Radiating influence? Spillover effects among physicians*

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Abstract

We study spillovers in healthcare by exploring how cardiologists' diagnostic choices are influenced by their peers. We use rich clinical quality data from Sweden to instrument peers' average weekly radiation output, our endogenous variable of interest, using the peer's lagged arrival of emergency cases. Our IV estimates imply that focal cardiologists change their own radiation output by 0.5 SD for each SD change in their peers' output. We show that our results are neither driven by endogenous peer formation nor patient selection. Effects are also stronger in academic hospitals and among younger cardiologists. These spillovers enhance patient welfare as well by increasing the share of appropriate radiation dosage and by reducing subsequent 30-day risk-adjusted mortality.

Keywords: Peer effects; Social interactions; Physicians

JEL Classifications: I12, J24, M54

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1 Introduction

Fostering approaches to deliver high-value care in the face of substantial challenges, like higher service demand, stagnating workforce, and rising costs of treatments, are central themes of the current debate on healthcare reform.[1] One such area with substantial potential that has been described as a "critical blind spot" is peer influences among healthcare professionals (McWilliams, 2022). Such influences may involve sharing experiences, motivation, and knowledge with colleagues at the workplace. In the healthcare setting, these could be harnessed through a range of methods and protocols, including optimal scheduling, team composition, and peer-to-peer teaching. While the impact of peers on individual productivity has been widely studied in other domains, particularly in education and the labor market (see, e.g., Sacerdote, 2011; Cornelissen *et al.*, 2017), the literature in healthcare remains scant (see Silver, 2021, for a recent exception).

In this paper, we document the existence of peer spillovers among specialized physicians in a high-stake setting: the treatment of heart attacks. We use rich clinical-quality administrative data, which includes the universe of diagnostic and interventional procedures performed in Sweden. The richness of the data set allows us to match physicians with patients and provides a detailed set of patient case-mix characteristics. We follow 186 cardiologists practicing in Swedish hospitals from 2008 to 2013, consisting of over 200,000 patient-level records with time-stamped information on the nature of the case, diagnostic information, applied treatments, and subsequent patient outcomes.

We focus on Coronary Angiography (CA) - a medical imaging technique to visualize and locate arterial blockages causing heart attacks. The procedure requires the use of a radioactive contrast agent administered by the attending cardiologist. In our data, we observe the exact amount of radiation dosage administered, providing us with an objective measure to study spillovers by exploring whether and how physicians respond to the dosage behavior of their peers.

Radiation dosage is a critical component of this procedure as it poses non-trivial and important trade-offs. First, physicians may need a certain amount of dosage to accurately locate the blockages and properly set up subsequent treatments (i.e., placement of the stent). On the other hand, excessive dosage may be directly harmful to patients and physicians (Richardson *et al.*, 2023), leading to quantity-quality trade-off (Kobayashi and Hirshfeld Jr, 2017).[2] Second, radiation administration and the employed amount depends to a large extent on the physician's skill and experience (Georges *et al.*, 2017;

[1] Some of these approaches are improvements in the use of precision medicine, enhanced use of digital healthcare and integration and consolidation of care episodes.

[2] The radiation output from a single procedure of CA and CA + stenting is equivalent to 155 and 755 chest x-rays, respectively (Mettler Jr *et al.*, 2008)

Chan *et al.*, 2022). Physicians may spend less time in a procedure (shorter radiation exposure per second) yet yield higher total radiation output and vice versa, implying a non-monotonic relationship between time and radiation output. Due to these ambiguities and the involvement of a skill set that can potentially be accrued over time, it is likely that interactions with peers are an important component of such settings. However, to date, there is limited evidence in the extant literature that empirically assesses skill-dependent decisions under uncertainty over the appropriate of care.

While our data enable us to link cardiologists to their work peers through detailed time stamps and workplaces, causal identification and estimation of peer effects are nevertheless wrought with challenges (Manski, 1993). A major concern in empirical peer effects literature revolves around endogenous sorting into peer groups based on observable and unobservable characteristics. In our healthcare setting, this is likely to have limited importance as physicians have limited control over their shift assignment at best and hence cannot perfectly choose the peers they work with. Yet, even partial control over group formation, as well as exposure to common time-varying shocks to the hospital environment and/or patient load, might challenge the identification of causal peer effects. To overcome these challenges, we employ a combination of two empirical strategies: instrumental variable (Bramoullé *et al.*, 2009; Nicoletti *et al.*, 2018; Harmon *et al.*, 2019; De Giorgi *et al.*, 2020) and fixed effects within-group design (Bayer *et al.*, 2008; Kirabo Jackson and Bruegmann, 2009).

Specifically, we instrument the radiation output of peers in a given week by leveraging the plausibly exogenous variation in the arrival of emergency cases treated by those peers. We use the lagged number of cases from the previous week to overcome potential reflection and reverse causality concerns. The motivation underlying our choice of instrument is based on three components that are empirically supported: (i) the arrival of emergency cases coupled with rotational assignment of clinicians is plausibly exogenous; (ii) emergency cases are qualitatively different than non-emergency patients and therefore require different radiation doses when performing diagnostic angiography; and (iii) variation in the arrival of emergency cases for peers should only indirectly affect the focal physicians' radiation output through its effect on the peers' altered radiation output. Thus, in our setup, we attribute changes in the focal physicians' radiation use to changes in the peers' behavior derived from random variation in peer's exposure to emergency cases.

Our instrumented estimates indicate that a one standard deviation (SD) increase in the radiation dosage of peers leads to around 0.5 SD increase in the focal physicians' own radiation output. This translates into an effect size of 25% relative to the mean, although the increase remains within the recommended dosage range. This finding is robust to several alterations of our main specification, such as the inclusion of hospital case volume, removing outliers, and the use of an alternative instrument, namely the peers' total amount of emergency cases in the previous week. We also control for potential time-varying unobservable correlated effects using an approach similar to Nicoletti *et al.* (2018) where we include both the total number of patients treated by the focal physician and their peers.

Studying heterogeneity in these estimated spillovers, we find no difference across genders but document stronger effects for academic hospitals and for junior physicians. These results are in line with previous findings in other contexts (Molitor, 2018; Barrenho *et al.*, 2021). This suggests that younger physicians and those in academic hospitals are more malleable, especially when practicing in a research-intensive setting.

We also present evidence that these spillovers in physician practice actually translate into improvements in patient outcomes via the provision of better quality healthcare. First, we find that they lead to an increase in the share of patients treated with the recommended radiation dosage. This is driven by fewer patients receiving too little dosage, as physicians may be emboldened to use higher amounts after observing their peers. Second, as highlighted earlier, this increased share of correct dosage is likely to have diagnostic gains as well. We empirically assess the existence of such gains by using patient-level outcome data. We find an improvement in the probability of risk-adjusted 30-day mortality and a reduction in the likelihood of future infarction and thrombosis (clot formation). Back-of-the-envelope calculations suggest an improvement in mortality and thrombosis in two out of every thousand patients who undergo the angiography procedure.

Investigating one potential channel of peer influence, we assess whether the spillover operates through a treatment choice channel.[3] We find that focal doctors switch their treatment modalities away from complex and increase the share of patients receiving the simpler option procedure (i.e., the leg option) by 0.3 SD. by 14 percentage points

Our paper adds to at least three strands of literature. First, our results contribute to the well-developed areas of research on variation in physicians' practice styles. Prior work has identified external factors which affect variation in care across physicians (Chandra *et al.*, 2011), for instance, training programs (Epstein and Nicholson, 2009), financial incentives (e.g. Clemens and Gottlieb, 2014; Johnson and Rehavi, 2016), hospital entrance to the market (Barro *et al.*, 2006; Cutler *et al.*, 2010; Avdic *et al.*, 2022a), hospital-specific environment (Molitor, 2018; Avdic *et al.*, 2023), and intrinsic factors such as physicians'

[3]Specifically, the entry point of the catheter insertion, where there are two options: 1. through the arm (radial artery) or 2. through the leg (femoral artery). The arm option is considered to pose a higher bleeding risk and is more difficult, yet has a positive long-term quality effect, whereas the leg option has a long history of success and technically simpler procedure (Gargiulo *et al.*, 2022). Typically, the leg option yields higher radiation output due to its distance to the heart. Our empirical exercise supports this difference; see Figure 4

skill and experience (e.g. Abaluck *et al.*, 2016; Currie and Macleod, 2017; Chan *et al.*, 2022; James *et al.*, 2022) and motivation (e.g. Kolstad, 2013).

Our paper also complements the existing literature on the organization of teams and teamwork in the workplace. Previous work on this topic focuses on team incentives (Hamilton *et al.*, 2003; Bandiera *et al.*, 2013; Friebel *et al.*, 2017), and how teamwork operates, either through collaboration (Chen, 2021), joint monitoring (Chan, 2016), or the influence of peers through peer pressure (Kandel and Lazear, 1992; Bandiera *et al.*, 2005; Mas and Moretti, 2009). Our findings also relate to the recent empirical papers in the context specific to healthcare (Barrenho *et al.*, 2021; Miraldo *et al.*, 2021; Agha and Zeltzer, 2022) where these studies directly speak to the influence of peers on physicians' technological adoption.

Our study, in particular, relates to the important recent work of Silver (2021), which looked at the peer influences on physicians in the emergency departments across the state of New York in the US. The key finding of the paper is that the peer induces focal doctors to speed up at the expense of quality of care, primarily through cost-cutting measures at the margin (i.e., omitting diagnostic tests). While this paper differs in settings, our findings are generally consistent with those of Silver (2021), specifically on the existence of peer influences on physicians' decision-making. Our results, more importantly, highlight the positive effect of peers on quality of care and therefore complement Silver (2021) and other important past work of peer effects in healthcare (Chan, 2016; Barrenho *et al.*, 2020).

Lastly, this paper relates to the wider literature on personnel economics. Previous studies in this literature also span broadly in settings specific to high-skill occupations such as professional athletes (Guryan *et al.*, 2009; Arcidiacono *et al.*, 2017), scientists (Waldinger, 2012; Jaravel *et al.*, 2018), medical students (Arcidiacono and Nicholson, 2005) and lower-skill occupation such as cashiers (Mas and Moretti, 2009) or fruit pickers (Bandiera *et al.*, 2010).

The remainder of the paper is structured as follows. Section 2 describes the background and the institutional features of our study. Section 3 lays out the data and the sample construction. Section 4 details the empirical approach and the identification challenges. Section 5 presents the results. Section 6 concludes.

2 Background

2.1 Clinical management of heart attacks

Heart attack or Acute coronary syndrome (ACS) is a leading cause of death globally (Roth *et al.*, 2020). It is caused by a sudden blockage in one or more of the coronary artery branches, reducing blood flow and oxygen delivery to adjacent heart cells. This can be followed by an infarction defined as irreversible damage to the heart impeding the maintenance of sufficient blood flow to other parts of the body. Finally, in extreme cases, the heart may stop as a result of the blockage leading to death.

While less severe cases may be treated with a non-interventionist approach involving medication and lifestyle changes, more serious episodes require surgical intervention. These directly treat the blockage by widening the impacted artery through a process called "catheterization" (or coronary angiography (CA)) and the insertion of a medical device (stents) to maintain the patency of the blocked artery.[4]

Catheterization is mainly a visualization exercise to identify and locate the blockages in the artery. Once the cath is inserted from either the patient's arm or leg, the specialist injects a contrast agent to check the patency of the artery. The necessary condition in this procedure is the use of an X-ray, a radiation material, to aid the visualization.[5] Accurately locating the impacted segment is crucial for the effective insertion of the stents. Furthermore, failure to identify the extent of the blockage may be detrimental to the patients in the long run.

The amount of radiation given is cardinally linked to a physician's skill and proficiency with the procedure (Hirshfeld *et al.*, 2005; Kobayashi and Hirshfeld Jr, 2017).[6] For example, cardiologists could position their patients at a different angle, or use intermittent beaming techniques during the procedure to minimize the radiation while maintaining the overall time duration of the procedures. Similarly, the choice of entry point, arm or leg, also maps into a physician's skillset as the former is harder to conduct due to smaller artery size but requires less radiation.

Finally, the above procedure can directly be harmful to cardiologists as well due to radiation exposure. A single procedure of coronary angiography is equivalent to 155 to 755 chest X-rays (Mettler Jr *et al.*, 2008), an amount that many regulatory bodies worldwide such as World Health Organization (WHO), International Labor Organization

[4] An alternative surgical option bypassing the blocked artery through the installation of a grafted artery.

[5] Cardiologists are able to observe the radiation dose produced in each operation through the monitor in the operation theatre.

[6] The amount needed also to some extent, dependant on the patient's characteristics such as body weights and age (Georges *et al.*, 2017)

(ILO) and Energy Commission in Europe [7], including the College of Radiologists deemed to be excessive to not only the patients but there is also a larger inherent risk of repetitive exposure to radiation for the performing cardiologists themselves (Cousins *et al.*, 2013; Picano *et al.*, 2014). Recent evidence suggests that even low radiation can have serious health implications (Richardson *et al.*, 2023).

2.2 Cardiologists in the workplace

Interventional cardiologists in Sweden are doctors working full-time (minimum 40 hours a week) at their hospitals. In practice, this means that doctors may, for example, work in the cath lab on Monday and Wednesday, work on outpatient cases on Tuesday, and Thursday, and then have an out-of-office shift on Friday. The work may extend to weekends (i.e., being on the on-call shift or for emergency cases) once every few weeks. These assignments alternate between available cardiologists at the hospital and the schedule typically changes every few months. In general, hospitals may work together with clinicians to work on the schedule but they cannot have deterministic control over it and shifts arrangement may vary between hospitals[8]

How do physicians learn about current state of medical technology and determine the optimal treatment strategy for a given patient? Learning for physicians are typically embedded in clinical work through deliberate practice (i.e., learning-by-doing) (Slotnick, 1999; Van de Wiel *et al.*, 2011) and through other avenues such as medical journals, professional meetings, and interactions with their colleagues (Burke *et al.*, 2007; Nair *et al.*, 2010), especially those who they regularly interact with in the hospitals where they practice (Gabbay and Le May, 2004).

Interactions with colleagues are an inexpensive source to expand physicians' information set (Epstein and Nicholson, 2009) and might occur through several instances. For one, hospitals may have routine ward rounds between doctors and nurses (Zwarenstein and Bryant, 2000) to report newly admitted patients and discuss care management of the existing patients with the objective to support the provision of quality services (Carter *et al.*, 2003; Braaf *et al.*, 2013). During ward rounds, topics discussed include diagnosis,

[7] WHO issued a statement on the importance of "implementing basic safety standards" https://www.who.int/news-room/fact-sheets/detail/ionizing-radiation-health-effects-and-protective-measures. Similarly, see ILO press release on the workers' exposure to ionizing radiation https://www.ilo.org/global/about-the-ilo/newsroom/news/WCMS_854878/lang--en/index.htm. The Energy Commission of the EU also published a technical report on "Medical Overexposures" in 2008 highlighting the importance of radiation safety. See here for more details https://energy.ec.europa.eu/system/files/2014-11/149_1.pdf

[8] Interviews with cardiologists, eg. https://www.intersystems.com/uk/resources/a-day-in-the-life-of-waist-coat-clad-cardiologist-dr-john-payne/ or https://www.acc.org/Membership/Sections-and-Councils/Early-Career-Section/Section-Updates/2020/02/24/24/42/A-Day-in-the-Life-of-an-Early-Career-Cardiologist-in-Canada provides intuition on the cardiologists' practice routine.

patient history including any adverse events, and prior therapeutic interventions given to the patients.

Doctors may also have regular team meetings to discuss challenging clinical case and/or review recent advancements in medical technology (eg. drugs, procedures, guidelines) where they share opinions (Williams and Baláž, 2008). Moreover, it is a common feature, particularly in the context of continuing medical education (CME), for hospitals to institute bedside teachings in which typically the younger doctors learn from their more experienced peers (McGee, 2014). Another potential channel for the peer effects to operate is through the "non-formal" interactions in the hospitals (Smith, 1996). In this channel, doctors may interact during breaks in the lounge room or in the cafeteria.

3 Data

3.1 Setup

Our primary data comes from the Swedish Coronary Angiography and Angioplasty Registry (SCAAR), a central administrative data for all angiography and angioplasty procedures in Sweden. Since 2005, all 30 medical facilities across Sweden have been reporting their data to the registry. For our purpose, the most important piece of information recorded by the registry is detailed measurements of the amount of radiation administered in each procedure. This provides an objective measure through which we can directly explore spillovers in physician practices.

The data also provides patient information such as the municipality of residence, basic demographic characteristics, as well as the severity of the case along with existing comorbidities.[9] We also observe some standard characteristics of the performing cardiologist like age and gender.

Finally, the data contains the exact date of admission and discharge and case details (e.g.: elective or an emergency) which are then linked to future outcomes of the patient. These include restenosis or reblocking of the artery, infarction, stent thrombosis, and mortality. Together this information allows us to study whether spillovers among physicians can lead to better patient outcomes.

We assess all procedures performed from 2008-2013. The choice of 2008 as the starting year is determined by data constraints since this is the earliest we observe all hospitals with consistently better quality measurement and record keeping. The initial sample consists of 219,559 patient-level records.[10] We bottom and top-code the outcome vari-

[9] For instance, we observe whether the patient has other conditions such as diabetes, has a smoking history, and any previous procedures they underwent.

[10] We exclude one hospital (out of 30) for which the main variable interest, radiation output, is missing

ables (radiation output) to 2.5 and 97.5 percentile respectively.[11] We aggregate the data into the physician-hospital-week level to allow us to investigate the relationship between physicians' own weekly average output and their peers' weekly average output. Our final estimation sample consists of 28,639 physician-hospital-week observations. Our sample covers 186 cardiologists working full-time at 29 hospitals (97%) from 2008 to 2013

3.2 Descriptive statistics

We present summary statistics for our estimation sample in Table 1. Panel A of Table 1 reports summary statistics on measures of physicians' output, including our main variables of interest. The weekly average radiation dose is 5,564 $\mu Gray/m^2$. Similarly, the peers' weekly average is 5,558 $\mu Gray/m^2$. We define the range of radiation output that is considered appropriate following National Diagnostic Reference Levels (DRLs) published by the European Commission on Radiation Protection (Commission and for Energy, 2015) to determine the recommended range of dosage to allow us to define the share of patients that are below or above the recommended range of dosage. We classify radiation output given to a patient to be "insufficient" if the amount is less than the specified DRLs. Similarly, for a given patient, we code the amount of radiation as "excessive" if the radiation output is given outside the DRLs. Using these definitions, the weekly average share of patients who had insufficient radiation dosage given by the physicians is 34.7%. In contrast, the weekly average share of patients who exceeded the amount of recommended radiation dose is 10.5%. Doctors on average, spent 9.2 minutes (554 seconds) of fluoroscopic time and used 114.7 ml of contrast agent when performing the procedures. The peers' average on these two measures is similar, with 9.2 minutes (553 seconds) on fluoroscopic time and 114 ml of contrast liquid.

Panel B of Table 1 provides insights into the work shift's context in our estimation sample. Doctors on an average week work with 3 other peers. Doctors' weekly intervention procedures are 7 cases. Among these, the weekly average of emergency cases is around 2 (1.8) cases. Similar to the focal doctors, peers' average of emergency cases is 1.79. Panel C summarizes doctors' characteristics in our analysis. On average, the doctors are 49 years old. More than half (57%) of the sample consists of doctors aged 45 to 58, 32% of doctors' age are between 30-44 years, and lastly, around 10.7% of doctors are considered senior (older than 58). Female cardiologists consist of only 10 percent of our sample.

for all years. For the remaining hospitals, we exclude any observations for which this variable is missing, which amounts to only 2 percent of the sample size.

[11] In the robustness checks we exclude observations that are below 2.5 percentile and above 97.5 percentile to assess the stability of our main results

Panel D presents the average characteristics of the patients treated by the cardiologists. The average patients are 66.5 years old with the oldest patients being 88. Roughly a quarter (0.23) of the patients are clinically categorized as relatively more severe (complex). About half of the procedures (50 percent) are PCI. Lastly, Panel E provides summary statistics on the patients' outcomes within 30 days of treatment. Among patients treated in a particular week, 2 percent of patients (roughly 1 of every 45 patients) died within one (1) month of treatment, 2.2 percent of the weekly average number of patients had an episode of thrombosis, a very small number the patients (roughly equal to 1 of every 400 patients) had an episode of narrowing of the coronary artery (restenosis), and 0.008 percent of the patients had an episode of infarction within 30 days following the intervention.

4 Empirical strategy

4.1 Main specification and Identification concerns

For physician i working at hospital h, consider the following specification:

$$Y_{ig(h,t)} = \alpha_i + \gamma_t + \beta \overline{Y}_{\sim ig(h,t)} + \delta X_{ig(h,t)} + \tau \overline{X}_{\sim ig(h,t)} + \epsilon_{ig(h,t)} \tag{1}$$

where Y is the average radiation dose administered by physician i at hospital h in week-year t. α is the physician-specific fixed effect, while γ_t is the time fixed effect. We are interested in $\overline{Y}$, which is the average radiation dose of physician i's peers in hospital h in week-year t. X is a vector of physicians' (and their peers') characteristics and their average patients' characteristics, and ϵ is the error term.

We define peer groups as physicians working at the same hospital in the same week. This is the finest temporal unit we can adequately study given the institutional structure we face due to at least two reasons. First, our registry data captures only patients receiving interventional procedures and does not, for instance, capture patients treated at outpatient clinics. As doctors may work only a few days a week and may also work different days in the lab we are likely not to consistently capture overlapping of physicians working with their peers at the daily level. Second, and perhaps more importantly, although doctors may be working on the same day, interaction with peers may not necessarily occur on a day-to-day basis as each doctor may have a different rotation assignment (i.e., inpatient wards vs outpatient clinics). For example, clinicians are more likely to have weekly case discussions instead of daily ones and therefore interact once a week.[12]

[12] Our settings differ to Mas and Moretti (2009) cashier workers where daily interaction is likely to occur and to Silver (2021) in which emergency department doctors are often rostered daily in groups

In the absence of endogeneity, β in equation (1) captures the causal relationship between the radiation administered by peers and the focal physician. However, isolating this causal relationship is subject to well-known identification challenges as specified in Manski (1993) and the ensuing literature.

First, physicians may selectively interact with those peers who share similar traits with them, observable or unobservable. For instance, physicians who went to the same medical school or share similar practice styles may interact more often, endogenous forming peer groups generating a spurious correlation between the focal physicians' skills and his peer's skills (i.e., radiation dose output). Similarly, hospital managers may systematically match patients to physicians according to the latter's preference towards radiation dose. For example, if the hospital is interested in keeping the average radiation output to a fixed amount in a given week, the manager could assign low-dose patients to high-dose physicians (i.e. the "aggressive" physician) and vice versa, thus erroneously creating a false negative correlation between physician i and their peers. The fixed effects we include in equation (1) help ameliorate these issues but one can nevertheless be worried about any leftover selection into peer groups.

Second, physicians working in the same hospital may be exposed to a similar working environment that may influence both physician i's own outcome and their peers' outcomes. For instance, the nursing staff assisting cardiologists in these surgical procedures may "pre-set" the radiation device based on the preferences of the average cardiologist. This would then result in a biased estimate of the effect of physicians' i radiation output and their respective peers' radiation output.

Third, the cause and effects of peers are empirically difficult to establish due to the "reflection problem", i.e., it is difficult to separate the peer effects if both focal physicians and their peers' output are determined simultaneously.

4.2 Instrument definition and suitability

To overcome the identification challenges highlighted above, we use an instrumental variables strategy in combination with high-dimensional fixed effects for doctors, years, and week-of-the-years as our main empirical strategy. We instrument the radiation dose of peers with the number of emergency cases. We employ a lagged version – the prior week's cases – to prevent contemporaneous spillovers from emergency cases.[13]. The IV is defined as follows:

$$Z_{\sim i,g(h,t)} = \frac{1}{J}\sum_{j\neq i} cases_{j,t-1}, \tag{2}$$

(i.e., more than one working doctor on a given shift).

[13]As a robustness check available in our extended analysis, we test our main specification using a set of various lagged measures.

where $cases_{j,t-1}$ refers to the total number of emergency cases handled by physician j in the previous week. Here each j belongs to focal physician i specific peer group in week t, i.e., it is the familiar leave-one-out definition of peer group structure. We thus leverage plausibly exogenous arrival of emergency cases in $t-1$ as a shifter of peers' radiation output in t.

4.2.1 Instrument relevance

The relevance of our IV relies on several propositions. First, emergency patients may be more severe in nature and thus are more likely to be "difficult encounters" (Chodick *et al.*, 2023).[14] This can induce persistence in the peers' radiation output across weeks particularly if administration of higher dosage in $t-1$ yields better results for the patient. Figure 2 plots the average radiation dose for both emergency and elective cases. We observe a clear pattern where emergency cases record higher radiation dosage relative to non-emergency ones. It is also important to note that we do not use the amount of radiation output given in the emergency cases it is likely to suffer from the correlated effects problem discussed earlier.

Second, we also employ a short-term temporal relationship where persistence is likely to be more plausible. However, the initiation of the persistence occurs through the random arrival of emergency cases. Moreover, recent studies have established the existence of short-term within-physician practice variability following a "difficult encounter". For example, Chodick *et al.* (2023) notes that doctors increase the number of referrals for additional tests for the next patient immediately following a difficult case. Similarly, Singh (2021) finds that doctors (ob-gyn specialists) switch their delivery methods if their previous patient had complications.

Together the above arguments establish the case for relevance. However, this aspect of an IV approach is easily verifiable empirically. We estimate the following first-stage specification:

$$\overline{Y}_{\sim ig(h,t)} = \phi Z_{\sim ig(h,t-1)} + \lambda \overline{W}_{\sim ig(h,t)} + \psi_{\sim ig(h,t)} + \mu_{ig(h,t)} \tag{3}$$

Where $\overline{Y}$ is the peers' average radiation output in a given week, Z is the instrument, the number of emergency cases that peers of physician i had in the past week $(t-1)$, $\overline{W}$ is the mean characteristics of the peers (excluding physician i), ψ is a set of doctor, year, and week-of-the-year fixed effects, and μ is the error term. Panel B in Table 3 reports the first stage estimates and the results suggest a strong first stage. We report

[14] This is plausible, given that doctors have to be prepared for assessing the case in a timely fashion, yet have to anticipate for any potential adverse outcome (e.g., complications, or in an extreme case, medical errors) from their treatment decisions (see e.g David and Brachet (2009)).

the Montiel-Pflueger F-statistics following Andrews *et al.* (2019) and Anderson-Rubin statistics following Keane and Neal (2023) to benchmark our instrument against the potential weak IV problem. We establish that our IV is indeed strong and robust across specifications.

4.2.2 Instrument validity

After establishing relevance, we now discuss whether the arrival of emergency cases in the past week can be plausibly exogenous and thus provide a valid IV. First, the occurrence of heart attacks is extremely difficult, if not impossible, to predict in any meaningful way. This feature of our setting itself is likely to deal with most concerns regarding any correlations between physicians' observable and unobservable characteristics and the arrival of emergency cases. Indeed, numerous empirical papers have used and exploited similar plausibly exogenous events to help with causal identification for a range of empirical problems in the economics of healthcare (Card *et al.*, 2008, 2009; Doyle Jr *et al.*, 2015; Chandra *et al.*, 2016).

While the exogeneity assumption is fundamentally untestable, we provide an indirect empirical exercise following the approach by Hoe (2022) to assess whether the arrival of emergency cases is ex-ante predictable. Figure 3, the left panel plots the actual and the predicted number of events, where the latter is estimated conditional on a set of hospital, year, and week-of-the-year fixed effects. The distribution of the number of arrivals closely tracks the theoretical distribution of a Poisson random variable (i.e., the actual number of arrivals), indicating that the arrival of emergency cases is indeed likely to be exogenous.

For IV validity, we also have to establish that the arrival of emergency cases for peers in the past week is unlikely to affect our focal physicians' i radiation output directly. In our settings, this would occur if there were a systematic allocation of emergency cases to doctors. For example, if the triage nurse in the emergency department assigns patients based on doctors' skills (i.e., matching severe patients to more experienced doctors). We primarily address this concern by using a subset of emergency cases – on-call cases – where doctors are likely to work on their own during the on-call shift, therefore minimizing the potential violation of the exclusion restriction for other physicians in the subsequent week. Moreover, in our baseline model, we control for the characteristics of the focal doctor and their peers, including several risk-adjuster measures such as patients' age, the severity of cases, previous history of heart attacks, and other co-morbidities, which will also help allay such issues.

We also empirically study whether there is any evidence of a systematic allocation of emergency cases in the first place. We estimate physicians' underlying preference for radiation by estimating each physician's random intercept using a mixed model approach and then plot the estimated intercepts against the distribution of emergency cases. In the absence of systematic pattern, the plot should show similar share of emergency cases across physicians' preference for radiation dosage. This approach has been used in prior research such as (Currie *et al.*, 2016; Dobbie *et al.*, 2018).

We do this by exploiting the cases in which the physician works in the operating theater by themselves (i.e., no overlapping peers working on the same day). Our assumption is that there would not be any contemporaneous spillovers from the peers when they were working by themselves, thus uncovering the focal physicians' underlying preference towards radiation dosage. The intuition of this approach is that the distribution of emergency cases should not follow a certain systematic pattern across the distribution of estimated physicians' random intercept, conditional on the hospital, year, and week of the year fixed effects, as well as focal physicians' age and gender.

Figure 3 plots the estimated intercept against the distribution of emergency cases. In this figure, the doctors' preference towards radiation dose ranges from the most conservative to the most aggressive towards radiation dosage. The plot indicates no systematic pattern of distribution of emergency cases, suggesting physicians' preference does not determine the assignment of emergency cases, further indirectly supporting our instrument validity.

Similarly, another potential channel that could threaten the exclusion restriction assumption is through the dynamic reallocation of patients at the hospital level. In one scenario, the focal doctor i may be crowded out by their peers on the allocation of emergency cases. Another plausible scenario is, after observing his peers' work on relatively more patients than him, he asked the hospital manager for more emergency shifts in order to work more cases. In these two scenarios, our instrument may affect the focal physician i outcome directly.

We address this, by first, controlling for the focal doctor i's own emergency cases in the past week. The inclusion of this variable captures the possibility of crowding out of emergency cases within peer groups. Second, we include the total number of patients treated by all members of the peer group (i.e., focal doctors and their peers') in the past week. The unobserved potential dynamic allocation of emergency patients will then be captured by this variable.

A remaining potential channel that would violate our instrument is through patients' choice of hospitals that is correlated with the peers' (and own) outcome. If, for example, patients systematically choose to be treated in specific hospitals that match their preferences. Yet, the Swedish healthcare system is largely a non-choice healthcare system, particularly for inpatient hospital care where patients are assigned based on the catchment areas of the hospitals. Additionally, heart attacks are considered emergencies that need to be treated timely and therefore patients are less likely to sort into hospitals.[15]

Finally, while the exclusion restriction assumption is fundamentally untestable, we supplement our analysis by performing a bounding exercise following Conley *et al.* (2012). The approach allows inference of the 2SLS estimates to proceed by allowing a direct effect of the instrument on the outcomes and conducts sensitivity analysis under this assumption.

4.2.3 Monotonicity

In the presence of heterogeneous treatment effects, the assumptions discussed above would need an additional condition to recover the LATE (Angrist *et al.*, 1996). The monotonicity assumption requires that the peers' exposure to emergency cases should weakly operate in the same direction for all peers of the focal doctors. The violation of this assumption would mean that the instrument induces a few of the doctors to not adhere to the treatment (i.e., deviation from the direction of the peers' average radiation output), creating the existence of "defiers". As a result, our 2SLS estimates would bias away from the well-defined LATE estimates.

The implication of this assumption is that the first stage relationship must have the same direction of effects in all subsamples. Table 2 reports our first-stage estimates. The results show the estimates are positive across age groups and physicians' genders, consistent with our monotonicity assumption.

5 Results

5.1 Main results

We begin by presenting our main estimates in Table 3. Panel A presents the OLS estimates and shows positive spillover effects from the peers to the focal physicians' own radiation output in all specifications: a 1 standard deviation (SD) increase in peers' radiation output, leads to a 0.36 SD increase in the focal physicians' own output (column 1) and 0.18 standard deviations (column 2) in the baseline model, i.e., the one corresponding to equation (1) above. In column 3, we augment our main specification with additional controls for the risk-adjuster measures such as patients' characteristics and their comorbidities and this does not impact the point estimates. As discussed at length

[15] In our robustness checks we control for the hospital fixed effects that capture the different composition of patients across the defined hospital catchment areas. While we don't rule out any referrals that might occur between hospitals (e.g., if patients need more sub-specialized care), this is unlikely to be an issue for our analysis as most patients went to their assigned hospitals. Patients' compliance to the designated catchment areas is generally above 90% Avdic *et al.* (2022b)

in the previous section, these estimates are unlikely to uncover the true underlying peer effects in physician behavior.

We report the 2SLS estimates in the subsequent panels. Panel B report the first-stage estimates of our instrument on the main endogenous variable. We instrument the peers' radiation output with the peers' total on-call emergency cases they encountered in the previous week ($t-1$). The first stage results show a positive relationship : i.e., exposure to emergency cases in the previous week increases peers' radiation output in the following week. We also test the strength of our instrument and report the Montiel-Pflueger F-statistics. Our instrument are strong across specifications.

Panel D present the second-stage estimates from the 2SLS based on our IV strategy. Relative to the OLS estimates, our 2SLS estimates predict slightly larger positive spillover effects from the peers to the focal doctor. We first estimate the naive model and find that when peers increase their radiation output by 1 SD, the focal physician increases their own radiation output by 0.57 SD. This suggests an increase of 1,700 units or 30% with respect to the mean. Our baseline estimates in column (2) report a marginally diminished point estimate of 0.52 (27% relative to the mean) while column (3) with additional controls finds an effect size of 0.54 SD. We also report the Anderson-Rubin test to establish the appropriateness of our IV approach.

We augment our baseline specification with a set of additional controls to address potential omitted variables that affects the main estimates. Table 4 provides the results of these checks. In the first column, we address the potential confounder that might not only correlated with the peers' radiation output but potentially violate our instrument exogeneity assumption. In particular, we control for the hospital case volume as a means to control for any workplace dynamic within hospitals that is related to how shifts (and corresponding allocation of case) are scheduled. One example of how this could happen in our settings if say, one doctor observed her peers' worked on relatively more case in the previous week and then asks the manager for more cases in the following week.[16]

Column 1 reports the estimate from the inclusion of the total hospital case volume in the main specification and is similar to the baseline estimate. The F-statistics, however, are slightly smaller but remain a strong predictor for the instrumented variable.

In column 2 we present the results from the inclusion of hospital fixed effects. In general, our doctors fixed effects subsume the hospital fixed effects, but the inclusion of hospital fixed effects is important in the context of switchers (i.e., doctors move to different hospitals).[17] The point estimate is slightly larger compared to the baseline

[16] Although this is unlikely as rotation assignment is usually set in advance and changes month, if not quarterly

[17] Our sample construction exclude doctors who are only visiting (e.g. temporary replacement to on-leave doctors) but may include doctors who, at a later point in the panel, move to different hospitals.

results but is similar in terms of magnitude. A one standard deviation increase of the peers' output increases the focal physicians' output by 39% with respect to the mean (compared to 27% in our baseline results).

Next, we address the concern that the spillovers might be affected by the focal physicians' own radiation output in the previous week. The estimate in column 3 indicates that spillover effects from the peers remain stable. As a last check, we consider removing observations that are considered outliers as these might extremely pull the point estimate. Removing the top-coded observations (above 97.5 percentile) from our sample (127 observations, less than 0.01% of our sample) did not change our point estimate. A one standard deviation increase in the peers' radiation output change the focal physicians' radiation output by 0.46 standard deviation or 22% relative to the mean. In general, our results are stable across the different specifications and the F-statistics from the first stage are strong.

One remaining concern with our baseline estimates is the potential autocorrelation of the instrument. For instance, if the number of emergency cases of the peers in the previous week predicts the peers' total emergency cases in the following week through some institutional mechanism (i.e., if the hospital planner alternates the shift rotation following a high-load emergency shift in the previous week), then the instrument assumption is invalid, and the 2SLS results may be spurious. We address this concern by augmenting our main specification by controlling for contemporaneous peers' emergency cases. If there is negative autocorrelation, we expect the estimates to tend towards zero. Columns 1-3 in Table 5 report these results.

Conditioning on the contemporaneous instrument generally did not alter the main estimates; in fact, these exercises suggest otherwise. While the estimates are slightly larger, their magnitudes are statistically similar. More importantly, we address this concern partly through the inclusion of focal doctors' own arrival of emergency cases in our main specification and in all robustness checks. Columns 4-6 in Table 5 report the estimates from controlling for focal doctors' emergency cases both in the previous week and contemporaneously. The inclusion of contemporaneous focal doctors' emergency cases allows for the correlation between our instrument and focal doctors' unobservables that are not captured by the fixed effects (i.e., through a similar displacement of cases/shifts arrangement argument). Our results remain robust to these specifications, as shown in columns 4-6. We thus conclude that autocorrelation is not a concern, as our estimates are robust to these specifications

As a supplementary analysis, we run an additional set of robustness checks using the same model specifications as in Table 4 but with a different instrument, specifically the number of emergency cases (including on-call emergency cases) of the peers. We present these results in Table 6. We find that using this instrument did not change our results from the baseline results in Table 3.

5.2 Heterogeneous effects

Our main baseline specification assumes the spillover effects are homogeneous across different characteristics of the focal doctors. It is, however, likely that the spillover effects to differ. For example, previous research have shown gender differences in peer effects (see eg. Han and Li (2009); Lavy and Schlosser (2011); Beugnot *et al.* (2019)). We proceed by reporting the 2SLS estimates to investigate the heterogeneous treatment effects. Table 9 presents these results. In the first two columns, we looked at gender-specific treatment effects. Interacting the peers' radiation output with both categories for female and male physicians, we find both the point estimate and the F-statistics for male doctors are comparable to our baseline. However, female focal physicians are affected higher relative to male focal physicians yet the corresponding F-stats is lower for the female focal doctors. This is likely due to the small number of female physicians in our data, where female doctors only consist of 10% of our sample (19 out of 186 doctors).

Next, we report the estimates from different age groups. In column 3 we show the estimation results for doctors below the age of 49 (the median age in our sample). The point estimate is broadly similar albeit slightly smaller to our baseline results (0.365 relative to 0.518 in the baseline estimate). In contrast to the younger doctors, we find no spillover effects on doctors who are older than 49. It is not surprising that older doctors do not seem to be affected by their peers. These results suggest that older doctors may have an established practice style relative to younger doctors who are more malleable to peer effects, a finding that is similar to existing literature (Molitor, 2018; Avdic *et al.*, 2023).

In our next set of results, we looked at whether the spillover effects vary based on the types of hospitals. One might reason that peer effects would be larger at academic hospitals (i.e., hospitals considered as university hospitals) due to their higher teaching and research intensity compared to local hospitals. However, our results seem to suggest otherwise. The point estimate is similar to our baseline. The spillover effects at local hospitals, however, are larger relative to academic hospitals but are broadly similar in terms of magnitude. A one standard deviation increase translates to a 41% increase with respect to the mean, in comparison to the baseline results of a 27% increase with respect to the mean. These results are not unexpected, as focal doctors at local hospitals might primarily rely on feedback and exchange with peers, unlike those doctors at academic hospitals where learning sources might slightly vary.

Lastly, we look at whether spillover effects vary according to the peer group size. A large peer group, for instance, may provide a larger information set for the focal doctors to learn from, relative to a smaller group size. On the other hand, a higher number of peers may influence the focal doctors' behavior through peer pressure or conformity. Although we are not able to distinguish the mechanism between the two, we find that the spillover effects mainly originate from groups with more than 3 peers. These effects are broadly similar to the baseline results (0.4 vs. 0.5 in the main estimate). On the contrary, we do not find spillover effects in groups with less than 3 peers.

5.3 Quality implication

In our next set of results, we assess the implication of peer effects on patients' outcomes. We look at the peer effects on a set of outcomes where we follow Chandra *et al.* (2016) in recovering the physician-week specific quality outcomes. To be precise, using our initial patient-level dataset, we estimate the 30-day quality outcomes on a set of controls: patients' characteristics, risk-adjuster measures such as past history of illness, co-morbidities, and including the physician-hospital-week fixed effects. We then extract the physician-hospital-week FEs which become the 30-day risk-adjusted quality measures for a given outcome: 30-day mortality rate, 30-day infarction rate, 30-day restenosis rate (reblocking of the coronary artery), and 30-day thrombosis rate (a clot formation due to the implanted stent/"balloon" device).

Generally, our results in Table 7 imply improvements in patients' outcomes. We find a positive effect (negative estimates) on the probability of the 30-day mortality, infarction, and stent thrombosis, but no effect for restenosis. The effects translate into 2 of 1,000 patients prevented from death and 2 of 1,000 patients avoided the adverse clot formation (stent thrombosis). Similarly, we find a reduction of 1 (of every 1,000 patients) less patient experienced re-infarction.

5.4 Peer effects on appropriateness of care

As an extended analysis, we assess the potential implication of peer influences on the appropriateness of care by looking at the effects on the share of patients at the margin of the recommended radiation output. The implication of these effects would differ depending on whether radiation dosage output is considered "insufficient", "appropriate", or "excessive". For instance, a reduction in the share of patients given an "insufficient" of radiation is considered as potentially welfare-improving as this would suggest an appropriate level of quality of care is given. A further increase in the share of patients given an "excessive" amount would not necessarily be a welfare improvement as this means that the patient could use a lesser amount of radiation while maintaining the quality of care.

Table 8 reports this analysis. In the first two columns, we assess the effects on the share of patients who had insufficient radiation dosage. The point estimates report negative effects, meaning that the spillover effects from the peers' radiation output reduce the share of patients classified in this category. In other words, it brings the patients into the recommended range of radiation (i.e., the specified range of reference levels (DRLs)). The magnitude of these effects translates into a decrease of 21 percentage points with the respect to the mean. In terms of absolute numbers, suppose there is an average of 100 patients on a given week, the effect suggests roughly 20 from 30 patients less in the insufficient radiation dosage range.

Moving to columns 3 and 4, we look at the spillover effects on the share of patients who are considered to receive beyond the recommended radiation dosage range. The point estimates are positive, meaning that the spillover effects increase the share of patients given an excessive amount of radiation dosage. However, this effect is small in magnitude. For example, one standard deviation increase of the peers' radiation output would result in an increase of 7 percentage points with respect to the mean (0.105). In absolute numbers, the effect suggests that 7 for every 100 patients would receive the amount of radiation that is considered above the recommended range.

In the last two columns, we provide the estimated results on the share of patients that are considered within the recommended dosage range. The estimates indicate positive spillover effects, meaning more patients would be in the recommended range of dosage (a 16 percentage points increase). This is likely a net result of the reduction of the share of patients that are considered "insufficient" and the increase on the share of patients that are given an "excessive".

5.5 Do peer effects persist over time?

We have established the existence of spillover effects within physicians across weeks. There are different policy implications depending on whether peer influences have a longer-lasting impact over time. To investigate this, we use Equation 1 but vary the outcome, i.e., $Y_{ig(h,t+j)}$ for $j = \{-4, ..., 4\}$

In this specification, we run the outcome variable at various t while keeping the right-hand side fixed, including the main endogenous variable and its instrument at $t = 0$, where the actual overlapping with peers occurs. For example, at $t = 0$, the coefficient β would be exactly the same as the main estimate in Equation 1. We assess whether the spillover effects on the focal doctors persist over time, i.e., at $t > 0$. Secondly, using the outcome at $t < 0$ allow us to check whether the spillover exists prior to the actual overlapping occurring at $t = 0$, similar to the assessment of pre-trend in the event study model.

Two features of Figure 5 are evident. First, the peer effects increase at the time when the actual overlapping occurs (i.e., $t = 0$) and then decline in the weeks following the overlapping. The spillover effects somewhat increase focal doctors' radiation output three weeks after overlap with the peers; however, this effect is modest, and the confidence interval of the estimate suggests the effect is not statistically different from zero. We determine that the spillover effects are short-term.

A second important feature of the plot is that by assessing the spillover effects at $t = 0$ on focal doctors' outcomes prior to $t = 0$ allow us to test our identifying assumption by providing a falsification test. There should be no spillover effect on the focal doctors' past outcomes as the overlapping occurs in the future. Figure 5 shows that we cannot reject the effects as statistically different from zero leading to the actual overlap at $t = 0$.

5.6 What explains the improvement in the quality of care?

In this section, we attempt to understand the potential different channels that drive our quality estimates.

5.6.1 Extensive vs intensive margins

In the first set of results, we seek to distinguish whether peer effects improve quality outcomes through changes in the extensive and intensive margins of healthcare delivery. In our setting, this means that the focal doctors could be affected by the peers in two different ways. First, peers might induce the focal doctors to treat more segments of the coronary artery or the heart's blood vessels, conditional on patients' characteristics.

Secondly, another potential channel is through changes in the intensive margins. The focal doctors might be induced by the peers into treating the affected part of the blood vessel more intensively by using a larger number of "ballooning" devices (i.e., stents). An example would be treating one blocked segment with three stents instead of one. Treating more segments and/or using more stents during the procedure has lower marginal costs and potentially higher returns in the long run, but it also implies unnecessary delivery of care.

We distinguish whether either of these two potential channels is at play in our cases by using the number of segments treated and the number of stents used as the main outcome variables. Table 10 presents the results.

Looking at column one, the sign is negative, suggesting a negative peer effect on the number of segments treated. However, the effect is statistically insignificant. Conversely, there is a positive effect on the number of stents used, as indicated in column 2. The marginal effect seems to be quite substantive (i.e., 14% relative to the mean). However, it is also not statistically different from zero. Our results therefore suggest that there are no changes on both the extensive and intensive margins.

5.6.2 Effects on treatment choice

Recall that radiation output is an end product resulting from various choice components from the physicians' side, conditional on patients' characteristics. For example, the physicians could decide the entry point to insert the catheter device that is required to locate the blockage (with the aid of X-ray). The mainstream entry points of the catheterization procedures are either through the leg (via femoral artery, i.e., the thigh) or through the arm (via radial artery, i.e., the arm). Each options possess its own cost-benefit.

Recently, international experts on the interventional cardiology calls for more arm entry points for its superior lower risk of bleeding, yet it is technically more difficult to perform given the smaller size of the artery (Gargiulo *et al.*, 2022). The leg option (through the femoral artery that runs underneath the thigh region), is historically been the "status-quo", providing a safer access given the artery's' larger size (relative to the arm) and thus require less complexity in performing the procedure. However, this approach typically warrants a larger radiation output and slightly inferior bleeding risk. Figure 4 show the different levels and trends of the average radiation dosage produced on both arm and leg entry points.

We investigate whether the positive spillover effects can be partly explained by the changes in the treatment choice decision as proxied by the share of patients who were given the procedure through the femoral artery. We estimate the baseline specification model using the share of patients operated through the femoral artery (leg) as the outcome. Table 11 column 1 reports the estimated spillover effects. We find that for every 1 SD increase in the peers' radiation output, the focal physician i switch their treatment option into more "status-quo" option (i.e., through the leg via femoral artery). The effect size is a 14 percentage points higher, which translates into roughly slightly more than 31% of the average weekly patients.

Though we cannot fully establish the mechanism of our estimates, our results seem to indicate that doctors "learn" from their peers to switch their treatment decision into "status quo"/procedurally less complex . We posit this as an indication of risk-aversion as doctors move away from the treatment option that is technically more difficult. Our results draws parallel to Chodick *et al.* (2023) where following a difficult encounter, doctors order more tests immediately on the next patient, an indication of risk-aversion in ensuring the diagnosis/treatment is accurate.

6 Conclusion

In this paper, we investigate the extent of peer influences in healthcare. Our focus is on cardiologists' radiation output—an objective yet crucial measure for accurate diagnosis in the event of heart attacks. To this end, we leverage the plausibly exogenous arrival of emergency cases to address endogeneity concerns (Manski, 1993) in an instrumental variable (IV) approach, allowing us to recover the causal impact of peers.

Our results suggest that physicians are indeed affected by their peers. Estimation results show that a one standard deviation increase in the amount of peers' radiation output leads to a 0.5 standard deviation increase (a 25% increase relative to the mean) in the focal physicians' own radiation output. A battery of robustness checks indicates that our main estimates remain largely unchanged across different specifications. Moreover, our instrument is consistently strong, providing assurance regarding the inference of our estimates.

Further investigation into heterogeneous treatment effects indicates no differential treatment effects between male and female physicians. While we find no spillover effect for older doctors, we do find peer effects among younger doctors. These results suggest that the evolution of physicians' practice styles does not occur at a later stage in a physician's career, aligning with previous literature in the context of cardiologists' practice style in the US (Molitor, 2018) and surgeons' technology adoption in the UK (Barrenho *et al.*, 2021).

To provide insights into potential welfare implications, we find improvements in patients' outcome measures, particularly in risk-adjusted 30-day mortality. Our results indicate a reduction rate of 2 out of 1000 patients. These findings hold substantive policy relevance, as 30-day outcomes are widely used as a proxy measure of the quality of care.

We find that our results are partly driven by changes in the focal physicians' treatment decisions, specifically the share of patients operated through the leg—one of the two mainstream options for performing the interventional procedure that is considered 'status quo' and easier to perform, being technically more approachable.

As is common in IV settings, our approach only allows us to recover the effect among the compliers (LATE), which may differ from the average treatment effect. Nevertheless, our results provide evidence of positive peer effects in healthcare practice, specifically in the high-stakes yet ambiguous nature of optimal radiation dosage. Our study complement a recent finding (Silver, 2021) and thus extend this literature. Our results may inform hospital organizational policy either through strategic scheduling of doctors. While we cannot establish the exact mechanism such as social learning or norm conformity, it is crucial for future research to explore the extent to which these channels affect physicians.

References

Abaluck, J., Agha, L., Kabrhel, C., Raja, A. and Venkatesh, A. (2016). The determinants of productivity in medical testing: Intensity and allocation of care. *American Economic Review*, **106** (12), 3730–3764.

Agha, L. and Zeltzer, D. (2022). Drug diffusion through peer networks: The influence of industry payments. *American Economic Journal: Economic Policy*, **14** (2), 1–33.

Andrews, I., Stock, J. H. and Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, **11**, 727–753.

Angrist, J. D., Imbens, G. W. and Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American statistical Association*, **91** (434), 444–455.

Arcidiacono, P., Kinsler, J. and Price, J. (2017). Productivity spillovers in team production: Evidence from professional basketball. *Journal of Labor Economics*, **35** (1), 191–225.

— and Nicholson, S. (2005). Peer effects in medical school. *Journal of public Economics*, **89** (2-3), 327–350.

Avdic, D., Gutacker, N., van Empel, G. and Vikström, J. (2022a). *Provider responses to market entry under competing health technologies*. Tech. rep., Working Paper.

—, Ivets, M., Lagerqvist, B. and Sriubaite, I. (2023). Providers, peers and patients. how do physicians' practice environments affect patient outcomes? *Journal of Health Economics*, **89**, 102741.

—, Lundborg, P. and Vikström, J. (2022b). Does healthcare consolidation harm patients? evidence from maternity ward closures. *American Economic Journal : Economic Policy*, **forthcoming**.

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

—, — and — (2010). Social incentives in the workplace. *The review of economic studies*, **77** (2), 417–458.

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

Barrenho, E., Gautier, E., Miraldo, M., Propper, C. and Rose, C. D. (2020). Innovation diffusion and physician networks: Keyhole surgery for cancer in the english nhs.

—, Miraldo, M., Propper, C. and Walsh, B. (2021). The importance of surgeons and their peers in adoption and diffusion of innovation: an observational study of laparoscopic colectomy adoption and diffusion in england. *Social Science & Medicine*, **272**, 113715.

Barro, J. R., Huckman, R. S. and Kessler, D. P. (2006). The effects of cardiac specialty hospitals on the cost and quality of medical care. *Journal of Health Economics*, **25** (4), 702–721.

Bayer, P., Ross, S. L. and Topa, G. (2008). Place of work and place of residence: Informal hiring networks and labor market outcomes. *Journal of political Economy*, **116** (6), 1150–1196.

Beugnot, J., Fortin, B., Lacroix, G. and Villeval, M. C. (2019). Gender and peer effects on performance in social networks. *European Economic Review*, **113**, 207–224.

Braaf, S., Manias, E. and Riley, R. (2013). The 'time-out'procedure: an institutional ethnography of how it is conducted in actual clinical practice. *BMJ quality & safety*, **22** (8), 647–655.

Bramoullé, Y., Djebbari, H. and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, **150** (1), 41–55.

Burke, M. A., Fournier, G. M. and Prasad, K. (2007). The diffusion of a medical innovation: Is success in the stars? *Southern Economic Journal*, **73** (3), 588–603.

Card, D., Dobkin, C. and Maestas, N. (2008). The impact of nearly universal insurance coverage on health care utilization: evidence from medicare. *American Economic Review*, **98** (5), 2242–58.

—, — and — (2009). Does medicare save lives? *The Quarterly Journal of Economics*, **124** (2), 597–636.

Carter, S., Garside, P. and Black, A. (2003). Multidisciplinary team working, clinical networks, and chambers; opportunities to work differently in the nhs. *BMJ Quality & Safety*, **12** (suppl 1), i25–i28.

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

—, Gentzkow, M. and Yu, C. (2022). Selection with Variation in Diagnostic Skill: Evidence from Radiologists. *Quarterly Journal of Economics*, **137** (2), 729–783.

Chandra, A., Cutler, D. and Song, Z. (2011). Who ordered that? the economics of treatment choices in medical care. *Handbook of health economics*, **2**, 397–432.

—, Finkelstein, A., Sacarny, A. and Syverson, C. (2016). Health care exceptionalism? performance and allocation in the us health care sector. *American Economic Review*, **106** (8), 2110–44.

Chen, Y. (2021). Team- Specific Human Capital and Team Performance: Evidence from Doctors. *American Economic Review*, **111** (12), 3923–3962.

Chodick, G., Goldstein, Y., Shurtz, I. and Zeltzer, D. (2023). Challenging Encounters and Within-Physician Practice Variability. *The Review of Economics and Statistics*, pp. 1–27.

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

Commission, E. and for Energy, D.-G. (2015). *Medical radiation exposure of the European population*. Publications Office.

Conley, T. G., Hansen, C. B. and Rossi, P. E. (2012). Plausibly exogenous. *Review of Economics and Statistics*, **94** (1), 260–272.

Cornelissen, T., Dustmann, C. and Schönberg, U. (2017). Peer effects in the workplace. *American Economic Review*, **107** (2), 425–456.

Cousins, C., Miller, D., Bernardi, G., Rehani, M., Schofield, P., Vañó, E., Einstein, A., Geiger, B., Heintz, P., Padovani, R. *et al.* (2013). Icrp publication 120: Radiological protection in cardiology. *Annals of the ICRP*, **42** (1), 1–125.

Currie, J. and Macleod, W. B. (2017). Diagnosing expertise: Human capital, decision making, and performance among physicians. *Journal of Labor Economics*, **35** (1), 1–43.

—, MacLeod, W. B. and Van Parys, J. (2016). Provider practice style and patient health outcomes: The case of heart attacks. *Journal of health economics*, **47**, 64–80.

Cutler, D. M., Huckman, R. S. and Kolstad, J. T. (2010). Input constraints and the efficiency of entry: Lessons from cardiac surgery. *American Economic Journal: Economic Policy*, **2** (1), 51–76.

David, G. and Brachet, T. (2009). Retention, learning by doing, and performance in emergency medical services. *Health services research*, **44** (3), 902–925.

De Giorgi, G., Frederiksen, A. and Pistaferri, L. (2020). Consumption network effects. *The Review of Economic Studies*, **87** (1), 130–163.

Dobbie, W., Goldin, J. and Yang, C. S. (2018). The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges†. *American Economic Review*, **108** (2), 201–240.

Doyle Jr, J. J., Graves, J. A., Gruber, J. and Kleiner, S. A. (2015). Measuring returns to hospital care: Evidence from ambulance referral patterns. *Journal of Political Economy*, **123** (1), 170–214.

Epstein, A. J. and Nicholson, S. (2009). The formation and evolution of physician treatment styles: An application to cesarean sections. *Journal of Health Economics*, **28** (6), 1126–1140.

Friebel, G., Heinz, M., Krueger, M. and Zubanov, N. (2017). Team incentives and performance: Evidence from a retail chain. *American Economic Review*, **107** (8), 2168–2203.

Gabbay, J. and Le May, A. (2004). Evidence based guidelines or collectively constructed "mindlines?" ethnographic study of knowledge management in primary care. *Bmj*, **329** (7473), 1013.

Gargiulo, G., Giacoppo, D., Jolly, S. S., Cairns, J., Le May, M., Bernat, I., Romagnoli, E., Rao, S. V., van Leeuwen, M. A., Mehta, S. R. *et al.* (2022). Effects on mortality and major bleeding of radial versus femoral artery access for coronary angiography or percutaneous coronary intervention: meta-analysis of individual patient data from 7 multicenter randomized clinical trials. *Circulation*, **146** (18), 1329–1343.

Georges, J.-L., Belle, L., Etard, C., Azowa, J.-B., Albert, F., Pansieri, M., Monsegu, J., Barbou, F., Trouillet, C., Leddet, P. *et al.* (2017). Radiation doses to patients in interventional coronary procedures—estimation of updated national reference levels by dose audit. *Radiation protection dosimetry*, **175** (1), 17–25.

Guryan, J., Kroft, K. and Notowidigdo, M. J. (2009). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics*, **1** (4), 34–68.

Hamilton, B. H., Nickerson, J. A. and Owan, H. (2003). Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. *Journal of political Economy*, **111** (3), 465–497.

Han, L. and Li, T. (2009). The gender difference of peer influence in higher education. *Economics of Education review*, **28** (1), 129–134.

Harmon, N., Fisman, R. and Kamenica, E. (2019). Peer effects in legislative voting. *American Economic Journal: Applied Economics*, **11** (4), 156–80.

Hirshfeld, J., Brinker, J. and Kern, M. (2005). Accf/aha/hrs/scai clinical competence statement on physician knowledge to optimize patient safety and image quality in fluoroscopically guided invasive cardiovascular procedures: a report of the american college of cardiology foundation/american heart association/american college of physicians task force on clinical competence and training. *Circulation*, **111** (4), 511–532.

Hoe, T. P. (2022). Does Hospital Crowding Matter? Evidence from Trauma and Orthopedics in England†. *American Economic Journal: Economic Policy*, **14** (2), 231–262.

James, S., Lagerqvist, B., Lundborg, P. and Vikström, J. (2022). *Learning-by-doing and productivity growth among high-skilled workers: evidence from the treatment of heart attacks*. Tech. rep., Working Paper.

Jaravel, X., Petkova, N. and Bell, A. (2018). Team-specific capital and innovation. *American Economic Review*, **108** (4-5), 1034–73.

Johnson, E. M. and Rehavi, M. M. (2016). Physicians treating physicians: Information and incentives in childbirth. *American Economic Journal: Economic Policy*, **8** (1), 115–41.

Kandel, E. and Lazear, E. P. (1992). Peer pressure and partnerships. *Journal of political Economy*, **100** (4), 801–817.

Keane, M. and Neal, T. (2023). Instrument strength in iv estimation and inference: A guide to theory and practice. *Journal of Econometrics*.

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

Kobayashi, T. and Hirshfeld Jr, J. W. (2017). Radiation exposure in cardiac catheterization: operator behavior matters.

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

Lavy, V. and Schlosser, A. (2011). Mechanisms and impacts of gender peer effects at school. *American Economic Journal: Applied Economics*, **3** (2), 1–33.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, **60** (3), 531–542.

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

McGee, S. (2014). Bedside teaching rounds reconsidered. *Jama*, **311** (19), 1971–1972.

McWilliams, J. M. (2022). Pay for performance: When slogans overtake science in health policy. *JAMA*, **328** (21), 2114–2116.

Mettler Jr, F. A., Huda, W., Yoshizumi, T. T. and Mahesh, M. (2008). Effective doses in radiology and diagnostic nuclear medicine: a catalog. *Radiology*, **248** (1), 254–263.

Miraldo, M., Propper, C. and Rose, C. D. (2021). Identification of Peer Effects using Panel Data. *SSRN Electronic Journal*, pp. 1–31.

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

Nair, H. S., Manchanda, P. and Bhatia, T. (2010). Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *Journal of Marketing Research*, **47** (5), 883–895.

Nicoletti, C., Salvanes, K. G. and Tominey, E. (2018). The family peer effect on mothers' labor supply. *American Economic Journal: Applied Economics*, **10** (3), 206–234.

Picano, E., Vano, E., Rehani, M. M., Cuocolo, A., Mont, L., Bodi, V., Bar, O., Maccia, C., Pierard, L., Sicari, R. *et al.* (2014). The appropriate and justified use of medical radiation in cardiovascular imaging: a position document of the esc associations of cardiovascular imaging, percutaneous cardiovascular interventions and electrophysiology. *European heart journal*, **35** (10), 665–672.

Richardson, D. B., Leuraud, K., Laurier, D., Gillies, M., Haylock, R., Kelly-Reif, K., Bertke, S., Daniels, R. D., Thierry-Chef, I., Moissonnier, M., Kesminiene, A. and Schubauer-Berigan, M. K. (2023). Cancer mortality after low dose exposure to ionising radiation in workers in france, the united kingdom, and the united states (inworks): cohort study. *BMJ*, **382**.

Roth, G. A., Mensah, G. A., Johnson, C. O., Addolorato, G., Ammirati, E., Baddour, L. M., Barengo, N. C., Beaton, A. Z., Benjamin, E. J., Benziger, C. P. *et al.* (2020). Global burden of cardiovascular diseases and risk factors, 1990–2019: update from the gbd 2019 study. *Journal of the American College of Cardiology*, **76** (25), 2982–3021.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? In *Handbook of the Economics of Education*, vol. 3, Elsevier, pp. 249–277.

Silver, D. (2021). Haste or Waste? Peer Pressure and Productivity in the Emergency Department. *The Review of Economic Studies*, **88** (3), 1385–1417.

Singh, M. (2021). Heuristics in the delivery room. *Science*, **374** (6565), 324–329.

Slotnick, H. (1999). How doctors learn: physicians' self-directed learning episodes. *Academic Medicine*, **74** (10), 1106–17.

Smith, R. (1996). What clinical information do doctors need? *Bmj*, **313** (7064), 1062–1068.

Van de Wiel, M. W., Van den Bossche, P., Janssen, S. and Jossberger, H. (2011). Exploring deliberate practice in medicine: how do physicians learn in the workplace? *Advances in health sciences education*, **16**, 81–95.

Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in nazi germany. *The review of economic studies*, **79** (2), 838–861.

Williams, A. M. and Baláž, V. (2008). International return mobility, learning and knowledge transfer: A case study of slovak doctors. *Social Science & Medicine*, **67** (11), 1924–1933.

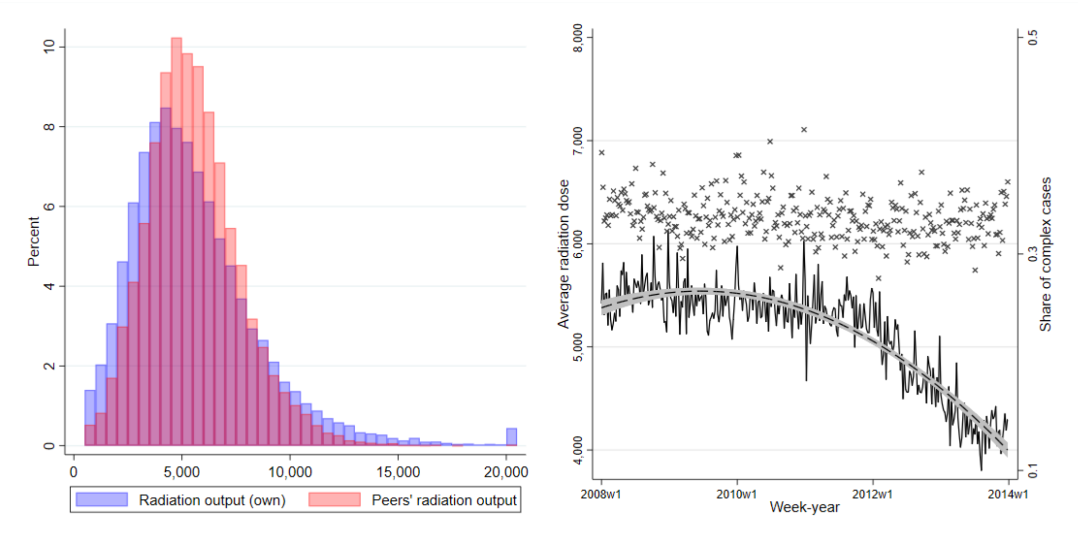
Zwarenstein, M. d. and Bryant, W. (2000). Interventions to promote collaboration between nurses and doctors. *The Cochrane database of systematic reviews*, (2), CD000072.

Tables and Figures

Table 1.
Summary statistics

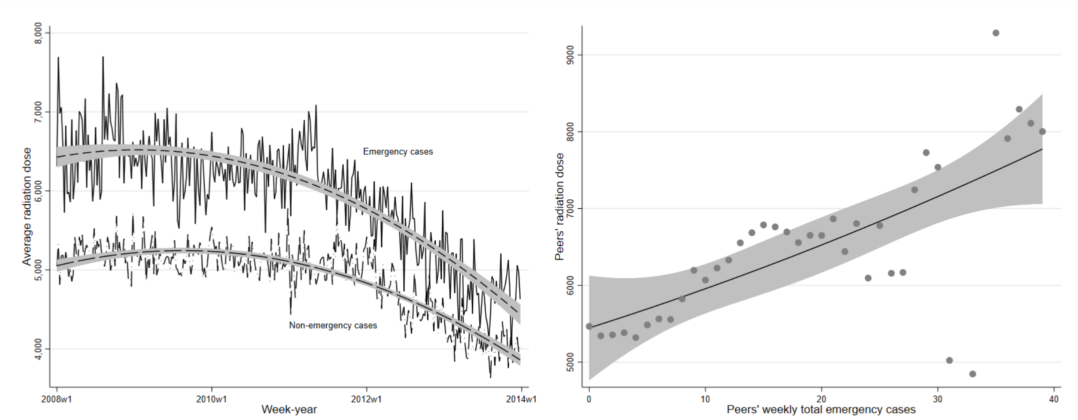
	Mean	SD	Min	Max
Physicians' output				
Radiation output	5,564	2,983	571	20,300
Peers' radiation output	5,558	2,158	571	20,300
Share of patients - excessive dosage	0.105	0.185	0	1
Share of patients - insufficient dosage	0.347	0.307	0	1
Share of patient - appropriate dosage	0.546	0.295	0	1
Fluoroscopic time (sec)	553.66	292.14	62	2,052
Contrast amount (ml)	114.74	40.07	30	300
Workplace				
Weekly cases	6.91	4.80	1	35
Emergency cases	1.79	2.18	0	22
Peers' emergency cases	1.80	1.50	0	21
Number of peers	3.30	1.80	1	12
Physicians' characteristics				
Age	48.95	7.48	31	68
Peers' age	48.95	4.09	37	64
Junior (30-44)	0.32	0.47	0	1
Mid-level (45-58)	0.57	0.50	0	1
Senior ($>$ 58)	0.11	0.31	0	1
Female doctors	0.10	0.30	0	1
Patients' characteristics				
Patients' age	66.50	6.16	38	88
Complex cases	0.23	0.23	0	1
PCI performed	0.50	0.28	0	1
Quality				
30-day Mortality	0.15	0.41	0	4
30-day Stent thrombosis	0.17	0.44	0	4
30-day Restenosis	0.017	0.13	0	2
30-day Infarction	0.06	0.25	0	3
Observations		28,639		

Figure 1.
Main outcome variable



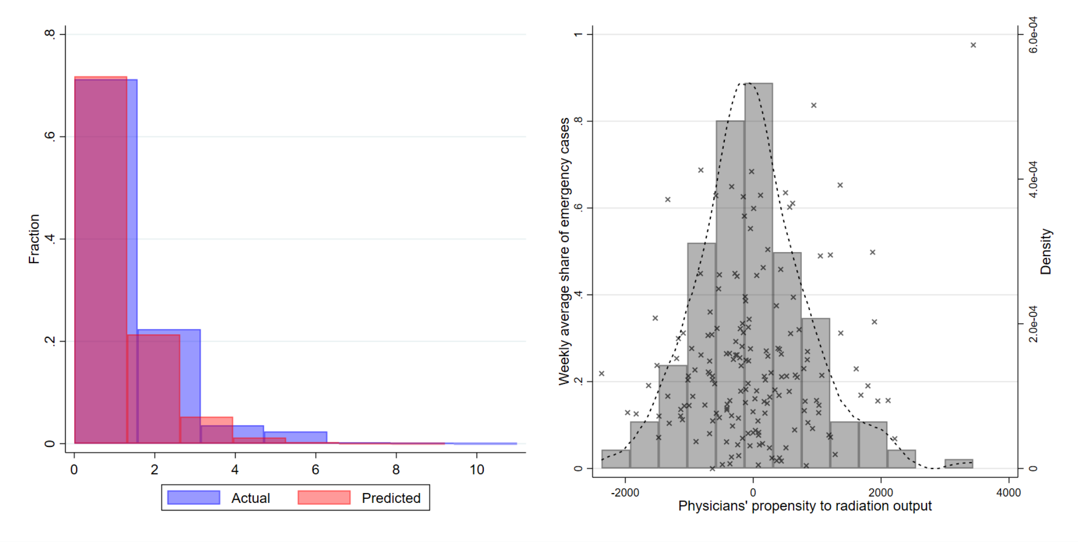
Note. Left panel plots the focal and the peers' radiation output. Right panel plots : 1. The actual weekly average trends of radiation output (solid line) and the predicted (dash line); 2. The share of complicated/severe cases over time (cross point

Figure 2.
IV Relevance



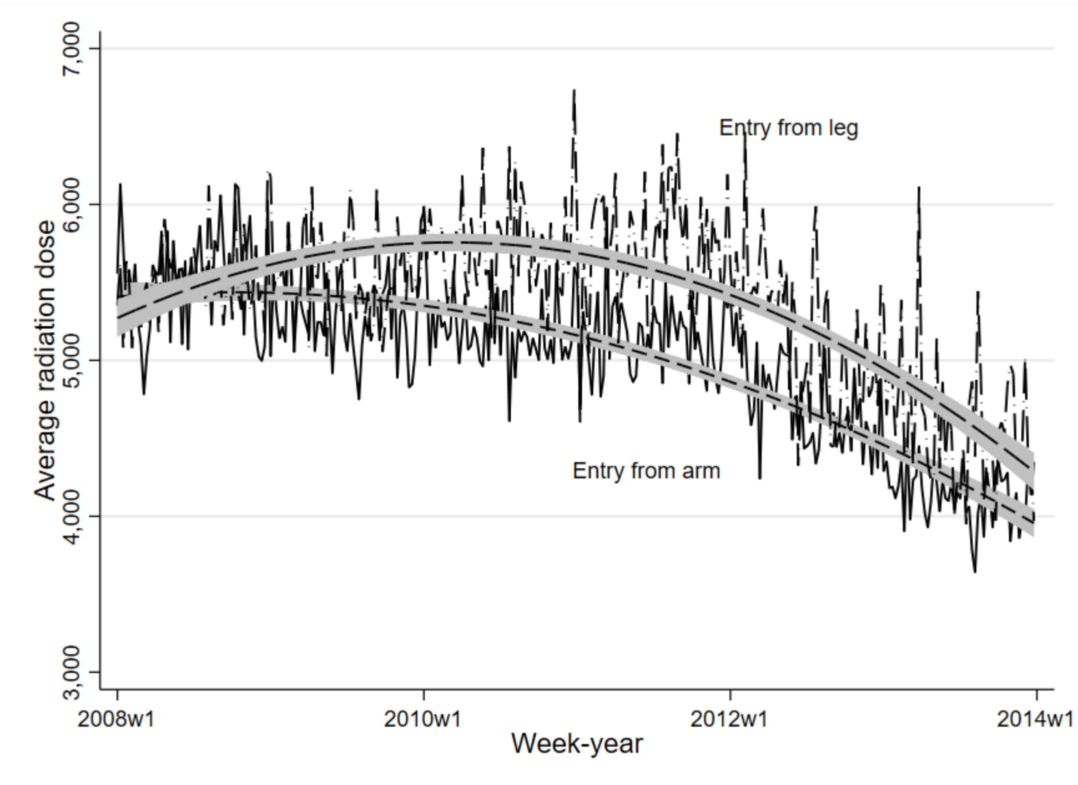
Note. Left panel shows the different levels of radiation output in emergency and non-emergency cases. Right panel plots the average peers' radiation on the peers' total weekly emergency cases.

Figure 3.
IV Validity



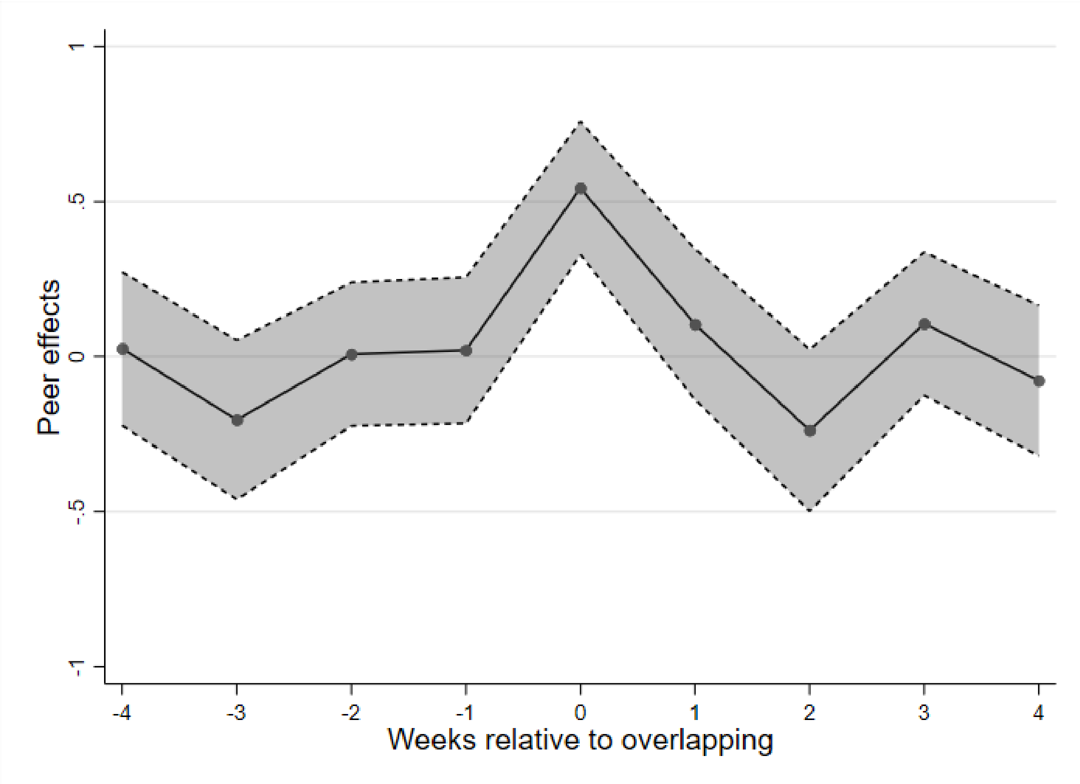
Note. Left panel plots the actual and the predicted results of the weekly arrival of emergency cases from the estimated poisson model. The poisson model controls for the hospital, year, and week-of-the-year fixed effects. Right panel plots the distribution of weekly number of emergency cases relative to the mixed-model estimated physicians' propensity to radiation output.

Figure 4.
Entry points



Note. The graph plots the different levels of radiation dosage based on the entry sites (i.e. leg or arm artery). Note that generally entry from the leg artery yield higher dosage.

FIGURE 5.
Event study



NOTE. The graph plots the estimated coefficient (solid point) and 95% confidence interval. The model vary the outcome variable at various t (i.e. the focal physicians' radiation output at various lag and lead) while kept the right side fixed at t. Model controls for doctor, year, week-of-the-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and risk-adjuster measures (patient's co-morbidity).

TABLE 2.
IV Monotonicity

	Gender		Age - median	
	(1)	(2)	(3)	(4)
Peers' emergency cases	0.114***	0.064***	0.109***	-0.020
	(0.028)	(0.013)	(0.014)	(0.018)
Observations	2,872	25,217	14,860	13,229

NOTE. Outcome and instrument variables are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer group level. Results are estimated using baseline OLS model specification. Model includes doctor's, year, and week-of-the year FEs, focal physician's emergency cases in the previous week (*t-1*).

Table 3.
Baseline estimates

	(1)	(2)	(3)
Panel A. OLS	Outcome : Focal radiation output		
Peers' radiation output	0.356***	0.178***	0.177***
	(0.013)	(0.010)	(0.010)
Panel B. 2SLS : First-stage	Outcome : Peers' radiation output		
Peers' emergency cases	0.153***	0.068***	0.067***
	(0.017)	(0.013)	(0.013)
Montiel-Pflueger F-stats	80.193	28.214	27.576
Panel C. 2SLS : Reduced form	Outcome : Focal radiation output		
Peers' emergency cases	0.088***	0.035***	0.036***
	(0.013)	(0.010)	(0.009)
Panel D. 2SLS : Second-stage	Outcome : Focal radiation output		
Peers' radiation output	0.572***	0.518***	0.544***
	(0.036)	(0.109)	(0.110)
Mean outcome	5562.610	5562.610	5562.610
SD outcome	2982.305	2982.305	2982.305
Time FE	-	✓	✓
Week-of-the-year FE	-	✓	✓
Doctors' FE	-	✓	✓
Risk adjuster	-	-	✓
Anderson-Rubin p-value	0.000	0.000	0.000
Observations	28,465	28,465	28,465

Note. Outcomes and main endogenous variable are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model includes the focal physician's emergency cases in the previous week (*t-1*).

Table 4.
Robustness check

	Radiation output				
	(1) Baseline	(2) Hospital volume	(3) Hospital FE	(4) Lagged outcome	(5) Excluding outliers
Peers' radiation output	0.544***	0.546***	0.720***	0.515***	0.509***
	(0.110)	(0.117)	(0.089)	(0.116)	(0.101)
Mean outcome	5562.610	5562.610	5562.610	5562.610	5478.437
SD outcome	2982.305	2982.305	2982.305	2982.305	2655.072
Montiel-Pflueger F-stats	27.576	20.702	24.982	24.355	31.703
Anderson-Rubin p-value	0.000	0.001	0.000	0.001	0.000
Observations	28,089	28,089	28,089	28,089	27,560

Note. Outcomes and main endogenous variable are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model includes doctor's, year, and week-of-the year FEs, focal physician's emergency cases in the previous week (*t-1*) and risk-adjusters (patient's co-morbidity).

Table 5.
Robustness check : Autocorrelation

	Radiation output					
	Peers' emergency cases (t)			Focal emergency cases (t)		
	(1)	(2)	(3)	(4)	(5)	(6)
	No control	Baseline	w/ risk-adjusters	No control	Baseline	w/ risk-adjusters
Peers' radiation output	0.786***	0.773***	0.777***	0.647***	0.582***	0.587***
	(0.061)	(0.151)	(0.157)	(0.033)	(0.107)	(0.108)
Mean outcome	5563	5563	5563	5563	5563	5563
SD outcome	2982	2982	2982	2982	2982	2982
Time FE	-	✓	✓	-	✓	✓
Week-of-the-year FE	-	✓	✓	-	✓	✓
Doctors' FE	-	✓	✓	-	✓	✓
Montiel-Pflueger F-stats	28.8	12.2	11.8	83.2	28.8	28.1
Anderson-Rubin p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	28,465	28,465	28,089	28,465	28,465	28,089

Note.2SLS estimates. Columns (1)-(3) control for peer's emergency cases at *t*; coColumns (4)-(6) control for focal emergency cases at *t*. All models control for focal physician's own emergency cases in the previous week *t-1*. Outcomes and main endogenous variable are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level.

Table 6.
Robustness check - Alternative Instrument

	Radiation output				
	(1)	(2)	(3)	(4)	(5)
	Baseline	Hospital volume	Hospital FE	Lagged outcome	Excluding outliers
Peers' radiation output	0.536***	0.537***	0.724***	0.513***	0.463***
	(0.107)	(0.115)	(0.110)	(0.112)	(0.106)
Mean outcome	5562.610	5562.610	5562.610	5562.610	5478.437
SD outcome	2982.305	2982.305	2982.305	2982.305	2655.072
Montiel-Pflueger F-stats	23.345	17.103	15.562	21.338	26.236
Anderson-Rubin p-value	0.000	0.002	0.000	0.001	0.000
Observations	28,089	28,089	28,089	28,089	27,560

Note. Outcomes and main endogenous variable are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model includes doctor's, year, and week-of-the year FEs, focal physician's emergency cases in the previous week (*t-1*) and risk-adjusters (patient's co-morbidity).

TABLE 7.
Quality implication

	Mortality (1)	Infarction (2)	Restenosis (3)	Stent thrombosis (4)
Peers' radiation output	-0.002*	-0.001**	-0.000	-0.002*
	(0.001)	(0.000)	(0.000)	(0.001)
Mean outcome	0.17	0.06	0.017	0.17
SD outcome	0.41	0.25	0.13	0.44
Time FE	✓	✓	✓	✓
Week-of-the-year FE	✓	✓	✓	✓
Doctors' FE	✓	✓	✓	✓
Risk adjuster	✓	✓	✓	✓
Montiel-Pflueger F-stats	27.797	27.797	27.797	27.797
Anderson-Rubin p-value	0.064	0.013	0.716	0.070
Observations	28,057	28,057	28,057	28,057

NOTE. Outcomes are rate of 1,000 patients. * $p < 0.1$; ** $p<0.05$; *** $p<0.01$. Standard errors are clustered at unique peer groups level.

Table 8.
Appropriateness of care

	Share of insufficient dosage		Share of excessive dosage		Share of appropriate dosage	
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' radiation output	-0.748***	-0.769***	0.405***	0.400***	0.526***	0.551***
	(0.153)	(0.158)	(0.120)	(0.119)	(0.170)	(0.174)
Mean outcome	0.347	0.347	0.105	0.105	0.546	0.546
SD outcome	0.307	0.307	0.185	0.185	0.295	0.295
Time FE	✓	✓	✓	✓	✓	✓
Week-of-the-year FE	✓	✓	✓	✓	✓	✓
Doctors' FE	✓	✓	✓	✓	✓	✓
Risk adjuster	-	✓	-	✓	-	✓
Montiel-Pflueger F-stats	28.214	27.576	28.214	27.576	28.214	27.576
Anderson-Rubin p-value	0.000	0.000	0.006	0.006	0.000	0.000
Observations	28,465	28,089	28,465	28,089	28,465	28,089

Note. Outcomes are defined as share of cases at physician-hospital-week level. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level.

TABLE 9.
Heterogeneity analysis

	(1) Male	(2) Age < 49	(3) Academic hospital	(4) >4 peers
Peers' radiation output X [...]	0.489***	0.365***	0.468***	0.394***
	(0.123)	(0.074)	(0.067)	(0.101)
Mean outcome	5555.343	5555.343	5555.343	5555.343
SD outcome	2952.185	2952.185	2952.185	2952.185
Montiel-Pflueger F-stats	24.405	71.264	44.127	20.055
Anderson-Rubin p-value	0.002	0.000	0.000	0.006
Observations	28,089	28,089	28,089	28,089

NOTE. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. All models include doctor, year, week-of-the-year FEs, focal physicians' emergency cases in the previous week *t-1*, and risk-adjusters (patients' characteristics and co-morbidities).

TABLE 10.
Do doctors increase their effort?

	Segments treated (1)	Stents used (2)
Peers' radiation output	-0.094	0.171
	(0.090)	(0.109)
Mean outcome	0.727	0.634
SD outcome	0.520	0.547
Montiel-Pflueger F-stats	27.576	27.576
Anderson-Rubin p-value	0.283	0.103
Observations	28,089	28,089

NOTE. Outcomes and main endogenous variable are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. All models include doctor, year, week-of-the-year FEs, focal physicians' emergency cases in the previous week *t-1*, and risk-adjusters (patients' characteristics and co-morbidities).

TABLE 11.
Effects on treatment decisions

	(1)
Peers' radiation output	0.321**
	(0.147)
Mean outcome	0.396
SD outcome	0.384
Montiel-Pflueger F-stats	27.576
Anderson-Rubin p-value	0.015
Observations	28,089

NOTE. Outcomes and main endogenous variable are standardized. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. All models include doctor, year, week-of-the-year FEs, focal physicians' emergency cases in the previous week *t-1*, and risk-adjusters (patients' characteristics and co-morbidities).