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Daniel Avdic,[*] Maryna Ivets,[†] Bo Lagerqvist,[‡] and Ieva Sriubaite[§]

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Abstract

We study the extent to which physician treatment styles are determined by their practice environment and whether such decisions affect the quality of care received by patients. Using rich data on all coronary angioplasty procedures in Sweden 2004–2013, our empirical approach compares stent choices of interventional cardiologists moving across hospitals to patient outcomes over time. To disentangle changes in practice styles attributable to physical (provider) and social (peer group) factors, we exploit quasi-random variation on physicians working on the same day in the same hospital. Our findings suggest that (i) moving cardiologists' stent choices rapidly adapt to their new practice environment after relocation; (ii) practice style changes are equally driven by the physical and social environments; and (iii) rates of decision errors, treatment costs and adverse clinical events among treated patients remain largely unchanged despite the altered practice styles.

Keywords: *Practice Style, Environment, Peers, Quality of Care*

JEL classification: *C23, D61, D91, I11, I18, O33*

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1 Introduction

It is well known that traditional demand factors, such as patient preferences and needs, are by and large unable to explain the substantial geographic variations in healthcare utilization observed in many countries (see, e.g., Wennberg and Gittelsohn, 1973; Skinner, 2011; Skinner *et al.*, 2011; Chandra *et al.*, 2012; Finkelstein *et al.*, 2016).[1] Furthermore, it is unclear whether areas with higher-than-average healthcare spending per capita perform better than lower-spending areas with respect to quality of care to legitimate such discrepancies (McClellan and Newhouse, 1997; Baicker and Chandra, 2004). These observations serve to fuel long-standing questions on the extent of resource waste and cost-efficiency in healthcare delivery (see, e.g., Wennberg *et al.*, 2002; Fisher *et al.*, 2003a,b; Doyle *et al.*, 2015, 2017; Shrank *et al.*, 2019).

The lack of explanatory power by demand factors in decomposing geographic variations in healthcare use has led some researchers to shift focus to the supply side and the behavior of healthcare providers. A small but growing literature has sought to understand the causes of variation in physician practice styles and their consequences for patients (see, e.g., Grytten and Sørensen, 2003; Epstein and Nicholson, 2009; Skinner and Staiger, 2015; Currie *et al.*, 2016; Molitor, 2018; Cutler *et al.*, 2019; Chandra and Staiger, 2020; Currie and MacLeod, 2020).[2] Understanding why variations in physician treatment behavior exist and how they impact healthcare delivery are important steps to design effective policies that seek to reduce inappropriate variations in healthcare use (OECD, 2014).

This paper seeks to add to the literature on the determinants of provider practice styles by studying how physicians' treatment choices are influenced by their practice environment and the consequences these choices have for their patients' welfare. To this end, we make two major contributions that so

[1] For studies based on non-US data, see Phelps (2000); Prieto and Lago-Peñas (2012); Reich *et al.* (2012); Bojke *et al.* (2013); Corallo *et al.* (2014); Kopetsch and Schmitz (2014); Moura *et al.* (2019); Godøy and Huitfeldt (2020). Salm and Wübker (2020) provide an exception to this rule, showing that the vast majority of variation in ambulatory care use stems from demand factors which they argue is due to supply-side constraints.

[2] Chandra *et al.* (2012) provide an overview of different explanations for why provider treatment decisions may vary across similar patients. Such reasons include (i) "defensive medicine", where providers perform unnecessary procedures to avoid complaints, bad reputation and possible lawsuits from patients; (ii) financial incentives associated with fee-for-service reimbursement models (McClellan, 2011); and (iii) unobserved heterogeneity across providers (Doyle *et al.*, 2010).

far have been largely overlooked in the literature. First, we propose a method to decompose the environmental effect into a physical and a social component, corresponding to a hospital-specific and a peer group-specific component. As we argue further below, this is an important distinction to make since the two components provide very different implications for policy. In addition, by relating data on physicians' treatment choices to optimal management and to associated patient outcomes, we are able to gauge and directly measure the impact of environmentally induced variation in physician treatment behavior on changes in the appropriateness, treatment costs and quality of care received by patients. This is in contrast to most existing studies on physician practice styles, which mainly rely on quantity, rather than quality, measures to evaluate the consequences of physician choices.

To provide an empirical framework for the identification and consistent estimation of causal effects, we apply and extend the physician migration approach used by Molitor (2018) in the important context of stent choice in coronary angioplasty. We identify physicians who move (migrate) across hospitals and relate variation in the rate of use of a specific stent type between the physician's pre-move (origin) and post-move (destination) hospitals to changes in the physician's own stent use across time in a difference-in-differences model. To estimate the model, we use rich administrative data from the Swedish Coronary Angiography and Angioplasty Register (SCAAR) on all percutaneous coronary interventions (PCI) performed in Sweden between 2004 and 2013 and study how interventional cardiologists' choices between the bare-metal stent (BMS) and the drug-eluting stent (DES) are determined by their environment. Since the procedure is identically executed irrespective of the type of stent used, this context provides an essentially ideal setting to study how the practice environment shapes physician treatment preferences.

While empirical evidence on the extent to which physician practice styles are influenced by their work environment is informative, it does not per se convey much detail on *which* environmental factors are the drivers of such changes. Yet, such knowledge could be important. For example, physical, or provider-specific, factors may be less informative about the malleability of physicians' underlying preferences if the possibility to operate in line with such preferences is restricted by factors beyond the individual physician's control, such as resource constraints or hospital-specific guidelines. In contrast, social, or peer group-specific, factors are more directly related to the adjustment

of physician beliefs for which much of the economic literature on physician practice styles lies at the heart of (see, e.g., Epstein and Nicholson, 2009).

To address this important question, we propose and implement a method to decompose the combined impact of the environment on physician treatment styles into a provider-specific and a peer group-specific factor by exploiting quasi-random variation on physicians working together on given days. Specifically, given sufficient practice style variation among migrating physicians' coworkers (peers) *within* a hospital, the inclusion of hospital fixed effects in our econometric model will effectively purge all time-invariant provider-specific variation in practice styles *across* hospitals from the analysis. Any remaining practice variation will consequently be derived from changes in the migrating physicians' coworker mix. Thus, resulting estimates of the environmental effect with and without hospital fixed effects gauge the relative magnitude of the adjustment in physician practice style arising from provider- and peer group-specific factors, respectively.

One potential concern with our decomposition approach is that migrating physicians are non-randomly matched with their peers after their move. Such matching would introduce bias in our estimated parameters if migrants exert some control over whom they are working with and use this control to choose coworkers with matching preferences. While this is unlikely to occur in practice, and would lead our estimates to be a lower bound on the true effect if it did, we nevertheless evaluate the robustness of our results to such endogeneity concerns by replacing our measure of practice environment with a *synthetic* environment. Based on the synthetic control method (see, e.g., Abadie and Gardeazabal, 2003; Abadie *et al.*, 2010, 2015), we construct an artificial matched comparison group using the sample of non-migrating cardiologists in our data. This method safeguards against estimation bias by comparing practice styles of migrating cardiologists with non-migrating cardiologists who were exposed to similar peer practice environments prior to the relocation. Reassuringly, we find that our estimates are largely robust to the definition of practice environment.

Our estimation results show that Swedish cardiologists' use of DES in angioplasty treatments are strongly determined by the practice style of the hospital they currently work in. Migrating cardiologists rapidly adapt to their prevailing practice environment after relocation by changing their DES use with on average half a percentage point for each percentage point difference in

DES utilization rates between the origin and destination hospitals. This result is robust to a set of alternative specifications and close to the corresponding estimate found by Molitor (2018). Furthermore, when decomposing the overall effect into a provider-specific and a peer group-specific effect, we find that each component is responsible for roughly half of the practice style adjustment. To assess the extent of heterogeneity in response across cardiologists, we also provide results from a series of split-sample regressions which reveal that our results are mainly driven by younger migrants who move to more innovative hospitals.

In contrast, we find no empirical evidence to support the hypothesis that environmentally induced changes in migrating physicians' practice styles had important consequences for the quality of care received by patients. In addition to analyzing a set of adverse clinical events related to the medical procedure, we employ a machine learning algorithm to classify appropriate stent choices for each case based on out-of-sample predictions from teaching hospitals and a rich set of patient characteristics. While our analyses do not reveal important systematic impacts on patient health as a result of changes in their physician's practice environment, we do find that migrating physicians are somewhat more likely to incorrectly apply DES after their move. This result suggests that the environmentally induced changes in physicians' practice behavior are mainly based on marginal "gray-zone" cases who run little risk of serious adverse medical events as a consequence of such choices. Moreover, a back-of-the-envelope calculation of the potential monetary savings from following the most efficient treatment approach suggests that the average migrating cardiologist incurred an additional cost of USD 1,200 per year from inappropriate stent choices, corresponding to roughly one-sixth of the price of a PCI.

Our findings contribute to the scant literature on peer effects and social learning in healthcare. Social learning is broadly defined as the process of information transmission between economic agents when they observe and interact with each other within their social networks (see, e.g., Lin *et al.*, 1981). In line with our results, Huesch (2011) finds evidence for intragroup spillovers in the use of DES, suggesting that physicians are influenced by their peers. Furthermore, Nair *et al.* (2010) study peer effects in prescribing choices of physicians and find that such behavior is particularly influenced by research-active peers within physician groups. Heijmans *et al.* (2017) find similar re-

sults studying peer effects in cardiovascular risk management in networks with and without opinion leaders. On the other hand, Yang *et al.* (2014) document only small peer effects in prescription behavior for new drugs among physicians working in the same hospital at the same time. Epstein and Nicholson (2009) find that physician's treatment styles are responsive to changes in treatment styles of other physicians in the same hospital region in the context of Cesarean sections, but the effect dampens when accounting for common shocks at the hospital level. This is in line with our finding that both providers and peers are influential in altering practice styles of physicians. Finally, Burke *et al.* (2003) find that patients are more likely to receive certain procedures if an attending physician is in a group that performs these procedures more frequently, and Yuan *et al.* (2020) show that shared beliefs are crucial for successful implementation of new health technology within a peer network. Complementing these findings, the results from our split-sample analyses show that our effects are mainly driven by younger cardiologists moving to more DES-intensive practice environments.

We also add contextual depth to the more general economic literature on peer effects. A number of papers have investigated the influence of peers on academic performance, yielding mixed results. While some authors find significant peer effects (Sacerdote, 2001; Zimmerman, 2003), others find no effects at all (Foster, 2006; Lyle, 2007), or effects only for particular subgroups (Stinebrickner and Stinebrickner, 2006). In contrast, there exists strong evidence for positive social spillovers on task-oriented work behavior and productivity in non-academic settings. Mas and Moretti (2009) study peer effects at the workplace by analyzing the productivity of coworkers within the same team. They find evidence of positive productivity spillovers when working with highly productive peers, especially when they interact more frequently. Moreover, in an experimental setting, Falk and Ichino (2006) study individuals working on separate tasks within the sight of one another, finding that the productivity of workers is influenced by the productivity of their peers. These results motivate our approach to use physicians working on the same days as relevant peers in the analysis. Finally, Bandiera *et al.* (2010) study whether workers' behaviors are affected by the presence of peers that they are socially tied to, with the main finding that a given worker's productivity is positively correlated with the ability of a worker's personal friends.

Lastly, our results have broad implications for healthcare system efficiency.

The fact that physicians' treatment behaviors are influenced not only by their physical but also by their social environment suggests a rationale for why specific practice styles cluster in certain areas. While such clustering may generate positive productivity and learning spillovers as in Chandra and Staiger (2007), it also implies that patients may receive suboptimal care depending on the prevailing practice style at the admitting healthcare provider. In particular in supply-sensitive areas of healthcare, where the frequency of use of a given activity is related to its local capacity, and where the choice of healthcare provider is subject to restrictions, such as place of residence, this may lead to substantial allocation inefficiencies. If the quality of provided care is largely insensitive to such variations, as this paper shows in the context of cardiac catheterizations, a more integrated system where inappropriate practice variation can be mitigated through enhanced care coordination, monitoring, and follow-up based on evidence-based clinical guidelines could be vastly resource-saving (Wennberg, 2010). However, broadly defined uniform guidelines may not be the most efficient way to reduce inappropriate healthcare variations when patient populations are clinically diverse. Specifically, Chan *et al.* (2019) show that decisions in diagnosing pneumonia vary substantially across physicians with different skill levels, and that less skilled physicians are more likely to choose lower thresholds to reduce the risk of failing to correctly diagnose a patient with pneumonia. Similarly, we find that younger and less experienced migrating physicians are more likely to inappropriately apply DES after their move. These findings suggest that investments in training to increase physician skill may be a cost-efficient alternative to national guidelines to reduce unwarranted resource use.

The paper proceeds as follows. Section 2 gives an overview of the Swedish healthcare system and the clinical context. Section 3 outlines our empirical framework. Section 4 describes the data, sample and variables we use in our analysis. Section 5 presents our estimation results. Section 6 concludes.

2 Institutional Setting

The empirical analyses in this paper are based on inpatient medical records on all percutaneous coronary interventions performed in Sweden between 2004 and 2013. In this section, we first provide relevant background information on

the Swedish healthcare system. This is followed by a brief description of the general treatment of coronary heart disease and the specific medical procedure we study.

2.1 Healthcare in Sweden[3]

Healthcare in Sweden is mainly funded by direct income taxes raised by the three different levels of government: central, regional (21 county councils) and local (290 municipalities). Responsibilities for health and medical care are shared between the governments according to a scheme stipulated in the Swedish Health and Medical Service Act from 1982. Within each government tier, principals (i.e., elected politicians and bureaucrats) have substantial discretion in designing the system in their area of administration subject to a few general principles, such as that all citizens are entitled to accessible and high-quality healthcare services based on their individual needs. Both county councils and municipality executive boards are political bodies that consist of representatives elected by residents every four years coinciding with the national election.

The main responsibilities of the central government are to set goals for national health policy, coordinate and provide advice to health and medical care providers and to regulate prices and approval of new medical services and products. Municipalities are mainly responsible for organizing long-term care for the elderly in their home or in aged care facilities and to accommodate the needs of residents with physical or psychological disabilities. Finally, the county councils are the main providers and financiers of healthcare in Sweden being responsible for primary and specialized healthcare on both the in- and outpatient basis in their respective geographical area. Since the end of the 1990's, both municipality and county healthcare boards are allowed to contract out services to private providers in purchaser-provider split models. While the outsourcing of healthcare services to private agents have become increasingly commonplace within the primary, outpatient and long-term care sectors over time, virtually all inpatient care is still operated by public providers.

The vast majority of healthcare spending in Sweden is paid for by county and municipal-level direct income taxes raised from area residents. Contri-

[3] www.kliniskastudier.se/english/sweden-research-country/swedish-healthcare-system.html provides a concise summary of the main features of the Swedish healthcare system in English.

butions from the central government are relatively small and mainly consist of provider pay-for-performance incentive schemes and redistribution between regions. Each county council sets its own patient fees, although there is a national limit for the amount a patient has to pay out of pocket (approximately USD 130 per annum as of 2020). Consequently, patient fees only account for around three percent of total spending on healthcare. Both employed and unemployed Swedish citizens are also covered by a national statutory sickness and disability insurance, replacing up to eighty percent of lost earnings and financed through employer social contributions. This insurance can be further topped up for employees covered by collective agreements or complementary private insurance schemes. Hence, virtually all Swedish citizens have strong financial protection from both direct healthcare costs as well as indirect income losses from temporary and permanent work disabilities.

One important feature of the Swedish inpatient healthcare system that is relevant for our empirical strategy is that recipients of healthcare are constrained in their choices of hospital service provider and treating physician. Specifically, each hospital is responsible for providing care to all residents within a geographical catchment area. This means that place of residence determines which hospital a patient will be admitted to when seeking care. Furthermore, hospitals are not obliged to accommodate patient requests for a specific treating physician. As a general rule, a patient will be assigned to an on-duty physician on the day of admission. This implies that patients are quasi-randomly allocated to physicians and that selection bias arising from endogenous patient-physician sorting is unlikely to be a concern in our setting.

2.2 Treatment of coronary heart disease

Coronary arteries supply oxygen and blood to the heart. When cholesterol and other fatty plaque build up inside these arteries, the wall of the blood vessel thickens, narrowing the channel within the artery and reduces blood flow to the heart. This process, called atherosclerosis, starves the heart muscle of oxygen and may cause heart tissue damage, known as Myocardial Infarction (MI) or, more commonly, a heart attack. Worldwide, about 15.9 million myocardial infarctions occurred in 2015 (Vos *et al.*, 2016).

Coronary heart disease is generally treated by interventional cardiologists using a catheter-based treatment method called percutaneous coronary inter-

vention (PCI), or coronary angioplasty.[4] In a PCI, the cardiologist first inserts a catheter through either the femoral or radial artery, which is subsequently transported to the site of the blockage using a guide wire. Once the obstructed area is reached, a tiny balloon attached to the catheter is inflated, compressing the atherosclerotic plaque against the artery wall and thereby restoring blood flow. To keep the artery open at the site of the blockage after balloon dilation, the cardiologist may also place and leave a stent (an expandable small metal mesh tube) in the artery to reinforce the blood vessel's wall and prevent it from reoccluding.

Prior to invasive treatment, a diagnostic technique, angiography, is used to determine the size, severity and location of the suspected artery blockage(s). To this end, a catheter is guided into one of the major coronary arteries to inject a contrast dye into the blood passing through the heart. The diagnosing physician, the *angiographer*, can then determine the locations with restricted blood flow from a series of images (angiograms) taken by an X-ray machine. Sometimes, when considered suitable by the responsible physician, the angiography is directly followed by a PCI in the same treatment session, a procedure known as *ad-hoc* PCI.

2.3 Bare-Metal and Drug-Eluting Stents

Two main types of stents are associated with performing a PCI: Bare-Metal Stents (BMS), commonly referred to as first-generation stents, and the newer Drug-Eluting Stents (DES), first approved in Europe in 2002. The principal difference between the BMS and the DES is that the latter is coated with a drug that reduces the incidence of restenosis, the medical term for the gradual re-narrowing of a coronary artery after a blockage has been treated with angioplasty. Because the process of compressing, or "crushing", the atherosclerotic plaque often causes trauma to the artery wall, the body will attempt to heal itself by repairing the tissue damage caused by the intervention by proliferation of endothelial cells (a layer on the surface of blood vessels). Restenosis occurs from excessive tissue growth as a consequence of such healing processes, which reoccludes the blood vessel at the site of the stent. In contrast to the BMS, the DES was developed to counteract reocclusion of the artery by being

[4]PCI began as percutaneous transluminal coronary angioplasty (PTCA), a term still found in the literature. It now encompasses balloons, stents, and other modifications to the catheter tip, including devices that cut out plaque to open narrowed arteries.

coated with drugs that inhibit cell proliferation, thus significantly reducing the risk of restenosis.

Although the DES represents a major medical advance for angioplasty over the BMS, it has also been associated with the more severe side effect of stent thrombosis (ST); the formation of blood clots in the blood vessels caused by the stent itself.[5] As the drugs coated on the DES inhibit the body's natural healing process (i.e., the formation of an endothelial layer), they simultaneously expose the body to an increased risk of thrombus formation (blood clots). Thus, the DES has been linked with an increased risk of ST occurring up to several years after the initial intervention. So-called Dual Anti-Platelet Therapy (DAPT), most commonly involving acetylsalicylic acid (aspirin) and clopidogrel, is considered crucial to reduce the risk of ST. Early cessation of these drugs after angioplasty using DES significantly increases the risk of both ST and MI.

The above discussion suggests that the choice between a BMS and a DES when performing angioplasty is not trivial. Although clearer guidelines exist today as to which type of stent should be used in each case, this choice belonged to the "gray zone" of medical decision-making, where guidance from clinical evidence is inadequate in providing clear indications for use, during the time period we study in this paper. In addition, the choice between a BMS and a DES does not involve significant differences in other categories of use, such as prices[6] (e.g., costs of equipment necessary for the procedure), mode of treatment (e.g., minimally invasive versus highly invasive), or physical attributes of the clinician (e.g., visual acuity or motor skills). This context provides us with a close to ideal setting for studying how physician preferences for treatments vary with their environment, since observed choices are likely

[5]While this is true for the first generation of DES (Taxus and Cypher), the second generation DES has been associated with significantly less ST than its predecessor (Chitkara and Gershlick, 2010). However, the latter stent type only began gaining popularity at the end of our analysis period.

[6]See, e.g., Ekman *et al.* (2006) who estimate that the expected one-year cost of a PCI with a Taxus DES in 2004 amounted to SEK 72,000 (USD 8,500) versus SEK 67,000 (USD 7,900) for a BMS. In 2014, the corresponding figures were SEK 67,000 and SEK 65,000, respectively (SBU, 2014). Both direct and indirect (i.e., repeat revascularization) treatment costs are included as Swedish hospitals are typically paid prospectively on a capitation basis with global budgets. This contrasts, for example, with much larger cost differences in the US (see, e.g., Karaca-Mandic *et al.*, 2017). In addition, we can rule out large incentives for adoption from lobbying by the medical device industry as this is much more muted in the Swedish centralized healthcare system compared to more market-based systems.

to be mainly a function of the physician's personal preferences with respect to the relative efficacy of each treatment option.

3 Econometric framework

In this section we describe our empirical approach for quantifying the effect of the environment on physician treatment styles in the context of the choice of stent type in angioplasty treatments. We first define how we measure physician exposure to their practice environment and how the overall environment can be partitioned into a provider-specific and a peer group-specific component. Next, we describe our empirical model from which physician responses to a change in their practice environment can be identified and estimated using empirical variation from cardiologists moving across hospitals.

3.1 Definition of physician practice environment

The practice environment a physician is exposed to is a latent variable, meaning that it exists but is not directly quantifiable. A challenge is therefore to define a variable that captures the relevant features of the practice environment for our purposes. Following the methodology taken in Molitor (2018) and adapted to our setting, we characterize cardiologist $j \in J$'s practice environment in hospital $h \in H$, where patient $i \in N_{ht}$ received a PCI in time period $t \in T$, as the ratio

$$E_{jht} = \frac{\sum_{i \in N_{kht}} \mathbb{1}(DES_i = 1)}{N_{kht}} \quad \forall\, k \neq j \in J, \tag{1}$$

where $N_{kht} \subset N_{ht}$ is the subset of patients *not* treated by cardiologist j. Hence, E_{jht} is j's exposure to the practice environment with respect to the rate of DES use among eligible patients in hospital h and time t. Next, we define the *difference* in practice environments between a migrating cardiologist's origin (h_{O_j}) and destination (h_{D_j}) hospital at a given point in time as

$$\Delta_{jt} = E_{jh_{D_j}t} - E_{jh_{O_j}t}. \tag{2}$$

In other words, Δ_{jt} is the period-specific difference in DES leave-out shares between the hospital that cardiologist j practiced in before and after reloca-

tion, respectively. Note that this setup provides an intuitive framework for defining counterfactual treatment states of migrating physicians that we will use to motivate our empirical approach below.

Equations (1) and (2) constitute the basic framework for quantifying physicians' exposure to their practice environment over time and across hospitals. We now extend this framework by partitioning the overall practice environment into two separate dimensions: a physical (provider-specific) and a social (peer group-specific) component, respectively. Conceptually, we can think of a physician's practice environment as a combination of physical (e.g., hospital infrastructure, technology, assets and resources) and social (e.g., peers, physician networks and coworkers) factors. The former component may be less relevant from a behavioral point of view, since physician responses to the availability of physical resources are not directly related to his or her preferences for a particular treatment.[7] On the other hand, social interactions may be highly influential in forming and developing physician preferences for treatments and beliefs in their efficacy. Studying the net as well as the relative impact of these components in their capacity to alter physician practice styles is therefore important; theoretically, in terms of understanding the anatomy of physician decision-making; and in practice, to provide a basis for policy to enhance the effectiveness of healthcare delivery.

To empirically disentangle provider- and peer group-specific components in physician practice environment, we postulate that cardiologists who are working in the same hospital on the same day form a relevant peer group from which we can draw inference.[8] Formally, let

$$P_{k_j ht} = \frac{\sum_{i \in N_{k_j ht}} \mathbb{1}(DES_i = 1)}{N_{k_j ht}} \quad \forall\, k_j \neq j \in K_j \tag{3}$$

be the average DES share used by cardiologist j's *peers* k_j in hospital h and period t. Cardiologist j's peers are defined as all other K_j cardiologists who performed PCI on patients in the same hospital and at the same point in time

[7]This is not to say that the provider-specific environment does not include *any* preference-related factors, such as, for example, hospital management cultures. The argument here is that such factors are assumed to be fixed within the specific provider in contrast to social factors that vary on the individual physician level.

[8]This definition makes intuitive sense, as individuals who work together are able to observe and directly influence each other. It is also supported by the economic literature on peer effects in the workplace (see, e.g., Falk and Ichino, 2006; Mas and Moretti, 2009).

as physician j. We use this within-hospital variation to define and estimate physician j's *peer exposure* in time period t by the relation

$$E^P_{jht} = \sum_{k_j \in K_j} \sum_{d_t \in D_t} \mathbb{1}(d_{t_j} = 1, d_{t_{k_j}} = 1) \times P_{k_j ht}, \tag{4}$$

where $d_t \in D_t$ is the specific calendar date *within* period t, and d_{t_j} and $d_{t_{k_j}}$ are indicator variables for whether physicians j and k_j were both treating patients on day d_t. In other words, E^P_{jht} is a weighted average of the overall practice environment of hospital h in time period t, with weights defined by the correspondence between cardiologist j and each of his or her peers with respect to the days they both performed PCI on admitted patients. Note that giving all K_j peers the same weight in Equation (3) would return E_{jht} from Equation (1).

The difference in peer practice environment between a migrating cardiologist's origin and destination hospitals, Δ^P_{jt}, is correspondingly defined by replacing E with E^P in Equation (2). The counterfactual practice environment (i.e., the environment in the hospital cardiologist j is not currently working in) is simply defined as the potential peer exposure derived from all cardiologists who worked in the counterfactual hospital over that period,

$$\Delta^P_{jt} = E^P_{jh_{D_j}t} - E^P_{jh_{O_j}t}. \tag{5}$$

The total variation in the hospital's practice environment is equal to the sum of the within- and the between-components, implying that we can decompose physician j's overall practice environment as

$$E_{jht} = E^P_{jht} + E^H_{ht}, \tag{6}$$

where E^H_{ht} is equal to the provider-specific component, varying only across hospitals and time, and E^P_{jht} as the peer group-specific component, varying across cardiologists within hospitals over time. It follows that the total change in a migrating physician's practice environment can be decomposed as

$$\Delta_{jt} = \Delta^P_{jt} + \Delta^H_{jt}. \tag{7}$$

That is, the total impact of the change in environment of a migrating cardi-

ologist at a given point in time consists of a physician-specific and a hospital-specific effect. Our approach to empirically disentangle these two effects is described in the following subsection.

3.2 Empirical model

The point of departure for our empirical modeling is based on the method in Molitor (2018) who uses longitudinal administrative data on cardiologists moving across hospitals to obtain empirical variation in physician practice environment. This variation is used to estimate causal effects of changes in the migrating physicians' practice environment on their own treatment choices in a difference-in-differences (DD) empirical design. The idea is simple yet intuitive: if physicians' practice styles are malleable to the environment they operate in, then we would expect to observe patients managed by migrating physicians to receive treatments more aligned with the practice environment in the destination hospital after, but not prior to, their relocation.

Formally, the patient-level DD model for patient $i \in N$, treated by cardiologist $j \in J$ at time $t \in T$ can be described by the equation

$$y_{ijt} = \alpha Post_t + \beta \Delta_{jt} + \gamma(\Delta_{jt} \times Post_t) + X'_{ijt}\Gamma + \lambda_j + \lambda_t + \epsilon_{ijt}. \tag{8}$$

The outcome y_{ijt} is defined by a dummy indicator variable equal to one if a patient undergoing PCI received a DES, and equal to zero if a BMS was used. Moreover, $Post_t = \mathbb{1}_{t \geq t_0}$ is a dummy variable which equals one for all time periods subsequent to cardiologist j's move to a new hospital at time t_0. The model also includes controls for cardiologist, λ_j, and time, λ_t, cluster-specific effects (i.e., $\sum_z \theta_z \mathbb{1}_{\lambda_{z'=z}}$ for $z = j, t$) and a vector of potentially time-varying observable patient and cardiologist characteristics, X_{ijt}, to adjust for observed and unobserved heterogeneity across patients, physicians and time. Finally, Δ_{jt}, defined in Equation (7), is a continuous variable with range $[-1, 1]$, characterized as the difference in physician j's practice environment between the *origin* (pre-migration) and *destination* (post-migration) hospitals with respect to the share of DES used in patients undergoing PCI at time t.

The main parameter of interest in Equation (8) is γ, which, under standard identifying assumptions of the DD estimator, captures the average physician response in their DES use to the difference in practice environments between

the origin and destination hospitals after, relative to before, their relocation. Defining practice environment as the hospital's risk-adjusted share of DES used on patients undergoing PCI, γ can be interpreted as the percentage change in physician j's *own* DES practice style for each percentage point difference in practice style *environment*. We refer to Equation (8) as our baseline model in order to provide a link to and compare the results in Molitor (2018) to our decomposition approach described below.

To study the dynamic pattern of the migrating cardiologists' responses to their practice environment and test the common trend assumption, we extend our baseline model in Equation (8) by replacing $Post_t$ with a set of period-specific indicators

$$y_{ijt} = \beta\Delta_{jt} + \sum_{s=-T'}^{T'} \mathbb{1}(s = t')\left(\alpha_{t'} + \gamma_{t'}\Delta_{jt'}\right) + X_{ijt}\Gamma + \lambda_j + \lambda_t + \epsilon_{ijt}, \tag{9}$$

where $t' = t - t_0 \in (-T', T')$ is the period-specific index recentered around the time of the cardiologist's move, t_0. This modification allows us to interpret the average period-specific cardiologist responses by time from their move on a common time index that can be plotted in an event-study fashion.

3.3 Effect decomposition and quality of care

Our approach to identify physician responses to their practice environment relies on empirical variation derived from cardiologists moving across hospitals at different points in time. Whenever this happens, we maintain that they are exposed to a combined shift in practice environment arising from two sources: a provider-specific, Δ^H_{jt}, and a peer group-specific, Δ^P_{jt}, component, as defined in Equation (7). To empirically disentangle these two effects, we make use of the fact that the former component is assumed to be constant within a hospital provider. Therefore, the additional inclusion of hospital-specific effects, λ_h, in Equations (8) and (9) will effectively purge the practice environment of the hospital-specific component and any remaining variation will hence be attributed to the peer effect, Δ^P_{jt}. Thus, we estimate Equations (8) and (9) with and without hospital fixed effects for our sample of movers and attribute the estimated γ without hospital fixed effects as the net impact of the practice environment. In contrast, the estimated effect with hospital fixed effects will be attributed to the peer group-specific effect component.

Finally, the relative difference between these two effects as a share of the net effect is interpreted as the provider-specific effect.[9]

So far our model framework has focused on changes in the practice styles of cardiologists induced by their practice environment. However, we are also interested in knowing whether any environmentally induced behavioral changes of physicians translate into changes in the quality of care received by patients who were treated by the migrating cardiologists. In particular, knowing *how* these behavioral changes affect the appropriateness of the treatment and patient health outcomes would provide useful information on whether and to which extent physician adaptation to their practice environment improved or worsened quality of healthcare services. To this end, we consider two additional sets of outcomes within our regression framework: physician decision errors and patient health outcomes. The latter category is based on a composite measure of relevant post-intervention adverse clinical events, including death, myocardial infarction and restenosis, requiring a new intervention. The former outcome category is based on defining a measure of stent appropriateness using an auxiliary sample from which we employ a classification exercise based on machine learning techniques. We defer the details of this approach to the next section.

4 Data

We use data from the Swedish Coronary Angiography and Angioplasty Registry (SCAAR) for our empirical analyses.[10] Since 1998, SCAAR registers cardiac catheterization procedures performed in Swedish hospitals, including detailed clinical information on patient health status and comorbidities (e.g.,

[9]It is possible that the hospital fixed effects do not capture the full range of dynamics in cardiologist responses since the estimated average response may conceal significant heterogeneity across migrants. Therefore, in Section 5.3 we also estimate split-sample models to study heterogeneity in cardiologist response by direction of the move (to more or less DES intensive hospitals) and by cardiologist experience (age in years).

[10]SCAAR is maintained by the Uppsala Clinical Research Center (UCR), sponsored by the Swedish Health Authorities and independent of commercial funding. Reporting in the SCAAR is Internet-based. The data are recorded online through a Web interface in the cardiac catheter laboratory, encrypted and sent to the UCR central server. Each hospital receives a feedback on the processes and quality of care measures. To monitor and maintain quality, a continuous screening process of the registry data is in place, operating by comparing 50 entered variables in 20 randomly selected interventions per hospital-year with the patients' hospital records. The overall correspondence in data during the study period is 95.2%.

diabetes mellitus, smoking status and BMI), angiography diagnostic results (e.g., location and severity of blockage by coronary artery segment) and relevant treatment outcomes (e.g., complications and adverse clinical events such as myocardial infarction or death). Importantly, the register also includes information on the treating hospital and responsible physician, performed procedure(s) and the time and dates of intervention, hospital admission and discharge.

4.1 Analysis sample

We initially sample all instances of PCI performed in Swedish hospitals and reported in SCAAR between 2004 and 2013.[11] To clearly identify our main outcome variable, the cardiologist's choice between using a DES and a BMS in the procedure, we drop patients who received multiple stents in the same treatment session from the sample. This restriction leaves us with a total of 51,381 PCI cases performed by 199 cardiologists in 28 hospitals.

The data include daily information on each cardiologist's angioplasty treatments and the hospital the activity takes place in. We use this information to define physician practice episodes by indicating the first and the last date a cardiologist practiced in a particular hospital. This method defines an origin and a destination hospital and a specific time-stamp for when the move took place. As a few cardiologists may occationally practice in several hospitals, we classify physician practice episodes to hospitals where the cardiologist continuously treated patients over a period of at least six months.[12] With these restrictions we identify 51 migrating cardiologists treating 8,589 patients across 25 hospitals over the analysis period. Remaining cardiologists, who were based at the same hospital throughout the analysis period, are referred to as non-migrating cardiologists.

Columns (1) and (2) of Table 1 present means and standard deviations for our analysis sample of migrating cardiologists while columns (3) and (4) present corresponding figures for non-migrating physicians for comparison.

[11] We restrict the starting year of our analysis to 2004 as this is the first year all hospital in Sweden that performed PCI contributed to the registry. The endpoint is chosen because the market for stents included additional options from 2013 onward due to the entry of a new second-generation DES and the corresponding sharp decline in the use of the BMS.

[12] We exclude a few cases where a cardiologist continuously practices in several hospitals over an extended time period (e.g., Karolinska hospital in Solna and Huddinge in Stockholm county and Lund and Malmö hospital in Skåne county).

The upper, middle and lower panels of the table partition this information into hospital-, cardiologist- and patient-specific characteristics, respectively. With respect to hospital characteristics, we observe no major differences across the two groups other than that non-moving cardiologists seem to work in moderately larger hospitals in terms of annual case volume. With respect to the characteristics of the cardiologists themselves, migrants tend to be somewhat younger and more likely to have a specialization in cardiology (in contrast to, e.g., radiology or surgery). Patient case-mix is remarkably similar in all aspects across the groups on average, although migrating cardiologists appear to be somewhat less prone to use DES. However, there are no differences in terms of patient health outcomes between migrants and non-migrants.

[Table 1 about here]

4.2 Decision errors and patient health outcomes

To study the impact of migrating cardiologists' changes in practice environment on quality of care, we replace our main outcome variable from Equations (8) and (9) with two sets of outcomes proxying for the appropriateness of the chosen treatment and for any adverse patient health consequence of such choices. We first define a dummy indicator variable for whether the treatment decision was the appropriate choice based on a risk-adjusted measure of treatment suitability and classified using an machine learning method for classification. To this end, we employ the Random Forest (RF) algorithm which has been demonstrated to have improved prediction accuracy in comparison with other supervised learning methods (Breiman, 2001; Svetnik *et al.*, 2003).[13]

We assess the appropriateness of cardiologists' stent choices by relating actual physician choices to predicted "gold standard" choices derived from the RF algorithm using auxiliary data based on angioplasty procedures performed

[13]RF is a supervised machine learning method for classification based on the construction of decision trees. The computational steps of the RF algorithm are illustrated in Figure A.1 of Appendix A. A decision tree splits the data into a set of subsamples defined by a classification rule represented by a tree branch. Each branch could either lead to another subtree or have a leaf/terminal node with an assigned class. The most frequently classified outcome among all individual decision trees performed defines the terminal prediction (class) of the RF. Application of this data splitting method can be further pruned by setting constraints on model parameters to boost the accuracy on the out-of-sample predictions and stability of the tree.

in Swedish teaching hospitals with no migrating cardiologists in 2011–2012.[14] We predict the appropriate stent choice for each case in our analysis sample and define a dummy variable for overall error, equal to one whenever the observed choice does not match the predicted choice irrespective of the choice of stent. Figure 1 shows the distribution of predicted probabilities (left panel) and respective error rates (right panel).

[Figure 1 about here]

We furthermore decompose the overall decision error into Type I and Type II errors under the null hypothesis that the BMS is the appropriate treatment choice. To this end, a Type I error (i.e., a false positive) pertains to incorrectly inserting a DES when a BMS is suitable and a Type II error (i.e., a false negative) is defined by inserting a BMS when a DES was the correct option. This decomposition may provide additional insights into the consequences of inappropriate treatment choices since incorrect use of the DES potentially put patients at risk of more severe adverse events, such as ST, and higher treatment costs, since the DES is more expensive than the BMS (although the stent itself only constitutes a minor part of the total cost of treatment).[15] Table 2 presents a matrix of the cardiologists' treatment decisions in our sample and corresponding error rates.

[Table 2 about here]

Finally, we include a set of patient outcomes based on the prevalence of one-year post-intervention adverse clinical events, including patient death,

[14] The auxiliary data sample was randomly divided into two parts: a training sample that is used to fit the RF algorithm and a validation sample used to validate the performance. This resampling procedure is based on a 70:30% split. We grow 500 individual decision trees to improve the performance of the RF and achieve the best prediction accuracy in the validation sample. Each tree's terminal node has at least 15 observations, but the total number of terminal nodes in each tree does not exceed 200 nodes in total. Out of total 190 predictors, we randomly sampled 50 variables at each split. The tuning of all parameters is based on the performance evaluation on the validation sample. Figure A.2 of Appendix A presents the importance of variables used in prediction.

[15] Another interesting analysis suggested by David Molitor is to study whether the decision errors of a migrating cardiologist's peers impacts his or her own performance. This could be evaluated by simply replacing the environmental variable by the average decision error among peers in the origin and destination hospitals for each migrant and using the decision error dummy as outcome in the regression model. Unfortunately, while constructing this analysis we realized that the variation in decision errors across hospitals in Sweden is too small to provide reliable inference for answering this question empirically.

myocardial infarction (MI), and total leison revascularization (TLR) to our regression model. The bottom panel of Table 1 shows the rates of these events in our analysis sample.

4.3 Estimation of physician practice environment

Since both the absolute number and the case-mix of patients treated by cardiologists may vary substantially, we modify each cardiologist's use of DES using the Empirical Bayes (EB) method. To this end, we estimate a mixed-effects model with both fixed (risk-adjustment) and random (shrinking imprecise physician DES shares to the population mean) elements to correct for potentially biased estimates of the physicians' practice environment as well as any existing risk selection between cardiologists and their patients (see, e.g., Rabe-Hesketh and Skrondal, 2008).

The distribution of the EB-adjusted practice environment across all migrating cardiologists and periods in our sample is shown in the upper left panel of Figure 2. The variation is large, covering almost the full range of the variable, and slightly skewed to the left with a mean of 0.31. The corresponding distribution after regression adjustment for hospital fixed effects (i.e., the within-hospital variation) is visualized in the upper right panel of the same figure. There is substantial variation remaining even after the hospital-specific component has been eliminated from the environment, suggesting that including provider-specific effects is unlikely to generate problems of model overfitting.[16] The lower left and right panels of Figure 2 show corresponding distributions of Δ_{jt} with and without hospital-specific fixed effects, respectively. Interestingly, the change in practice environment among migrating cardiologists in our sample is symmetrically distributed across higher and lower shares of DES. Hence, our empirical approach is able to capture a wide range of treatment effects in both the positive and negative domains of changes in the physicians' practice environment.

[Figure 2 about here]

Figure 3 provides a graphical illustration of the intuition behind the identification approach we use in our empirical analysis. The solid lines indicate

[16] The distribution of the risk-adjusted DES rates across the 21 county councils in Sweden is displayed in Figure A.3 of Appendix A.

the average practice style environment, measured by the average quarterly share of DES used among migrating cardiologists' peers, by time from their relocation. To avoid canceling out positive and negative changes in the practice environment, physicians moving from more to less DES-intensive environments and from less to more DES-intensive environments are plotted in the left and right panels of the figure, respectively. Moreover, the dashed lines show the corresponding estimated *counterfactual* environment in the hospitals associated with the migrating cardiologists: the destination hospital, prior to the relocation, and the origin hospital, after the relocation took place. At any point in time, the vertical difference between the two lines is computationally equivalent to the average difference in physician practice environments, Δ_{jt}, averaged over all J migrating cardiologists.

The figure shows that there are significant jumps in the practice environment for both groups of migrating cardiologists at the time of relocation when the actual and the counterfactual environments are switched. The quarter of the move has been interpolated in the graph (and omitted from our analysis), since the cardiologist may treat patients in both the origin and destination hospitals during this period. The counterfactual environment can hence be interpreted as an estimate of the hypothetical environment that would have prevailed if the migrating physician would not have relocated. We can use this estimate to derive and evaluate the common trend assumption when estimating our DD model. In particular, if migrants react to the counterfactual environment prior to their move, we would conclude that our empirical approach is invalid. We study this in further detail in the next section.

[Figure 3 about here]

5 Results

This section reports results from estimation of the econometric models described in Section 3 using our analysis sample explained in Section 4. We first provide main results obtained from estimation of our DD model on migrating cardiologists' responses to a change in their practice environment with respect to their use of DES when performing PCI. Next, we investigate the extent to which these responses improved or worsened the appropriateness of physicians' treatment choices and whether they were associated with signifi-

cant changes in patient health outcomes and costs of treatment. Finally, we provide results from a set of robustness checks and heterogeneity analyses to evaluate the stability of our inference with respect to model specification and variable definitions.

5.1 Do physicians adapt to their practice environment?

Columns (1)–(4) of Table 3 report results from estimation of different models using our sample of migrating cardiologists. Column (1) provides corresponding coefficient estimates from the model used in Molitor (2018) to estimate the response of migrating cardiologists to changes in their practice environment. Our reported DD estimate of 0.72, interpreted as the average percentage point change in the physician's own practice style for each percentage point change in the practice environment between the origin and destination hospitals after relocation, is very close to the estimate of 0.67 found in Molitor (2018). Moreover, the coefficient of Δ_{jt}, interpreted as migrating physicians' average response to the destination hospital's practice environment *prior* to the move, is insignificant. This result supports our maintained common trend assumption that migrating cardiologists do not systematically change their own practice style in response to the destination hospital's practice environment before they relocate.

Next, Columns (2) and (3) show estimation results from our baseline DD model, defined in Equation (8), by successive inclusion of control variables. While the results from Column (2), in which only the control variables listed in Table 1 have been added, suggest a marginally significant response to Δ_{jt} prior to the move, this coefficient is once again insignificant after further adjustment for period-specific and cardiologist-specific effects in Column (3). The DD point estimates for these model specifications suggest a somewhat smaller physician response of between 0.49 and 0.52. In other words, about half of the migrating cardiologists' DES use can be attributed to their overall practice environment for our sample.

Finally, in Column (4) we decompose the overall effect from the change in practice environment by including hospital fixed effects in our regression model. Recall that migrating cardiologists face both a change in the provider-specific and the peer group-specific practice environment when they move across hospitals. Assuming that the provider-specific component is constant

within a hospital, whereas the peer group-specific component varies within hospitals, we include hospital fixed effects to eliminate the impact of the former from the practice environment variable. This adjustment reduces the DD estimate by another fifty percent to 0.25. We interpret this result as that the peer group-specific effect is responsible for roughly half of the response in physician practice style. This suggests that physicians' reactions to their practice environment embody both the characteristics of the hospital itself, such as infrastructure, management and resources, as well as the social environment, captured by the physicians' workplace peers.

[Table 3 about here]

The left and right panels of Figure 4 display estimation results from the event study model in Equation (9) without and with hospital fixed effects, corresponding to the specifications in Columns (3) and (4) of Table 3, respectively. Each dot in the figure refers to an estimated $\gamma_{t'}$ parameter and the associated vertical spikes indicate corresponding 95% confidence bands. The solid vertical line in each panel pertains to the specific recentered year-quarter of cardiologists' move from the origin to the destination hospital. The quarter of relocation is omitted from the analysis and replaced with the predicted value based on a cubic polynomial, indicated by the solid line, and estimated separately for quarters before and after the move. The predicted discontinuity at the quarter of move is reported in the panel header. To ensure sufficient number of leads and lags while simultaneously keeping the panel of migrating cardiologists balanced, we follow the migrating cardiologist for eight quarters before and after the move. As the estimated parameters are only identified up to scale, we use the quarter prior to the move normalized to zero as baseline.

The estimated parameters prior to the physician's relocation are not significantly distinguishable from zero (i.e., the baseline period), suggesting that migrating physicians did not systematically respond to the counterfactual practice environment prior to their move. Moreover, for the model without hospital fixed effects, there is a visible sharp discontinuity occurring at the time of cardiologist relocation where the estimated $\gamma_{t'}$ coefficients become positive and highly significant. The estimated magnitude of this discontinuity is around 0.51 and close to the one reported in Column (3) of Table 3. Interestingly, the cardiologists appear to rapidly and permanently adapt to the

prevailing practice style at the destination hospital for the entire duration of the follow-up period.

The corresponding period-specific effect pattern in the right figure panel, where hospital fixed effects have been added to the model, describes a smaller, but still pronounced, change in the moving cardiologist's behavior at the time of relocation. In this case, we observe a somewhat more gradual adaptation to the destination hospital's practice environment over time and that the initial discontinuity at the time of relocation is somewhat smaller. We conclude from this analysis that cardiologists in our sample are partially malleable to their practice environment in terms of their own practice behavior, and that they are responsive to both their social and their physical environments.

[Figure 4 about here]

5.2 Impact on quality of care

We next study the extent to which the environmentally induced changes in migrating cardiologists' DES use affected the appropriateness of physician treatment choice and their consequences for patients' health outcomes and the costs of treatment. To this end, we estimate versions of Equation (8) and Equation (9) by replacing our outcome variable with the three indicators for major adverse cardiac events we consider: patient death, myocardial infarction (MI), and total lesion revascularization (TLR) within a year from the initial intervention. Moreover, we compare changes in physicians' rates of decision errors before and after their relocation using predictions from the RF machine learning algorithm to predict optimal treatment choice. Based on the results from these analyses, we conclude by providing a back-of-the-envelope calculation of the excess costs incurred from the inappropriate use of stents as a consequence of the change in practice environment.

5.2.1 Decision errors

Table 4 reports DD estimation results using decision errors, based on the correspondence between migrating cardiologists' choices and predictions from our RF machine learning algorithm, as outcomes. Columns (1), (2) and (3) show the estimates on the overall propensity to make inappropriate decisions, and for Type I and Type II errors, respectively. Recall that Type I errors (false

positives) refer to the application of DES when BMS is the recommended treatment choice, and vice versa for Type II errors (false negatives). This distinction is relevant as it is possible that making errors of the former type may be subject to more severe risks for the patient due to the possibility of ST and higher medical expenses due to increased unit costs of DES. In contrast, the latter error type may be associated with higher total treatment costs in the form of a higher prevalence of restenosis and the consequential need for subsequent intervention.

The results from estimation show that the overall probability of making a treatment error is positive, although not significantly different after, relative to before, cardiologist relocation. Splitting the decision errors into Type I and Type II errors, we find that physicians are somewhat more likely to make Type I errors after their change in practice environment. In contrast, the risk of committing Type II errors is reduced, but not significantly so. Hence, this result suggests that migrating cardiologists are more likely to overuse DES when they move to a hospital with higher use of DES than they are to overuse BMS when moving to a hospital with lower DES use.

[Table 4 about here]

5.2.2 Patient health outcomes

Columns (2)-(4) of Table 5 report results from estimation of Equation (8) for the three adverse patient health outcomes we consider: patient death, myocardial infarction (MI), and total lesion revascularization (TLR) within a year from the initial intervention. For comparison, the first column of the table reproduces the results from our preferred specification in Column (4) of Table 3. Each column corresponds to a specific outcome for our model with hospital fixed effects, implying that the reported point estimates refer to physician responses to the change in their peer environment. As before, the reported parameter estimates are interpreted as the rate of change in the outcome from a one percentage point change in the physicians' practice environment between the origin and destination hospitals. A negative sign implies that the risk of the event is less likely, whereas a positive coefficient indicates a higher risk.

The reported parameter estimates suggest that rates of changes in patient outcomes are generally small and statistically indistinguishable from zero. The

point estimate of 0.04 for MI is greatest in magnitude, but is only one-sixth of the response for the choice of stent. We interpret this finding as indicating that patient health outcomes are not systematically related to migrating physicians' adaptation to their peer practice environment. One possible reason for this result could be that the estimated changes in the cardiologists' use of DES after relocation were mainly based on low-risk patients for which the choice between a BMS and a DES was unlikely to put patients at serious health risks.

[Table 5 about here]

Figure 5 illustrates the corresponding event study graphs based on Equation (9) and the outcomes from Table 5. The four panels in the figure, separated by patient outcome, provide a similar pattern as above with no indications of important changes in patient health outcomes at any point over the two years before or after cardiologists' relocation. These results show that the changes in treatment behavior induced by variation in the migrating cardiologists' peer practice environment did not affect the quality of care in terms of patient outcomes to any important extent.

[Figure 5 about here]

5.2.3 Costs of treatment

We have previously argued in Section 2 that the costs of using DES and BMS are comparable in terms of the direct and indirect costs of treatment. In particular, using figures from the Swedish agency for health technology assessment (SBU), the total expected cost of using a DES and a BMS for an average patient in Sweden in 2014 was SEK 66,901 and SEK 64,866, respectively. The lion's share of this cost (SEK 59,000) is derived from a fixed hospital reimbursement fee based on the PCI procedure and two nights stay at the hospital, according to figures used in the Nordic DRG patient classification system.[17] The remainder is the cost of the stent, modified by the expected number of stents inserted per intervention and the probability of a subsequent intervention. While the expected cost of a DES is significantly higher than the cost of a BMS, SEK 3,500 versus SEK 1,000, this is traded

[17] See http://www.nordcase.org/eng/materials/manuals

off against a lower risk of restenosis, 0.039 versus 0.074, while the expected number of inserted stents is the same for both stent types (SBU, 2014).

We use our previous estimation results in this section to calculate a rough estimate of the average excess cost that a migrating cardiologist incurred from adaptation to the new practice environment after relocation. Given that we do not find a difference in the propensity of revascularization for the migrating cardiologists, a back-of-the-envelope calculation of the increased cost burden from the additional Type I errors we estimate can be produced by multiplying the estimated number of inappropriately used DES by the difference in unit costs between the two stent types. Table 1 shows that the average absolute change in practice environment for the migrating cardiologists is 0.3 and the average annual number of PCIs per cardiologist is 65. The estimated increase in Type I errors in roughly 0.2 percentage points for each percentage point change in practice environment. Thus, on average, a migrating cardiologist inappropriately inserted $0.3 \times 0.2 = 0.06$ additional DES after relocation, amounting to an increase of around four stents per year. Multiplying this number with the cost difference between the BMS and the DES yields a cost increase of approximately SEK 10,000 (USD 1,200), or around one-sixth of the total cost of a PCI per migrating cardiologist. We conclude that this figure is rather small in the specific context of treatment of coronary heart disease.

5.3 Robustness and sensitivity checks

Lastly, we report estimation results from a set of extensions to our main analysis to gauge the sensitivity of our findings to alternative model and sample specifications. We first study effect heterogeneity with respect to physician age and the direction of the change in practice environment of migrants. Next, we analyze the stability of our results with respect to the definition of the practice environment by reestimating our main DD model using a synthetic environment and non-moving cardiologists to predict counterfactual states.

5.3.1 Heterogeneity across physicians and change in practice environment

Table 6 reports split-sample results from estimation of our main DD model separately for cardiologists moving to hospitals with higher and lower shares of DES, displayed in Columns (1) and (2), and for younger and older migrants,

based on the median age of migrating cardiologists, displayed in Columns (3) and (4), respectively. Again, we focus on the peer environment by including hospital fixed effects in the model. The motive behind this analysis is to evaluate whether our main results are driven by specific subgroups. We anticipate that relatively younger physicians' practice styles are likely to be more malleable due to their lower practical experience and being in an earlier stage of their careers, consistent with the theory of champions, or opinion leaders, of clinical care (see, e.g., Shortell *et al.*, 2004). Furthermore, it is possible that migrating physicians are more susceptible to adopting treatment styles in more innovative practice environments, here characterized as a higher share of the relatively newer DES, due to the attractiveness of new technology (see, e.g., Hofmann, 2015).

Our predictions align with the empirical evidence reported in Table 6 in that the estimated response to the change in practice environment is mainly driven by younger cardiologists who move to more innovative environments. While the first two columns suggest that the effect is positive for both positive and negative Δ_{jt}'s (albeit the latter coefficient is not statistically significant), the last two columns indicate that more senior cardiologists do not respond at all to their peer practice environment when relocating. Thus, heterogeneity in the effect across both physicians and their environments seem to be important to understand clinicians' reactions to their practice environment.

[Table 6 about here]

5.3.2 Synthetic environment

One empirical issue with the DD approach outlined so far is that migrating cardiologists are unlikely to randomly relocate between hospitals. This leads to two inferential problems with respect to the interpretation of our main findings. The first problem relates to the external validity of our estimated effects. Migrating physicians may constitute a selected group that is unrepresentative for the physician population at large. While Table 1 suggests some differences in observable characteristics between moving and non-moving physicians, such as age, the case-mix of patients they treat and the quality of care they provide is indistinguishable from those of non-moving cardiologists. We take this as evidence supporting the notion that the subpopulation of cardiologists moving across hospitals is not widely different from non-moving cardiologists with

respect to relevant characteristics.

The second problem relates to the internal validity of our estimates and is potentially more severe as it may invalidate our approach altogether. Specifically, if physicians generally move to hospitals based on their preferences for using DES, the associations we estimate and interpret as caused by changes in practice environment cannot be empirically distinguished from the sorting of physicians to hospitals with practice environments based on their clinical preferences. A similar argument can be raised with respect to the specific peers that the physicians are working together with within a hospital. Although the results from Figure 3 and Table 3 are reassuring in the sense that the common trend assumption is not rejected, we may still be concerned that the counterfactual practice environment is estimated with bias.[18] To test whether our approach is robust to alternative definitions of practice environments, we propose to extend our analysis by using a synthetic control method derived from a different source of variation to estimate the counterfactual practice environment.

To find a suitable control group that can serve to identify the counterfactual state of migrating cardiologists should they not have moved, we define a synthetic practice style environment from the pool of non-migrating cardiologists (see, e.g., Abadie and Gardeazabal, 2003; Abadie *et al.*, 2010, 2015).[19] For each migrating cardiologist $j \in J$, we define $\tilde{\Delta}_{jt} = \sum_c w_c \Delta_{ct}$ as the counterfactual environment based on non-migrating cardiologists, $c \in C \notin J$. The weights, w_c, are chosen to minimize functions of pre-migration DES share levels ($\sum_{s \in t < t_0} \Delta_{js} - \tilde{\Delta}_{js}$) and slopes ($\sum_{s \in t < t_0} \partial \Delta_{js} / \partial s - \partial \tilde{\Delta}_{js} / \partial s$) based on a constrained quadratic optimization routine. A corresponding approach is

[18] It is a priori unlikely that physician sorting based on preferences for individual treatments occurs due to that they do not possess the individual freedom to schedule their work hours in such detail. Moreover, such sorting would most likely generate conservative bias in our estimates since estimated changes in both the practice environment and the responses therefrom would be based on matching of physicians with similar preferences. In such cases, these changes would thus be smaller than if they were truly random.

[19] Although the synthetic control method was originally developed for a single treated unit, the framework can easily accommodate estimation with multiple treated units by fitting separate synthetic controls for each of the treated units (see, e.g., Abadie, 2020). While there is no important conceptual difference in the contexts of one versus multiple treated units, practice issues relating to the non-uniqueness of the solution to the minimization problem when selecting weights for the synthetic controls are exacerbated in the latter. To address this issue, Abadie and L'Hour (2019) propose a synthetic control estimator that incorporates a penalty for pairwise matching discrepancies between the treated units and each of the units that contributes to their synthetic controls.

applied to estimate the counterfactual environment in the pre-migration period using post-migration DES share levels and slopes. Finally, the resulting counterfactual estimates are applied to versions of the event study model in Equation (9) where the original practice style environment, Δ_{jt}, has been replaced with its synthetic equivalent, $\tilde{\Delta}_{jt}$.

Figure 6 illustrates the synthetic environment approach (darker-colored lines) and how it relates to the previous approach by overlaying the corresponding trends in practice environment from Figure 3 (brighter-colored lines). The two definitions mostly overlap, with the exception of the post-migration counterfactual environment among cardiologists moving to less DES-intensive hospitals that is somewhat lower than the corresponding environment using the original approach. This suggests that, while the two types of counterfactual environments are partially based on the same empirical variation, there are also some notable differences between them.

[Figure 6 about here]

Finally, we study whether our main estimation results are sensitive to the definition of practice environment. Table 7 reports estimation results from our main DD model where we have replaced Δ_{jt} with $\tilde{\Delta}_{jt}$ in the analysis. Reassuringly, the results are close to our main estimation from Table 5: a change in DES use of migrating cardiologists of around 0.31 percentage points for each percentage point change difference in synthetic practice environment between origin and destination hospitals but no corresponding impacts on adverse patient outcomes. We conclude from this analysis that our main results are robust to the definition of practice environment with respect to whether it is derived from the hospital or from the pool of non-migrating cardiologists.

[Table 7 about here]

6 Conclusions

This paper empirically analyzes how physicians' treatment decisions are influenced by their practice environment and how such decisions affect the quality of care received by patients. We study these questions in the context of the choice between using bare metal stents (BMS) or drug-eluting stents (DES)

among interventional cardiologists in Sweden performing percutaneous coronary interventions (PCI) on patients diagnosed with coronary artery disease. To obtain empirical variation in a physician's practice environment, we identify cardiologists who moved between hospitals and relate changes in their own treatment behavior and subsequent patient outcomes to differences in the hospital's practice environment before and after they relocated. The overall physician response to their environment is then decomposed into a physical (provider-specific) and a social (peer group-specific) component by exploiting quasi-random information on the practice behavior of migrating physicians' coworkers within a hospital. Finally, we relate the environmentally induced changes in practice environment to variations in physicians' rate of decision errors and patient adverse clinical events to gauge whether the practice style changes led to important changes in quality of care provision.

Similar to the results reported in Molitor (2018), we find that migrating cardiologists rapidly, but not fully, adapt to the prevailing practice environment in their use of DES after relocating. Our estimates suggest that cardiologists change their use of DES with around 0.5 percentage points for each percentage point difference in practice environment between the origin and destination hospitals. Decomposing the overall effect into a provider-specific and a peer group-specific component, we find that around half of the response is driven by the latter effect, suggesting that a physician's peer group is as influential as the physical work environment in altering treatment styles. Furthermore, we find no evidence that either major adverse cardiac events, such as heart attacks or patient death, physician decision errors, measured using a Random Forest (RF) machine learning algorithm, or treatment costs, were strongly associated with changes in the migrating physicians' treatment styles. This could potentially be explained by the fact that medical decisions were still made within prevailing medical guidelines and did not lead to significantly increased health risks for cardiac patients. Finally, estimation results from a set of split-sample heterogeneity analyses show that our main effects are primarily driven by younger cardiologists who move to more innovative environments (i.e., with higher use of DES), suggesting that both environmental as well as individual characteristics appear to be important for the magnitude of physician response.

In conclusion, the results obtained in this paper have important bearing on current health policy with respect to the causes and consequences of

unwarranted regional variations in healthcare use (see, e.g., Corallo *et al.*, 2014). Recent evidence on the extent to which regional variations are driven by providers or individual clinicians have emphasized the role of the latter (see, e.g., Gutacker *et al.*, 2018). That physicians strongly respond and adapt to their prevailing practice environment, and that such conforming arises from both the provider itself and from the workplace peers, suggest a rationale for why physician treatment styles may cluster in specific areas. The absence of an impact on patient outcomes from such adjustments also provides an explanation for the conundrum of a weak observable correlation between regional variations in the costs and the quality of healthcare provision (see, e.g., Fisher *et al.*, 2003a,b). Although concrete policy advice may require more substantiated evidence which we leave for further work, we believe that our results show that information campaigns aimed at harmonizing treatment choice among healthcare professionals, such as clinical guidelines, may need to be complemented with alternative measures, such as additional physician training, to significantly reduce unwarranted variations in healthcare use.

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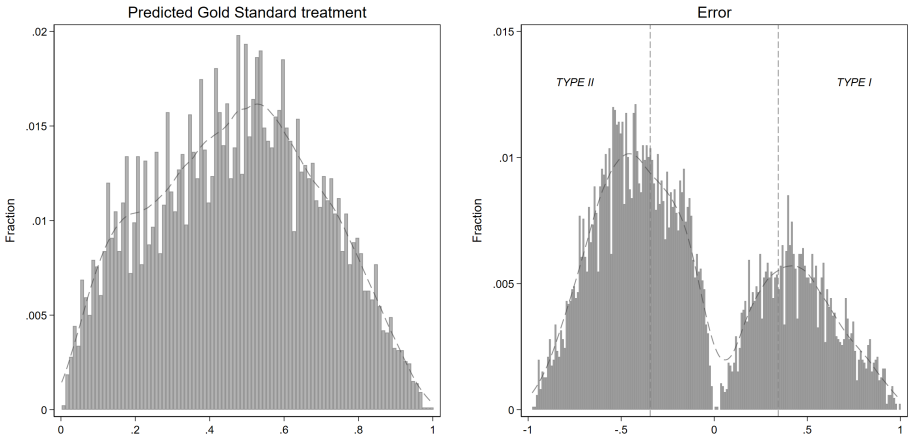
Tables and figures

Table 1.
Descriptive sample statistics

	Moving cardiologists		Non-moving cardiologists	
	Mean	SD	Mean	SD
Hospital characteristics				
Teaching hospital	0.38	0.49	0.41	0.49
RiksHIA quality index	3.73	1.95	3.84	1.95
Case volume	7,861	7,349	8,912	7,468
Hospitals	25		28	
Cardiologist characteristics				
Male	0.93	0.25	0.90	0.30
Age	46.59	6.45	49.00	7.20
Specialization in cardiology	0.85	0.35	0.70	0.46
Total error rate	0.40	0.05	0.39	0.07
Type I error rate	0.14	0.06	0.15	0.08
Type II error rate	0.26	0.08	0.24	0.10
Cardiologists	51		148	
Patient characteristics				
Risk factors				
Male	0.73	0.45	0.72	0.45
Age	65.81	10.94	66.00	11.11
Smoker	0.79	0.79	0.82	0.79
Diabetes	0.17	0.37	0.17	0.37
Chronic obstructive pulmonary disease	0.01	0.11	0.02	0.12
Peripheral vascular disease	0.00	0.05	0.00	0.07
Hypertension	0.49	0.50	0.50	0.50
Previous infarction	0.20	0.40	0.18	0.39
Previous CABG	0.09	0.28	0.08	0.27
Previous PCI	0.11	0.31	0.10	0.30
Outcomes				
DES treatment	0.36	0.48	0.42	0.49
Death (1 year)	0.04	0.19	0.04	0.19
MI (1 year)	0.07	0.26	0.07	0.26
TLR (1 year)	0.06	0.24	0.06	0.23
Total error rate	0.42	0.49	0.40	0.49
Type I error rate	0.12	0.32	0.15	0.36
Type II error rate	0.30	0.46	0.25	0.43
Cases	8,589		51,381	

Note.— SCAAR data for years 2004–2013. Means and standard deviations for samples of moving and non-moving cardiologists. Patient characteristics are missing for a subset of observations: gender (28 cases), smoking (4,893 cases), diabetes (680 cases), hypertension (1,535 cases), previous infarction (1,724 cases), previous CABG (158 cases), previous PCI (168 cases); and cardiologist characteristics: age (739 cases); specialization (692 cases); and hospital characteristics: RiksHIA quality index (693 cases). All observations with missing characteristics are included in the analysis by defining dummy variables for the missing categories.

Figure 1.
Distributions of predicted gold standard DES probabilities and cardiologists' decision errors



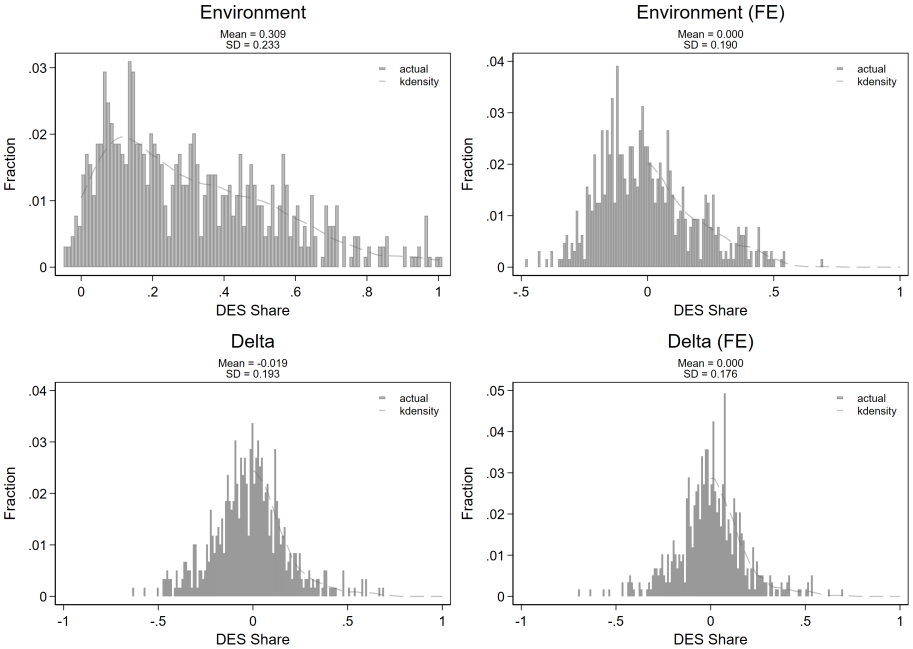
Note.— SCAAR data for years 2004–2013. Left panel presents distribution of predictions of "gold standard" treatment, with respect to use of DES in angioplasty treatments, from estimation of the random forest (RF) machine learning algorithm explained in Section 4.2. Predictions are based on an auxiliary sample of non-moving cardiologists working in university hospitals years 2011–2012. See also Breiman (2001); Svetnik *et al.* (2003). Right panel shows corresponding decision errors by comparing migrating cardiologists' actual choices to gold standard predictions. Vertical lines correspond to thresholds for classification into Type I and Type II errors.

Table 2.
Cardiologist treatment decision matrix

	BMS recommended	DES recommended	Error rate
Treated BMS	3,026	2,603	46%
Treated DES	982	1,972	33%

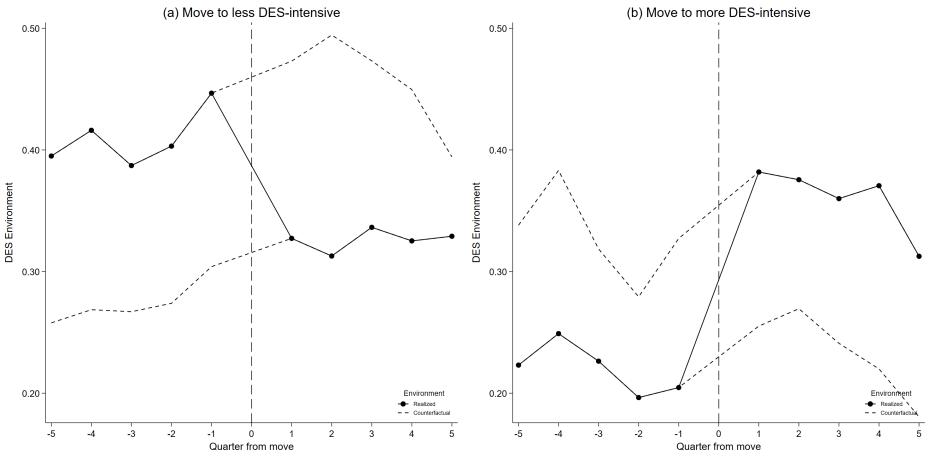
Note.— SCAAR data for years 2004–2013. Recommended treatments are classified according to predictions from estimation of the random forest (RF) machine learning algorithm explained in Section 4.2. Predictions are based on an auxiliary sample of non-moving cardiologists working in university hospitals years 2011–2012. Error rates are defined as the share of chosen non-recommended treatments among all treatments using the specific stent type. See also Figure 1.

Figure 2.
Distributions of migrating cardiologists' practice environments



Note.— SCAAR data for years 2004–2013. Upper panels pertain to physicians' practice environment prior to relocation without (left panel) and with (right panel) adjustment for hospital fixed effects. Lower panels show corresponding distributions for the difference in practice environment between migrating cardiologists' origin and destination hospitals, Δ_{jt}

Figure 3.
Average trends in migrating cardiologists' practice environments



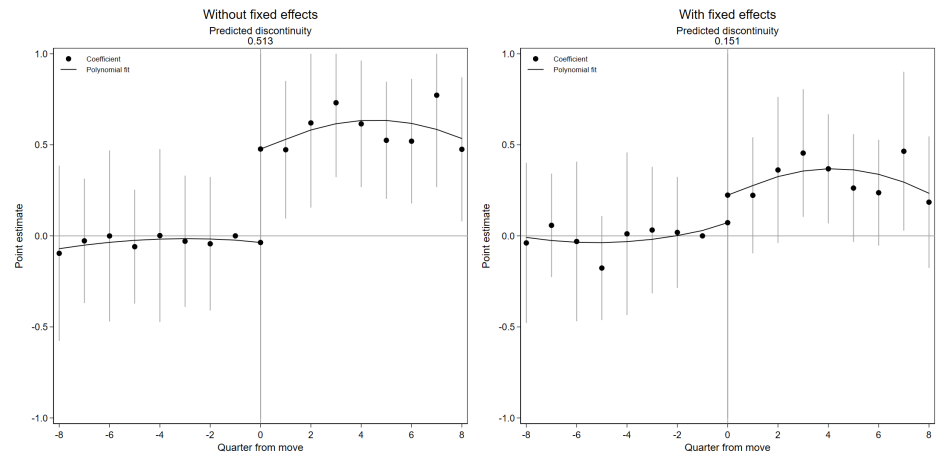
Note.— SCAAR data for years 2004–2013. Practice environment defined as the share of DES used in angioplasty treatments in realized (solid lines) and counterfactual (dashed lines) hospitals by quarter from the cardiologist's move. Separate plots for cardiologists moving to hospitals with lower and higher intensity of DES use. Vertical dashed line indicates recentered quarter of physician relocation from the origin to the destination hospital. Quarter of move linearly interpolated.

Table 3.
Difference-in-Differences estimates of migrating cardiologists' changes in practice environment: Use of DES

	(1) DES	(2) DES	(3) DES	(4) DES
Post	-0.003	-0.030	0.014	0.003
	(0.022)	(0.034)	(0.020)	(0.023)
Δ_{jt}	-0.131	-0.253**	-0.164	0.013
	(0.085)	(0.126)	(0.105)	(0.087)
$Post \times \Delta_{jt}$	0.719***	0.485**	0.523***	0.247***
	(0.130)	(0.201)	(0.114)	(0.090)
Covariates		✓	✓	✓
Year FE	✓			
Origin hospital FE	✓			
Year-quarter FE			✓	✓
Cardiologist FE			✓	✓
Hospital FE				✓
Cardiologists	51	51	51	51
Observations	8,589	8,589	8,589	8,589

Note.— SCAAR data for years 2004–2013. Coefficient estimates from OLS estimation of Equation (8). Dependent variable is an indicator for whether a patient undergoing PCI received a DES. Covariates include all hospital and cardiologist characteristics as well as patient risk factors reported in Table 1. Robust standard errors clustered by hospital in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4.
Event study estimates of migrating cardiologists' changes in practice environment: Use of DES



Note.— SCAAR data for years 2004–2013. Dots correspond to coefficient estimates of $\gamma_{t'}$ from OLS estimation of Equation (9). Dependent variable is an indicator for whether a patient undergoing PCI received a DES. Covariates include hospital, cardiologist characteristics and patient risk factors reported in Table 1 and fixed effects for year-quarter, cardiologist, and hospital (right panel only). Vertical spikes around coefficient estimates pertain to robust 95 percent confidence intervals clustered by hospital.

Table 4.
Difference-in-Differences estimates of migrating cardiologists' changes in practice environment: Decision errors

	(1) Error	(2) Type I	(3) Type II
Post	0.005	0.026	-0.020
	(0.027)	(0.018)	(0.024)
Δ_{jt}	-0.025	-0.014	-0.014
	(0.068)	(0.053)	(0.069)
$Post \times \Delta_{jt}$	0.096	0.185**	-0.081
	(0.081)	(0.075)	(0.077)
Covariates	✓	✓	✓
Year-quarter FE	✓	✓	✓
Cardiologist FE	✓	✓	✓
Hospital FE	✓	✓	✓
Cardiologists	51	51	51
Observations	8,589	8,589	8,589

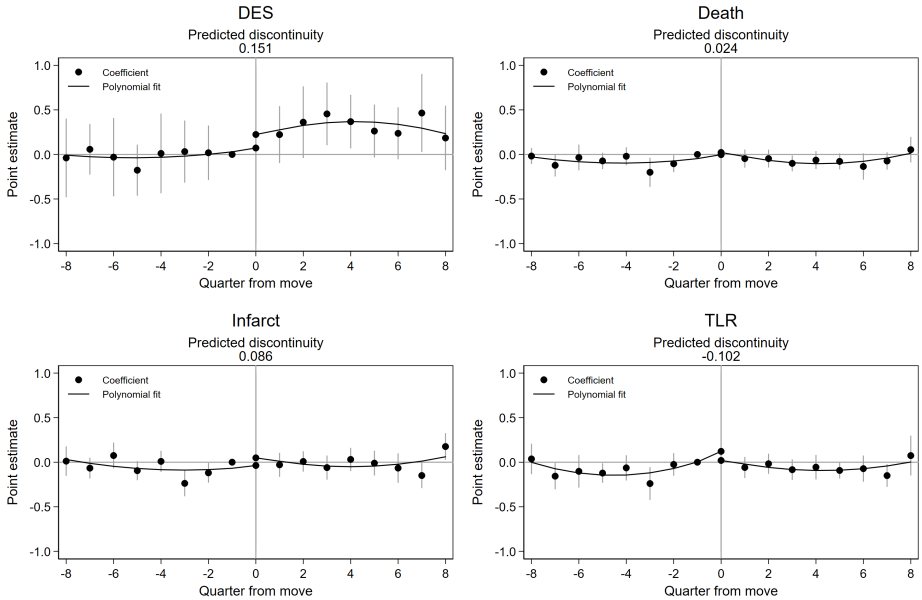
Note.— SCAAR data for years 2004–2013. Coefficient estimates from OLS estimation of Equation (8). Dependent variables are indicators for whether a patient undergoing PCI received a non-recommended stent type. See Section 4.2 for details. Column (1) reports results for the propensity to commit any error while Column (2) and (3) reports error decomposition results for false positives and false negatives, respectively. Covariates include all hospital and cardiologist characteristics as well as patient risk factors reported in Table 1. Robust standard errors clustered by hospital in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.
Difference-in-Differences estimates of migrating cardiologists' changes in practice environment: Patient outcomes

	(1) DES	(2) Death	(3) Infarct	(4) TLR
Post	0.003	-0.009	0.001	-0.009
	(0.023)	(0.008)	(0.011)	(0.011)
Δ_{jt}	0.013	-0.047	-0.069*	-0.053
	(0.087)	(0.030)	(0.037)	(0.033)
$Post \times \Delta_{jt}$	0.247***	-0.011	0.041	0.028
	(0.090)	(0.027)	(0.042)	(0.033)
Covariates	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Cardiologist FE	✓	✓	✓	✓
Hospital FE	✓	✓	✓	✓
Cardiologists	51	51	51	51
Observations	8,589	8,589	8,589	8,589

Note.— SCAAR data for years 2004–2013. Coefficient estimates from OLS estimation of Equation (8). Dependent variables from left to right are indicators for whether a patient undergoing PCI received a DES and whether the patient died, suffered a myocardial infarction, or had another angioplasty within one year from the intervention, respectively. See Section 4.2 for details. Covariates include all hospital and cardiologist characteristics as well as patient risk factors reported in Table 1. Robust standard errors clustered by hospital in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5.
Event study estimates of migrating cardiologists' changes in practice environment: Patient outcomes



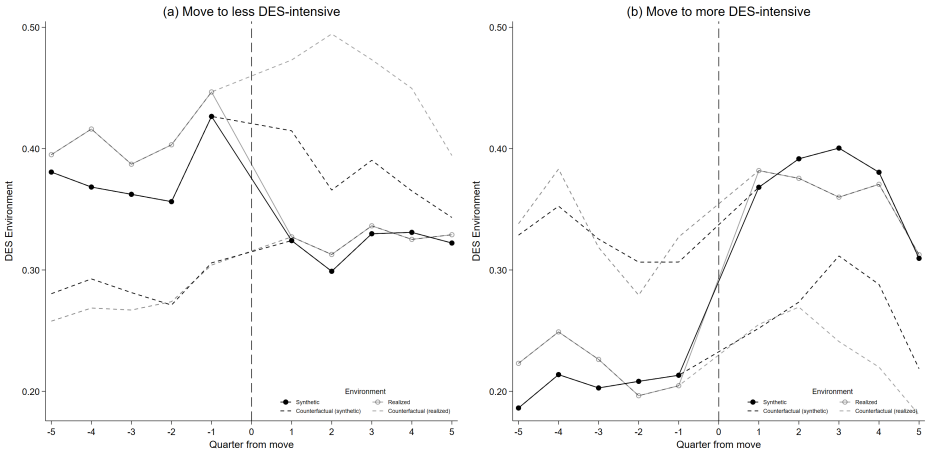
Note.— SCAAR data for years 2004–2013. Dots correspond to coefficient estimates of $\gamma_{t'}$ from OLS estimation of Equation (9). Dependent variables from top left to bottom right are indicators for whether a patient undergoing PCI received a DES and whether the patient died, suffered a myocardial infarction, or had another angioplasty within one year from the intervention, respectively. Covariates include hospital, cardiologist characteristics and patient risk factors reported in Table 1 and fixed effects for year-quarter, cardiologist, and hospital. Vertical spikes around coefficient estimates pertain to robust 95 percent confidence intervals clustered by hospital.

Table 6.
Difference-in-Differences estimates of migrating cardiologists' changes in practice environment: Heterogeneity analyses

	Environment ±		Physician age	
	(1) $\Delta_{jt} > 0$	(2) $\Delta_{jt} < 0$	(3) Below median	(4) Above median
Post	-0.021	-0.002	0.020	-0.059
	(0.051)	(0.043)	(0.025)	(0.038)
Δ_{jt}	-0.077	0.075	0.161	-0.032
	(0.129)	(0.146)	(0.142)	(0.106)
$Post \times \Delta_{jt}$	0.323**	0.184	0.292*	-0.080
	(0.154)	(0.187)	(0.159)	(0.121)
Covariates	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Cardiologist FE	✓	✓	✓	✓
Hospital FE	✓	✓	✓	✓
Cardiologists	24	27	23	28
Observations	3,776	4,813	4,429	4,160

Note.— SCAAR data for years 2004–2013. Coefficient estimates from OLS estimation of Equation (8). Dependent variable is an indicator for whether a patient undergoing PCI received a DES for different subsamples. Columns (1) and (2) splits the sample into cardiologists moving to more and less DES-intensive hospitals. Columns (3) and (4) splits the sample into younger and older cardiologists with median cardiologist age as threshold. Covariates include all hospital and cardiologist characteristics as well as patient risk factors reported in Table 1. Robust standard errors clustered by hospital in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 6.
Average trends in migrating cardiologists' realized and synthetic practice environments



Note.— SCAAR data for years 2004–2013. Practice environment defined as the share of DES used in angioplasty treatments in realized (solid lines) and counterfactual (dashed lines) hospitals by quarter from cardiologist move. Brighter lines pertain to estimates of Δ_{jt} while darker lines pertain to the estimated synthetic practice environment, $\tilde{\Delta}_{jt}$. See Section 5.3.2 for details on the construction of this variable. Separate plots for cardiologists moving to hospitals with higher and lower intensity of DES use. Vertical dashed line indicates recentered quarter of physician relocation from the origin to the destination hospital. Quarter of move linearly interpolated.

Table 7.
Difference-in-Differences estimates of migrating cardiologists' changes in synthetic practice environment: Patient outcomes

	(1) DES	(2) Death	(3) Infarct	(4) TLR
Post	-0.022	-0.009	0.005	-0.011
	(0.023)	(0.008)	(0.012)	(0.011)
$\tilde{\Delta}_{jt}$	0.122	-0.060	-0.019	-0.047
	(0.139)	(0.036)	(0.025)	(0.043)
$Post \times \tilde{\Delta}_{jt}$	0.312**	0.019	0.006	0.056
	(0.128)	(0.028)	(0.038)	(0.053)
Covariates	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Cardiologist FE	✓	✓	✓	✓
Hospital FE	✓	✓	✓	✓
Cardiologists	51	51	51	51
Observations	6,729	6,729	6,729	6,729

Note.— SCAAR data for years 2004–2013. Coefficient estimates from OLS estimation of Equation (8) using the estimated synthetic practice environment, $\tilde{\Delta}_{jt}$ in place of Δ_{jt}. See Section 5.3.2 for details on the construction of this variable. Dependent variables from left to right are indicators for whether a patient undergoing PCI received a DES and whether the patient died, suffered a myocardial infarction, or had another angioplasty within one year from the intervention, respectively. See Section 4.2 for details. Covariates include all hospital and cardiologist characteristics as well as patient risk factors reported in Table 1. Robust standard errors clustered by hospital in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A Additional tables and figures

FIGURE A.1.
Random Forest machine learning algorithm

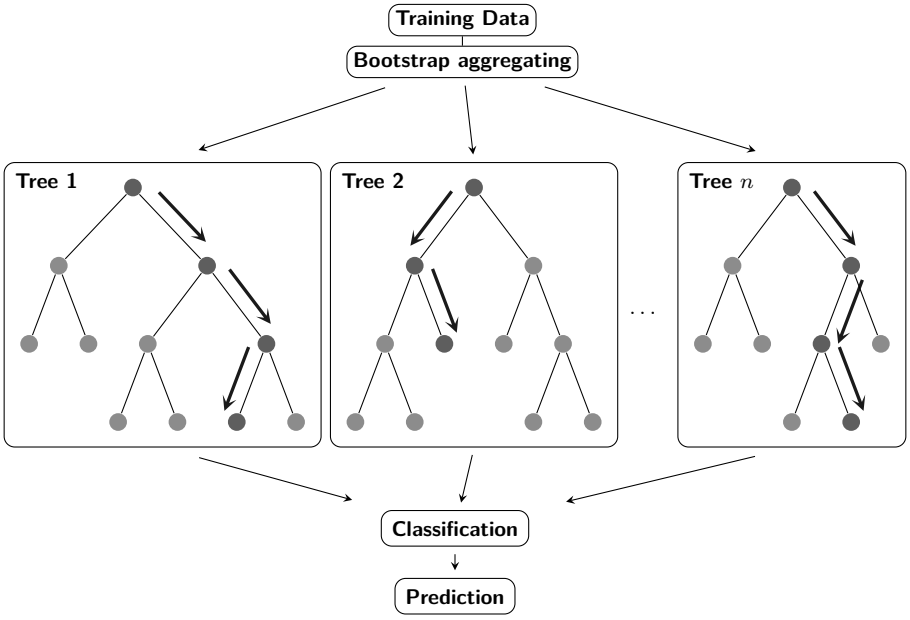
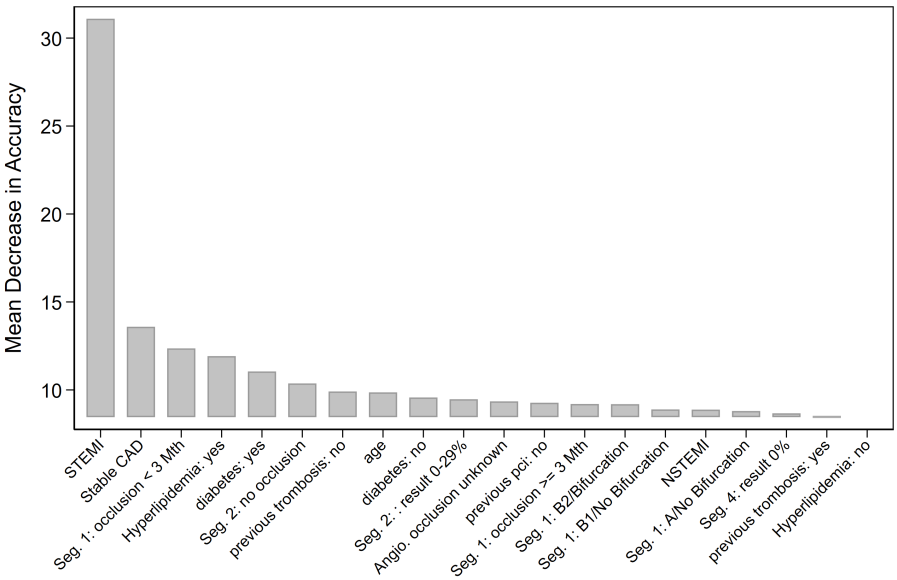
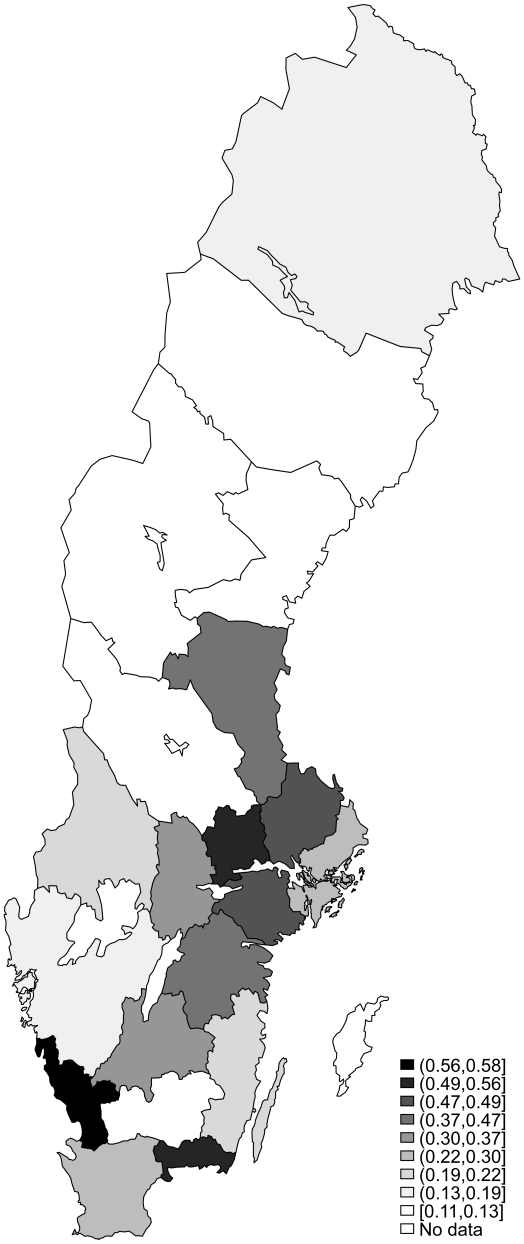


FIGURE A.2.
Variable importance weights in Random Forest prediction



NOTE.— SCAAR data for years 2011–2012. Higher values indicate greater importance of variable in predicting outcomes. Included variables: patient's gender; age; reason for hospitalization; diabetes; COPD; peripheral vascular disease; hypertension; hyperlipidemia; previous infarction; previous CABG; previous PCI; previous stroke; patient creatinin clear; hemoglobin test; any occlusion; angiography results by segment including degree of stenosis severity and duration ; left ventricular ejection fraction; location of lesions; 3-vessel and/or LM lesion; number of treated segments; primary diagnosis.

Figure A.3.
Distribution of raw DES rates across hospital regions in Sweden, 2004–2013



Note.— SCAAR data for years 2004–2013. Regional administrative map of the 21 county councils in Sweden. Intensity of shaded areas reflect average shares of DES use among patients undergoing angioplasty treatment across all years.

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