (mortality or infarction).

	Mortality/Infarction		Any Complication	
	Exp. < 250	Exp. < 100	Exp. < 250	Exp. < 100
	(1)	(2)		
Log(experience)	-0.019	-0.072**	0.0061	-0.0031
	(0.012)	(0.029)	(0.020)	(0.028)
Observations	1,178	284	1,178	284

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Operators with experience < 100. In columns 1-2 the outcome is mortality or infarction within 1-year and in columns 3-4 an indicator of any complication arising during the PCI. All models include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C in Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-4: Operator experience, number of procedures per on-call shift and treatment response times (in hours)

	Number of PCIs per work-shift	Time from symptom to PCI	Time from EKG to PCI	Time from admission to PCI
	(1)	(2)	(3)	(4)
Experience 251–500	0.0038	-13.6	-12.8	-14.5
	(0.019)	(19.9)	(17.0)	(20.4)
Experience 501–1000	0.029	-28.6	-31.9**	-24.8
	(0.019)	(20.2)	(15.0)	(16.8)
Experience 1000+	0.032	-17.8	-22.3	-29.3
	(0.027)	(26.3)	(20.6)	(24.1)
Observations	6,742	7,346	7,467	6,833
Mean:	1.21	352.4	149.0	100.4

Notes: STEMI PCIs in Sweden during 2004-2013. Response times are in minutes and measure time to the PCI starts from: (2) the first recorded symptom PCI starts, (3) from the first ECG (hospital or ambulance), (4) from time of admission to the hospital. The bottow row shows mean outcomes for the omitted reference category (1–250 cases). Adjusted for hospital and time (year, month, weekday) fixed effects. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-5: Robustness analyses other variables

	Main (1)	Time of the day (2)	Time since last on-call shift (3)	Physician FE (4)	Physicians who continue (5)	Physician attributes (6)	No patient risk factors (7)
			Proficiency: Radial technique				
Experience 251–500	0.044	0.046	0.043	0.040	0.052	0.060*	0.044
	(0.027)	(0.030)	(0.026)	(0.027)	(0.058)	(0.034)	(0.028)
Experience 501–1000	0.053	0.055*	0.052	0.059	0.054	0.081	0.054
	(0.033)	(0.031)	(0.032)	(0.041)	(0.084)	(0.053)	(0.035)
Experience 1000+	0.042	0.039	0.040	0.026	0.074	0.078	0.040
	(0.029)	(0.027)	(0.029)	(0.059)	(0.085)	(0.059)	(0.031)
			Invasiveness: Total stent length				
Experience 251–500	-0.0090	0.011	0.0043	0.54	1.10	-0.21	-0.18
	(0.74)	(0.81)	(0.74)	(1.01)	(0.76)	(0.59)	(0.71)
Experience 501–1000	0.53	0.56	0.54	1.33	0.56	-0.013	0.37
	(0.72)	(0.76)	(0.70)	(1.24)	(1.32)	(0.95)	(0.67)
Experience 1000+	1.82	1.81	1.84	2.47	1.30	0.91	1.76
	(1.22)	(1.25)	(1.21)	(1.63)	(2.02)	(1.80)	(1.20)
			Patient health: Any complication				
Experience 251–500	-0.011	-0.0053	-0.011	-0.018**	-0.010	-0.0098	-0.011
	(0.0089)	(0.0092)	(0.0088)	(0.0086)	(0.018)	(0.0099)	(0.0093)
Experience 501–1000	-0.011	-0.0094	-0.011	-0.028***	0.0027	-0.0094	-0.012
	(0.012)	(0.012)	(0.012)	(0.0071)	(0.019)	(0.017)	(0.012)
Experience 1000+	-0.0031	0.0013	-0.0032	-0.031***	0.019	-0.0012	-0.0027
	(0.015)	(0.015)	(0.015)	(0.0082)	(0.026)	(0.022)	(0.015)

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Outcome variables defined in Section 3. Experience is the number of previous PCIs. (1) Main specification. (2) Adjusts for hour of the day fixed effects. (3) Adjusts for days since last on-call time work-shift. (4) Adjusts for physician fixed effects. (5) Restricts the sample to physicians who are observed to perform 1000+ PCIs during the sampling period. (6) Adjusts for other observable physician attributes (gender, an indicator for having a physician degree outside Sweden and time (months) since the first PCI as proxy for age). (7) Excludes the patient risk factors included in the main specification. All models include hospital and time (year, month, weekday) fixed effects. (1)-(6) include the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-6: Early performance and later career (number of PCIs)

	Dependent variable: Later number of PCIs	
	(1)	(2)
Early mortality/infarction rate	-242.4	
	(499.1)	
Early fluoroscopy time		-5.2
		(4.12)

Notes: Early mortality/infarction rate and early fluoroscopy time are defined as the average rates in years 1–2 of the career. Later number of PCIs is the number of PCIs performed during years 3–4 of the career. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-7: Learning mechanisms 1: different experience, different environment and forgetting

	Proficiency: Radial technique				*Invasiveness: Total stent length*			
	High-risk-case exp.	Shifts w. 1000+ exp. physician	Shifts w. 2000+ exp. physician	Learning and forgetting	STEMI exp.	Shifts w. 1000+ exp. physician	Shifts w. 2000+ exp. physician	Learning and forgetting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience 251–500	0.045	0.042	0.046	0.025	-0.073	-0.072	-0.030	-0.27
	(0.030)	(0.029)	(0.029)	(0.029)	(0.73)	(0.75)	(0.73)	(0.68)
Experience 501–1000	0.056	0.052	0.061	0.041	0.61	0.42	0.49	0.18
	(0.042)	(0.038)	(0.038)	(0.037)	(0.74)	(0.74)	(0.64)	(0.63)
Experience 1000+	0.044	0.054	0.060**	0.025	2.56*	1.78	2.55*	2.05
	(0.042)	(0.047)	(0.025)	(0.036)	(1.35)	(1.36)	(1.39)	(1.34)
STEMI-experience 251–500	0.023				-0.53			
	(0.023)				(0.49)			
STEMI-experience 500+	-0.059				2.95			
	(0.081)				(3.86)			
Experience w. 1000+ physician 251–500		0.046				1.19		
		(0.051)				(1.09)		
Experience w. 1000+ physician 500+		-0.088				1.82		
		(0.11)				(1.52)		
Experience w. 2000+ physician 251–500			-0.18**				-2.56**	
			(0.075)				(1.16)	
Experience w. 2000+ physician 500+			-0.43***				1.45	
			(0.076)				(1.09)	
Experience last year 100–250				0.077				0.36
				(0.051)				(0.44)
Experience last year 250+				0.076				1.02
				(0.054)				(0.82)

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Outcome variables defined in Section 3. Experience is the number of previous PCIs. Besides total experience (1) and (5) examine experience from high-risk PCIs, (2-3) and (6-7) experience from PCIs during work-shifts with a physician with 1000+ or 2000+ PCI experience, and (4) and (8) experience in the last year before the current PCI. All models also include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A-8: Learning mechanisms 2: different experience, different environment and forgetting

	Health: Mortality or infarction				*Health: Any complication*			
	High-risk-case exp.	Shifts w. 1000+ exp. physician	Shifts w. 2000+ exp. physician	Learning and forgetting	STEMI exp.	Shifts w. 1000+ exp. physician	Shifts w. 2000+ exp. physician	Learning and forgetting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience 251–500	0.0085	0.0082	0.0083	0.0061	-0.073	-0.072	-0.030	-0.27
	(0.014)	(0.015)	(0.014)	(0.017)	(0.73)	(0.75)	(0.73)	(0.68)
Experience 501–1000	0.011	0.0074	0.0077	0.0052	0.61	0.42	0.49	0.18
	(0.014)	(0.014)	(0.014)	(0.016)	(0.74)	(0.74)	(0.64)	(0.63)
Experience 1000+	0.026**	0.011	0.012	0.0080	2.56*	1.78	2.55*	2.05
	(0.012)	(0.015)	(0.013)	(0.018)	(1.35)	(1.36)	(1.39)	(1.34)
High-risk-case-experience 251–500	-0.017				-0.53			
	(0.012)				(0.49)			
High-risk-case-experience 500+	-0.061**				2.95			
	(0.024)				(3.86)			
Experience w. 1000+ physician 251–500		0.0015				1.19		
		(0.015)				(1.09)		
Experience w. 1000+ physician 500+		-0.0019				1.82		
		(0.016)				(1.52)		
Experience w. 2000+ physician 251–500			-0.0094				-2.56**	
			(0.013)				(1.16)	
Experience w. 2000+ physician 500+			-0.0021				1.45	
			(0.032)				(1.09)	
Experience last year 100–250				0.0060				0.36
				(0.0099)				(0.44)
Experience last year 250+				0.0089				1.02
				(0.014)				(0.82)

Notes: STEMI PCIs during on-call time, Sweden, 2004-2013. Outcome variables defined in Section 3. Experience is the number of previous PCIs. Besides total experience (1) and (5) examine experience from high-risk PCIs, (2-3) and (6-7) experience from PCIs during work-shifts with a physician with 1000+ or 2000+ PCI experience, and (4) and (8) experience in the last year before the current PCI. All models also include hospital and time (year, month, weekday) fixed effects, and the patient risk factors in Panels B–C of Table 1. Standard errors are clustered at the hospital level. *, ** and *** denote significance at the 10, 5 and 1 percent levels.