MONASH University

MONASH BUSINESS SCHOOL

CENTRE FOR HEALTH ECONOMICS

WORKING PAPERS

Radiating influence? Spillover effects among physicians

Discussion Paper no. 2025-01

Giovanni van Empel, Daniel Avdic, Umair Khalil, Johannes S. Kunz, Bo Lagerqvist and Johan Vikström

Keywords: peer effect, team management, physician practice style, healthcare quality

JEL Classification: D83, I11, I12, J24, M12, M54

Giovanni van Empel: Australian National University (email: giovanni.empel@anu.edu.au); Daniel Avdic: Deakin University (email: d.avdic@deakin.edu.au); Umair Khalil: Deakin University (email: umair.khalil@deakin.edu.au); Johannes S. Kunz: Monash University (email: johannes.kunz@monash.edu); Bo Lagerqvist: UCR and SCAAR Study Group, Uppsala University (email: Bo.Lagerqvist@ucr.uu.se); Johan Vikström: IFAU and Uppsala University (email: johan.vikstrom@ifau.uu.se).

Radiating influence? Spillover effects among physicians*

Giovanni van Empel† Daniel Avdic‡ Umair Khalil§
Johannes S. Kunz¶ Bo Lagerqvist‖ Johan Vikström**

14 January 2025

Abstract

We study spillovers in healthcare by exploring how cardiologists' treatment choices are influenced by their peers. We employ clinical quality data from Sweden on the use of radiation in diagnostic angiography procedures. To account for endogeneity concerns, we instrument peers' weekly radiation output using the plausibly exogenous arrival of emergency cases they handle. Our estimates suggest that focal cardiologists increase their radiation output by 0.7 standard deviations for each standard deviation increase in their peers' output. These workplace spillovers lead to improved quality of care. Focal physicians detect additional blocked arteries, which increases treatment intensity and leads to lower risk-adjusted patient mortality.

Keywords: peer effect; team management; physician practice style; healthcare quality

JEL Classifications: D83, I11, I12, J24, M12, M54

*We are grateful to Bob Gregory, Xin Meng, Damien Eldridge, Josh Kinsler, Gordon Dahl, Carol Propper, Beatrix Eugster, Julie Moschion, Matt Sutton, Anthony Scott, Chris Rose, Miguel Alquezar-Yus, and Manuel Arellano for many detailed comments. We are also thankful to seminar participants at AASLE, ANU, AYEW, ESAM, EuHEA, and European Workshop on Econometrics and Health Economics, Labour Econometrics Workshop, SMU, Workshop on the Economics of Health and Wellbeing, for valuable comments and suggestions. Funding by the Australian Research Council (DP220103306) is gratefully acknowledged. All remaining errors are our own.

†Corresponding Author: Giovanni van Empel. Department of Health Economics, Wellbeing, and Society, The Australian National University, Building 63A, Eggleston Road, Acton, Canberra 2601, Australia. E-mail: giovanni.empel@anu.edu.au.

‡Department of Economics, Deakin University

§Department of Economics, Deakin University

¶Centre for Health Economics, Monash Business School, Monash University

‖UCR and SCAAR Study Group, Uppsala University

**IFAU and Uppsala University

1 Introduction

A central theme in the healthcare reform debate revolves around fostering approaches to continue delivering high-value care while facing threats from increased service demand, a stagnant workforce, and rising treatment costs. Improvements in precision medicine, digital healthcare, and consolidation of care are some of the lauded avenues to mitigate these challenges. However, one area with enormous potential that has so far been overlooked is the influence of peers among healthcare professionals (McWilliams, 2022). Although there exists ample evidence of peer spillovers on labor market productivity in many settings (see, e.g., Herkenhoff et al., 2024), their underlying channels and which choices they affect are still poorly understood due to the inherent complexity of social interactions and unobserved behavioral influences.[1] This is particularly relevant in the healthcare context where many complicated and time-sensitive decisions must be made under considerable uncertainty.[2]

In this paper, we document peer spillovers among specialized physicians in an important and high-stakes clinical setting: the treatment of heart attacks. Heart attacks are common but deadly events that contribute to around half of global mortality each year (Bergmark et al., 2022). Since the onset of heart attacks is primarily stochastic with limited scope to prepare or plan for, they provide an important healthcare context to study the consequences of behavioral spillovers where timely treatment decisions may constitute the difference between life and death. In our analysis, we focus on Coronary Angiography (CA), an ionizing radiation medical imaging technique used to visualize and locate arterial blockages that cause heart attacks. The diagnostic procedure requires the use of a radioactive contrast agent administered by an attending specialist (cardiologist). The peer influences we study are based on the empirical relation between the amount of radiation dosage administered by a (focal) cardiologist and the corresponding radiation use of their colleagues (peers) in their recently undertaken procedures.

We argue that studying radiation dosage employed in CA procedures is well suited to explore peer influences in healthcare because of the non-trivial nature and complex trade-off this choice presents to the attending clinician. On the one hand, to help determine appropriate treatment, the physician must choose a radiation dose high enough to accurately identify and locate blockages in the coronary arteries, which is only partially a function of patient characteristics. On the other hand, excessive radiation dosage is harmful to both patients and clinicians due to the resulting exposure to ionizing radiation (Richardson et al., 2023).[3] This is

[1]See DellaVigna (2009) for a summary of potential behavioral influences on decisions in social settings.

[2]Previous studies on decision-making in healthcare have focused on settings with relatively clear, optimal- and discrete choices, such as technology adoption (Barrenho et al., 2020; Agha and Zeltzer, 2022) and guideline concordance (Meeker et al., 2016). Silver (2021) is a notable exception, which focuses on timely decision-making in the healthcare setting.

[3]The radiation output from a single procedure of CA and CA combined with an angioplasty procedure are

akin to a constrained optimization problem under uncertainty where the physician must minimize radiation exposure subject to adequate visualization of arterial blockages (Kobayashi and Hirshfeld Jr, 2017). Appropriate use of radiation for diagnostic imaging also depends critically on the physician's diagnostic skill, knowledge, and practical experience (Georges et al., 2017; Chan et al., 2022), but there are limited clinical guidelines to follow, in contrast to many other established clinical practices (see e.g., Haynes et al., 2009, on surgery checklists). Therefore, in our setting, there exists ample room for peer workplace interactions to potentially influence and impact physician decision-making.

Our empirical analysis is based on rich, clinical quality data from the Swedish Coronary Angiography and Angioplasty Register (SCAAR), covering the universe of both diagnostic and interventional invasive coronary procedures performed in Swedish hospitals. We link physicians to their peers (co-workers) and the patients they treat on a granular level. We follow 175 cardiologists who were practicing in Swedish hospitals between 2008 and 2013 using a dataset consisting of over 200,000 patient-level records with time-stamped data on diagnostic and procedural information, patient characteristics, and subsequent health outcomes.

We define a focal physician's peer group as consisting of other physicians who are treating patients in the same hospital-week cell. The main empirical concern in our (as in any peer effect) setting, is endogenous sorting into peer groups based on both observable and unobservable characteristics. Moreover, common time-varying shocks to the hospital environment may also complicate causal identification of peer effects. To overcome these challenges, we use a combination of two popular empirical strategies in the estimation of peer effects: instrumental variables (Bramoullé et al., 2009; Nicoletti et al., 2018; Harmon et al., 2019; De Giorgi et al., 2020) and high dimensional fixed effects (Bayer et al., 2008; Kirabo Jackson and Bruegmann, 2009). Specifically, we propose a novel instrument to exogenously shift our endogenous variable of interest, the average radiation dose of the focal physician's peers in the *current* week, with plausibly exogenous variation in the arrival of on-call emergency heart attack cases treated by the same peers in the *previous* week. The main motivation for the lagged instrument draws from several recent studies showing that exposure to emergency cases may induce persistence in physician behavior, in particular following difficult encounters (see, e.g., Singh, 2021; Chodick et al., 2024; Jin et al., 2024).[4] Time-invariant unobservable factors are accounted for by the inclusion of fixed effects at the individual cardiologist level, while year-month fixed effects capture overall temporal shocks. We also control for the focal physician's own emergency cases from the previous week to ensure that potential crowding

equivalent to 155 and 755 chest x-rays, respectively (Mettler Jr et al., 2008).

[4]This instrument also helps avoid reverse causality issues from the well-known reflection problem which could invalidate instrument exogeneity if peers' and focal physicians radiation output were measured concurrently. Other studies on peer effects have used similar reasoning for motivating lagged instruments (see, e.g., De Giorgi et al., 2010; Nicoletti et al., 2018).

out of emergency cases is not affecting our estimates.

The suitability of our proposed instrument is based on three assumptions which we motivate and underpin in several empirical tests: (i) the arrival of emergency cases coupled with rotational assignment of clinicians is plausibly exogenous (exogeneity); (ii) emergency cases are qualitatively different than non-emergency cases and therefore require different radiation doses when undergoing CA (relevance); and (iii) by using a subset of all emergency cases (i.e., on-call cases) where each peer is treating patients in isolation, the arrival of emergency cases for peers is likely to affect the focal physicians' radiation output only through the first stage relationship (exclusion).[5]

Naive OLS estimates show that focal physicians' radiation output is associated with a 0.37 standard deviation (SD) increase for every one SD increase in the radiation dosage of their peers, on average. Accounting for high dimensional fixed effects and case-mix controls reduces the point estimate to 0.17 SD. When we instrument the peer's radiation dose with the number of emergency heart attacks in our preferred specification, the coefficient estimate increases to 0.71 SD and is robust to the inclusion of controls. This estimate corresponds to an increase of 38 percent relative to the sample average radiation dose and suggests that a cardiologist operating at the bottom 25th percentile of the radiation distribution in the sample would be bumped up to the 58th percentile if exposed to a peer group at the median of the distribution. Our baseline results are robust to several modifications of our preferred specification, such as combinations of fixed effects, controlling for time-varying correlated shocks on the hospital level, and excluding extreme outliers.

Several potential explanations help contextualize our higher IV point estimates. First, even if peers are randomly assigned, a mechanical bias arises in the OLS estimates because individual doctors cannot be their own peers. This generates a negative correlation, so-called *exclusion bias*, between the focal doctor's radiation output and the peer's radiation output (see, e.g., Guryan et al., 2009; Caeyers and Fafchamps, 2016). Secondly, any unobserved correlated shocks not captured by controls, such as time-varying shocks within the same hospital-week, would induce a negative correlation in outcomes between focal physicians and their peers (see, e.g., Godøy and Dale-Olsen, 2018). This occur naturally in our setting where types of admitted patients may vary across weeks.[6] While our IV approach avoids these issues, the IV-OLS difference may also indicate presence of individual effect heterogeneity since the causal effect identified from the instrument is the local average treatment effect of instrument compliers (i.e., physicians who responded more to their peers' radiation output). In line with previous

[5] We conceptualize the total radiation dose we observe as a proxy encapsulating relevant information that impacts dosage beyond directly setting the dose level, such as choice of entry point, image resolution, and fluoroscopic time. We also study these channels directly in the paper.

[6] Another form of time-varying shock that induces negative bias is the potentially strategic matching of focal physicians with their peers. For example, hospital managers may pair peers with more conservative practice styles with more aggressive focal physicians (Currie et al., 2016).

findings (e.g., Molitor, 2018; Barrenho et al., 2021; Avdic et al., 2023), we document stronger effects for junior and male physicians and for physicians practicing in academic hospitals.

Next, we evaluate whether the peer effects impacted quality of care received by patients. We consider a range of clinical endpoints relating to appropriateness of care and adverse patient outcomes. We find that focal physicians' exposure to their peers increases the share of patients they treat within the recommended radiation dosage range. However, we show that this improvement is mainly due to a monotonic increase in the radiation dosage applied rather than an effect of increased adherence to radiation guidelines. We next ask whether the resulting increased radiation output among focal physicians increased detection of additional arterial blockages and, consequentially, altered the intensity of treatments. Our results show that focal physicians both identify and treat more arterial segments as well as spend more time in the initial intervention. Patient outcomes are also improved through a lower likelihood of future repeat interventions (revascularizations), new infarctions and a reduction in one-year risk-adjusted mortality. Finally, we assess effect dynamics and show that our estimated peer effects materialize only in the week of peer interaction. Hence, this result suggests that the peer effects we estimate are likely to be transitory behavioral responses to social conformity or peer pressure in contrast to more learning-based channels (see, e.g., Mas and Moretti, 2009; DellaVigna, 2009).

Our paper relates to three main strands of literature. First, our results contribute to the literature on the causes and consequences of variation in physician practice styles (see, e.g., Chandra et al., 2011, for a review of the literature) where practice variation across physicians are driven by factors such as professional training programs (Epstein and Nicholson, 2009), financial incentives (e.g., Clemens and Gottlieb, 2014; Johnson and Rehavi, 2016), provider market entry (Barro et al., 2006; Cutler et al., 2010; Avdic et al., 2024), and intrinsic factors such as physician 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 results speak in particular to the importance of hospital environments in shaping practice styles as documented by Molitor (2018), and delineating the dynamics of social interactions among physicians within hospitals investigated in Avdic et al. (2023).

Moreover, our paper complements the broader literature on the organization of teams and peer effects in the workplace.[7] Existing work on teams has mainly focused on how teamwork operates through collaboration (e.g., Chen, 2021), joint monitoring (e.g., Chan, 2016), or peer influence (e.g., Kandel and Lazear, 1992; Bandiera et al., 2005; Mas and Moretti, 2009). Our findings specifically relate to the healthcare context in which most related papers on peer

[7] Studies in this literature span from high-skill contexts 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) to more routine-based jobs such as cashiers (Mas and Moretti, 2009) and fruit pickers (Bandiera et al., 2010).

influences have focused on settings with relatively clear, optimal- and discrete choices decisions such as technological adoption (Barrenho et al., 2020, 2021; Miraldo et al., 2021; Agha and Zeltzer, 2022) and guideline concordance (Meeker et al., 2016). Our focus on radiation output in diagnosing arterial blockages in the heart extends this literature to an important and high-stakes context where the clinician's task is non-trivial in nature and for which optimal treatment protocols are lacking.

Our paper builds on a few recent studies. Using switchers design to examine peer influences on physicians' treatment intensity, Doyle Jr and Staiger (2024) find that exposure to within-hospitals higher (lower) intensity groups induces focal physicians to increase (decrease) their own treatment intensity immediately after switching groups with no implication on the quality of care. Although the empirical design differs from ours, our results on the intensity of treatments speak similarly to their findings. Another closely related paper to ours is Silver (2021) which analyzed daily peer influences on physicians in US emergency departments. The key finding of the paper is that peers induce pressure on focal physicians to speed up at the expense of quality of care, primarily through cost-cutting measures at the margin. Our findings are consistent with those of Silver (2021) in that peer influences are likely to be based on behavioral mechanisms, such as social conformity or peer pressure, rather than learning, but also highlight the important result that peers can induce positive behavior that leads to quality improvements in healthcare.

Lastly, our study contributes to the limited but growing literature on the sources of within-physician practice variability. A few recent studies examine, for instance, difficult cases (Chodick et al., 2024) and patient complications (Singh, 2021) as factors that may temporarily shift physician practice behavior. Findings from these studies are consistent with the anchoring model of physician decisions proposed in Jin et al. (2024). The short-term nature of peer influence we estimate in our paper hence provides another important rationale for why physician practice behavior is observed to vary across patients, contexts, and over time.

2 Institutional setting

2.1 Use of radiation in the treatment of heart attacks

Acute coronary syndrome (ACS), commonly known as a heart attack, ranks among the leading causes of death worldwide (Roth et al., 2020). ACS results from a sudden partial or complete blockage of a coronary artery, which can be fatal if not promptly treated during the acute phase. ACS can also lead to several non-fatal consequences that may affect productivity, such as reduced labor supply or unemployment, disability, and diminished quality of life (Luo et al., 2023; Hall et al., 2024). In recent decades, the vast advancement of medical technology and innovative management strategies in the field of cardiology have significantly improved both survival rates and the quality of life for heart attack patients (Cutler and McClellan, 2001).

The primary clinical objective of managing patients with ACS is to restore blood flow to the heart, which is typically achieved through the application of a minimally invasive technology called Percutaneous Coronary Angioplasty (PTCA).[8] PTCA consists of coronary angiography (CA); a diagnostic procedure for visualizing and assessing the patency of the coronary arteries, and angioplasty – a therapeutic method involving the use of an inflating device (balloon) to unblock the coronary artery, and a metal mesh tube (stent) to act as a scaffold to prevent reocclusion. CA enables the attending cardiologist to identify and locate blockages in the arteries through the use of a catheter device inserted in the patient's wrist or groin. The device is then remotely guided to the heart where it injects a small amount of contrast dye into the coronary arteries to visualize blood flow through dynamic X-rays (fluoroscopy) projected to a screen monitor. Ionizing radiation is required throughout the procedure to visualize the vessels, to locate any blocked segments (lesions), and to effectively carry out therapeutic care (Chambers et al., 2011).[9]

Since failure to detect coronary lesions could cause severe health risks for patients, a high radiation dose is often warranted to produce high-quality x-ray images (Catalano et al., 2007). However, a single CA procedure is equivalent to between 155 and 755 chest x-rays (Mettler Jr et al., 2008). Experts in interventional cardiology and many regulatory bodies such as the World Health Organization (WHO), International Labor Organization (ILO), and Energy Commission in Europe deem such levels excessive[10], not only for patients but also for clinicians (ICRP, 2013; Picano et al., 2014). Moreover, recent evidence suggests that even relatively low radiation doses can have serious health implications (Richardson et al., 2023).

Against this backdrop, the proliferation of National Diagnostic Reference Levels (DRLs) and wider radiation safety culture protocols to moderate radiation output in healthcare has recently become a priority (WHO, 2024).[11] The scope of policies spans from stewardship by healthcare authorities and clinical champions, through equipment management and audit activities, to training programs and guidelines and checklists for individual healthcare

[8]An alternative therapeutic technology is Coronary Artery Bypass Graft surgery (CABG). Performed since the 1960s, CABG is a highly invasive procedure in which cardio-thoracic surgeons install a surgically grafted artery to bypass a section of a blocked artery, thereby restoring blood flow to the distal part of the heart.

[9]Additional details on the procedure are provided in Appendix A.

[10]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.

[11]DRLs are defined as upper bounds on radiation dose levels for medical imaging procedures when appropriate practice is followed. They are typically based on the observed distribution of doses given to comparable reference patients (usually set at the upper quartile). Professional and regulatory bodies decide on the appropriate dose ranges which are reviewed regularly. For more details, see https://www.iaea.org/resources/rpop/health-professionals/radiology/diagnostic-reference-levels.

professionals. Yet, such protocols were not introduced before the first comprehensive set of guidelines on radiation safety was released by the International Radiation Protection Association (IRPA) in 2014. Recent calls for professional training programs on radiation safety suggest that the use of radiation is cardinally linked to a physician's skill and proficiency with the procedure (Hirshfeld et al., 2005; Kobayashi and Hirshfeld Jr, 2017). Cardiologists may position their patients at different angles, choose an entry point for the catheter, and use intermittent beaming techniques to minimize overall radiation exposure (Georges et al., 2017).

2.2 The Swedish healthcare system

Healthcare in Sweden is mainly provided and financed by the public sector, which operates at three levels: national, regional, and local. Healthcare delivery is primarily managed at the regional level through 21 county councils which are legally obligated to ensure equal access to health services and medical care for all residents. While county councils can contract with private providers, most healthcare services are delivered by public entities. This system implies that elected politicians and government officials, rather than competition among healthcare providers, determine the number, size, location, and coverage of hospitals within each region.

Patient fees are negligible and subject to national caps, and all Swedish residents are covered by universal health and disability insurance which compensates for lost earnings from health-related work absence up to 80 percent of earnings. This generous safety net ensures individuals are well-protected against both the direct costs of care and any income loss due to illness. Each hospital provider is exclusively responsible for specialized care inside its defined catchment area, meaning that patient's place of residence generally determines the admitting hospital. Patients have no legal right to choose their treating hospital physician, implying that they are quasi-randomly matched depending on which physician is on duty at the time of patient admission. Furthermore, hospital physicians are salaried employees and have no direct financial ties with referring primary care physicians or the medical industry.

CA and PTCA is performed by interventional cardiologists, physicians specialized in cardiology with a one-year sub-specialty training in catheter-based cardiac interventions. In Sweden, cardiologists are normally full-time salaried employees in hospitals where their typical work week is split across several tasks, including performing CA/PTCA in the catheterization laboratory ("cath lab"), attending and consulting outpatient cases, and undertaking clinical research. The cath lab is also used frequently to treat patients with other diagnosed conditions. For instance, patients with heart valve problems or irregular heartbeats may require catheterization for diagnostic and/or therapeutic purposes. Work typically conforms to regular office working hours, although on-call shifts may be assigned every few weeks. Work schedules are assigned by the hospital management in conjunction with any specific requests from clinicians and typically rotate every other month.

Cardiologists in Sweden typically work independently but partake in clinical teams, including registered nurses and radiographers, that vary depending on the day and case. In the specific setting of CA/PTCA, the treating cardiologist is only responsible for performing the procedure and does not see the patient with regard to other tasks, such as consulting or setting up care management plans. Formal and informal interactions between cardiologists might occur through several venues, including department meetings to discuss "difficult" cases (e.g., Williams and Baláž, 2008), "bedside teachings" where junior doctors learn from more experienced peers (e.g., McGee, 2014), or routine ward rounds where doctors and nurses report on newly admitted patients (e.g., Zwarenstein and Bryant, 2000). In this paper, we abstract from specifying the exact mechanisms through which peer effects in the use of radiation occur since spillovers might arise from either of these channels, which are difficult to disentangle. The important consideration we make is that the treating cardiologist is the sole decision-maker in the cath lab, meaning that the treatment choices we observe in our data are directly linked to the attending physician.

3 Data

Our empirical analysis is based on the Swedish Coronary Angiography and Angioplasty Registry (SCAAR), a clinical quality dataset covering the universe of angiography and angioplasty procedures in Sweden. Since 2005, all 30 hospitals in Sweden with capability to provide CA/PTCA have been reporting their data to the registry's database using an online tool. The registry is collected prospectively and includes a rich set of patient clinical and demographic characteristics, such as age, gender, type of ACS (unstable angina, NSTEMI or STEMI), types and level (in percentages) of blockages (one vessel, multi-vessel, complex or non-complex) from coronary angiograms, lifestyle factors (BMI and smoking status), relevant co-morbidities (hypertension, renal function, diabetes or COPD), and medical history (previous infarctions and cardiac interventions). For each case, SCAAR also records treatment decisions for both diagnostic (total radiation dose, radiation time and number of investigated vessels) and therapeutic (PTCA, CABG, or no coronary intervention) procedures, whether the patient underwent PTCA treatment, and a set of clinical endpoints (patient death, reinfarction, and subsequent interventions). Details regarding treatments other than angioplasty or angiography, including CABG, are not recorded in the registry.

We consider all CA procedures performed from 2008-2013 in our analysis sample. The choice of starting year is determined by data constraints since this is the earliest period we observe all hospitals with adequate information on all critical variables required for the analysis.[12] The initial sample consists of 219,559 patient-level records. For our purposes, the

[12]We exclude two hospitals (three percent of patient-level observations) for which the main variable interest,

most important piece of information recorded in the registry is detailed measurements of the amount of radiation administered in each CA procedure. We winsorize radiation output to the 2.5th and 97.5th percentiles of the distribution to remove any impacts from extreme outliers.[13] We also aggregate the data into physician-hospital-week cells to improve the precision of our estimates, as the number of interventions performed on a given day is typically small. Our final estimation sample consists of 28,467 physician-hospital-week observations, including 175 cardiologists employed in 28 hospitals between 2008 and 2013.

We define peers as all physicians who are observed to perform CA/PTCA procedures in the same hospital in the same week. We opted against using daily detail to match peers since assigned rotations across physicians may vary by day, meaning that physicians observed in the cath lab one day are likely to have other (unobserved) responsibilities in the hospital on different days in the same week. Thus, since cardiologists typically work alone in the cath lab (excepting perioperative nurses and other support staff), there is an inverse relationship for the likelihood of observing multiple cardiologists performing CA/PTCA on the same day. However, two cardiologists who are observed to treat patients with CA/PTCA in the same hospital-week cell are likely to have interacted at some point. In contrast, cardiologists who are not observed to perform CA/PTCA during an entire week are unlikely to have been present in the hospital during that week.

Following Li et al. (2020), we convert the raw radiation doses recorded in our data to *effective doses* to align with the conventions in medical imaging.[14] Table 1 presents summary statistics for our estimation sample. The top panel reports measures of physician radiation output, showing that weekly average radiation dose in the sample is 5.6 mSv (millisieverts), which is very similar to the peers' weekly average of 5.5 mSv. Furthermore, employing the standard of National Diagnostic Reference Levels (DRLs) for radiation output, we observe that only 54% of procedures fall in the appropriate dosage range, while 35% use insufficient, and 11% use excessive dosages for CA procedures.[15] This again highlights the potential role that peer spillovers can theoretically play in our setting. The last row of the panel shows that physicians spend on average 9.2 minutes (554 seconds) of fluoroscopic time (i.e., the total time x-rays are continually used to visualize blood flow) per intervention.

The second and third panels of the table describe workplace- and cardiologist-specific characteristics in the data. In terms of the former, we see that a cardiologist performs, on

radiation output, is missing for all years. For the remaining hospitals, we exclude any observations for which this variable is missing, amounting to around two percent of the full sample.

[13]We also estimate models where we instead drop observations outside this range.

[14]Details on the conversion process are provided in Appendix B.

[15]DRLs are published by the European Commission on Radiation Protection (European Commission: Directorate-General for Energy, 2015). As explained in Section 2.1, DRLs are not considered formal clinical guidelines that are based on trial-assessed benefits and risks but rather serve as benchmarks of acceptable practice.

average, 6.8 CA/PTCA procedures per week, of which one is an on-call emergency case. Focal physicians work together with, on average, 3.3 peers each week, undertaking a total of 3.8 on-call cases (or roughly one per peer). With respect to physician characteristics in the third panel, the average age is 49 with around one-third being junior (30-44), 60 percent mid-level (45-58), and ten percent senior (over 58). Only ten percent of cardiologists are female.

The penultimate panel presents summary characteristics of the patients in our sample. The average patient age is 67 years, and one-third of patients are female. Roughly one quarter (0.23) of patients are categorized with complex lesions (blockages in the left-main coronary artery or in three or more vessels). One-half of the procedures documented in the data involve CA only, while the other half are PTCA (CA and stenting). As expected for this population, the prevalence of co-morbidities is high, in particular with respect to hypertension, and more than half of patients are either smokers or ex-smokers. Finally, the last panel reports post-intervention clinical endpoints in the form of rates of one-year mortality, revascularization (new intervention), restenosis (reocclusion), and reinfarction per 1,000 procedures, ranging from 0.3 to 1.1.

4 Methods

4.1 Econometric context

We are interested in the causal relation between a (focal) physician's use of radiation in CA procedures as a function of their peers' radiation output, as defined in the previous section. To fix ideas, let focal physician i's and their peers' average radiation output be equal to Y_{ig} and $\bar{Y}_{\sim ig}$, respectively, where $g = (h, t)$ is the peer group matching function for hospital h and week-year combination t. Furthermore, $\sim i$ represents the leave-one-out estimate from excluding physician i. We consider the following regression specification in our analysis:

$$Y_{ig} = \alpha_i + \gamma_t + \lambda_h \times t + \beta \bar{Y}_{\sim ig} + \delta X_{ig} + \tau \bar{X}_{\sim ig} + \varepsilon_{ig} \tag{1}$$

where α_i and γ_t are physician and time fixed-effects (capturing, e.g., physician time-invariant preferences and global time trends in radiation use), $\lambda_h \times t$ are hospital-specific linear time trends (capturing, e.g., variation in radiation technology and equipment across hospitals over time), and X_{ig} and $\bar{X}_{\sim ig}$ are vectors of case-mix controls for focal physicians' and their peers', respectively, summarized in Table 1. Importantly, X additionally includes the number of *emergency cases* the focal physician treated in the *previous week* in order to ensure that potential crowding out of emergency cases is not affecting our estimates in our instrumental variables approach described below. Finally, ε_{ig} is a random error term from which we estimate standard errors that are clustered at the peer group level.

Direct estimation of Equation (1) will likely suffer from several endogeneity problems often encountered in the empirical peer effects literature (Manski, 1993; Angrist, 2014). Most pertinently, physicians may sort into peer groups based on, for example, clinical practice styles, thereby generating a spurious correlation between the outcomes (i.e., radiation output) of focal physicians and their peers. Although physicians in our setting cannot choose with whom to work on given days, they still have partial discretion which could impact our results.[16]

Another technical issue in estimating peer effects arises from computing the average radiation output of the peers in Equation (1). Omitting the focal physician's contributions to $\bar{Y}$ will give rise to *exclusion bias* because it creates a mechanical negative correlation between the focal physician's own and their peers' radiation output, even in the presence of random assignment of peers. This is due to the fact that physicians cannot be their own peers (see, e.g., Guryan et al., 2009; Caeyers and Fafchamps, 2016).

Furthermore, physicians working in the same hospital are exposed to the same environment, meaning that unobserved shocks to the hospital influence both focal physicians' and their peers' behaviors. For instance, hospital management may decide to streamline certain tasks, such as pre-setting radiation doses on diagnostic imaging devices, or implement hospital policies, such as checklists and audits. Such common shocks would lead to correlated effects across physicians in the same peer environment and confound causal relationships.

Finally, it is difficult to establish causality when the behaviors and outcomes of focal physicians and their peers are determined simultaneously. This is the well-known reflection problem described by Manski (1993) where potential reverse causality and feedback effects between peers create a simultaneity problem where causal identification can only be obtained through exclusion restrictions on the data-generating process.

4.2 Identification strategy

To overcome the identification challenges discussed in the previous section, we employ an instrumental variables approach coupled with high-dimensional fixed effects. Specifically, we instrument our endogenous variable in Equation (1), the leave-out average radiation output of focal physician i's peers ($\bar{Y}$), with the number of *on-call emergency cases* for the same peers

[16]We conduct conditional random assignment tests as proposed by Jochmans (2023). The test builds on regression-based methods that check for systematic correlation between the characteristics of focal individuals and their peers', adjusting for within-urn fixed effects that contain all potential peer groups of the focal physician within a hospital-time window. The test accounts for biases that might arise from heterogeneous group sizes and tests the null of random assignments. Table C.1 of Appendix C shows that the test fails to reject the null, suggesting that non-random assignments are less likely to be an issue in our context.

in the *previous* week. Formally, the instrument is defined by:

$$Z_{\sim ig} = \sum_{j|i \notin J} N^{oc}_{j,t-1}, \tag{2}$$

where $N^{oc}_{j,t-1}$ refers to the total number of on-call emergency cases handled by peer $j \in J$ in week-year $t - 1$, where J are all physicians belonging to group $g = (h, t)$. Thus, the instrument Z in Equation (2) is equal to the total number of on-call emergency cases handled by the focal physician's peer group in the preceding week. The first-stage specification of the two-stage least-squares (2SLS) estimator is consequently defined by:

$$\bar{Y}_{\sim ig} = \alpha_i + \gamma_t + \lambda_h \times t + \phi Z_{\sim ig} + \delta X_{ig} + \tau \bar{X}_{\sim ig} + \varepsilon_{ig} \tag{3}$$

where $Z_{\sim ig}$ is defined as per Equation (2). The projection of $\bar{Y}_{\sim ig}$ from Equation (3) is then used in the second stage to replace $\bar{Y}_{\sim ig}$ from Equation (1) where $\hat{\beta}$ is now the 2SLS estimator of β. We standardize radiation output to have a mean of zero and a standard deviation of one, so that $\hat{\beta}$ is interpreted as the number of standard deviations a focal physician changes their radiation output in response to a one standard deviation change in peers' (instrumented) average radiation output. We next discuss the logic behind the different assumptions required for the 2SLS estimator to provide valid causal inference.

4.2.1 Relevance

The relevance of the instrument is motivated by the context of our setting. Specifically, emergency patients constitute more urgent and risky cases, implying that the benefits of using lower radiation doses are small compared to the risks of failing to detect important information in the diagnostic phase of the intervention (Pope et al., 2000; David and Brachet, 2009; Bragard et al., 2015). Emergency cases are also generally more challenging, which is another predictor of higher radiation doses (Chodick et al., 2024). The left panel of Figure 1 displays distributions of radiation doses for emergency and non-emergency cases in our data. The fact that radiation doses for emergency cases are more skewed to the right than non-emergency cases provides empirical evidence in support of the previous conjectures.

Several recent studies have shown that exposure to emergency cases may induce persistence in physician behavior, in particular following difficult encounters (see, e.g., Singh, 2021; Chodick et al., 2024; Jin et al., 2024). The right panel of Figure 1 visualizes the first stage variation for our instrument, showing that treating additional emergency cases in a given week is strongly associated with a higher average radiation dose by peers in the following week. Formal first-stage regression results from the estimation of Equation (3) are reported in Panel B of Table 2 and indicate a robust statistical relationship corresponding with the graphical evidence. We report both the Montiel-Pflueger F-statistics, following Andrews et al. (2019), and Anderson-Rubin statistics to formally test for weak instruments, as suggested by Keane and Neal (2023).

4.2.2 Exogeneity and exclusion

We next assess the instrument exogeneity and exclusion assumptions. In our context, exogeneity implies that the arrival of on-call emergency cases to peers should follow a quasi-random distribution. We argue that the occurrence and timing of heart attacks are inherently difficult to predict, and patients with such symptoms must be promptly attended to by on-call physicians thus reducing their ability to self-select into cases. Following the approach set out in Hoe (2022), we conduct an indirect test of instrument exogeneity by evaluating whether the arrival of emergency cases can be predicted ex-ante. The left panel of Figure 2 displays the actual and predicted numbers of weekly emergencies, where the latter is estimated from a Poisson regression model including hospital and week-year fixed effects. The actual arrival distribution of cases closely tracks the theoretical Poisson distribution, suggesting that we cannot reject the null hypothesis of exogenous arrival of emergency cases in our setting.

The exclusion restriction requires that the arrival of emergency cases treated by peers in the previous week has no direct impact on a focal physician's current radiation output. This assumption is violated if, for instance, emergency cases were systematically allocated to physicians with specific practice styles or skills. Such sorting could arise through a "crowding out" mechanism wherein a focal physician's exposure to emergency cases is inversely related to their peers' exposure. We address this potential issue in two ways: first, we include only the subset of on-call emergency cases where the on-duty physician is solely responsible for handling incoming patients. This restriction should address concerns regarding systematic sorting of physicians to emergency cases (see, e.g., Card et al., 2008, 2009; Doyle Jr et al., 2015; Chandra et al., 2016, for other papers using similar arguments). Furthermore, we control for the focal physicians' own emergency cases in the previous week to directly close down any direct links between their exposure to emergency cases (which may be correlated with peers' exposure) and their subsequent radiation output. In addition to the set of case-mix controls, these adjustments arguably improve the validity of the exclusion restriction.

We also provide informal evidence supporting the validity of the exclusion restriction by investigating systematic allocation of emergency cases to physicians in our data. We estimate a mixed model to estimate physician-specific random intercepts as a measure of each physician's underlying preference for radiation and then plot the estimated intercepts against the distribution of emergency cases. To reduce the likelihood of peer influence contamination in the estimated preference parameters, we only include days where the physicians work by themselves (i.e., no overlapping observed activity from peers on the same day) in the model and estimate the random intercepts conditional on hospital and week-year fixed effects.

The right panel of Figure 2 plots the estimated random intercepts against the weekly share of emergency cases for each physician in our estimation sample. The horizontal axis displays physicians' relative preference for radiation recentered at zero. In the case of systematic sorting of physicians to emergency cases, the resulting plot should show a significant relationship between shares of emergency cases and physicians' preference for radiation dosage (see, e.g., Currie et al., 2016; Dobbie et al., 2018). The statistically insignificant slope suggests that such sorting is unlikely to be present in our physician sample.

4.2.3 Monotonicity

In the presence of heterogeneous treatment effects, our empirical approach also requires an additional condition of instrument monotonicity to recover the local average treatment effect (Angrist et al., 1996). In our setting, the monotonicity assumption implies that the average radiation output in the current week for all peer groups of the focal physicians should weakly increase with the average number of emergency cases treated by the same peers in the previous week. In other words, the first stage relationship should have the same sign in all subsamples. To assess the validity of this assumption, we follow common practice from the economic literature on judges' decisions (see, e.g., Arnold et al., 2018; Bhuller et al., 2020) and estimate the first-stage relationship across a set of observable physician characteristics.[17]

5 Results

5.1 Peer effects on radiation output

Results from the estimation of our instrumental variables model are reported in Table 2. Radiation output for both peers and focal physicians are standardized with a mean of zero and a standard deviation of one. Each column refers to a different model specification: from left to right, excluding all controls and fixed effects, including fixed effects for physician and week-year, and including both patient controls and fixed effects, respectively. Standard errors in all regressions are clustered on the peer group level.

Panel A presents OLS estimates of β from Equation (1). The point estimate from Column 1 shows that a one standard deviation (SD) increase in peers' radiation output is associated with a 0.37 SD increase in the focal physicians' own output. Including physician and time-fixed effects attenuates this estimate by approximately 50 percent, while the inclusion of patient risk adjusters seems to have little impact on the estimated coefficient. However, as discussed

[17] Table C.2 in Appendix C reports the first stage results from this exercise, showing that estimates are positive and statistically significant for different age groups and gender of the physicians.

in Section 4.1, these estimates are unlikely to uncover causal peer effects on physician behavior in our data.

Panel B reports the first stage estimates from Equation (3). The results indicate a positive relationship, implying that increased exposure to on-call emergency cases among peers in one week increases their average radiation output in the following week. An increase of one additional on-call emergency case in the peer group increases the average radiation output of peers by 0.018-0.031 SD, depending on the model. The Montiel-Pflueger F-statistics range between 35 and 73 across specifications, indicating that the instrument is strong.

Panel C and D report the reduced form and second-stage estimates, respectively. The former suggests that one additional peer on-call emergency case increases the focal physician's average radiation output by between 0.013 to 0.025 SD, similar to the corresponding impact on peers' radiation output. Given that the 2SLS estimate is computationally equivalent to the ratio between the reduced form and the first stage, it comes as no surprise that the second-stage estimate in Panel D ranges between 0.70-0.80. Thus, peers pass on most of their increased radiation behavior from treating emergency cases to focal physicians. Based on the summary statistics from Table 1, the estimates from our preferred specification in column (3) suggest that exposure to one more emergency case per peer increases peers' average radiation dose output by 0.13 mSv which in turn induces a 0.09 mSv increase in focal physicians' average dose through peer influence.[18]

The magnitude of the 2SLS estimates are considerably larger than the corresponding OLS estimates. As mentioned in Section 4.1, this could be due to several factors including systematic sorting of physicians into peer groups. Negative sorting that leads to downward bias of OLS could arise if hospital management chooses to assign physicians with higher preferences for radiation to physicians with lower preferences to manage overall radiation output administered in a given shift. Another explanation is the possibility of heterogeneity in peer effects since the 2SLS estimate is interpreted as a local average treatment effects for the sample of compliers. We study effect heterogeneity in more detail in Section 5.3 below.

5.2 Appropriateness and quality of care

5.2.1 Adherence to acceptable radiation levels

After establishing that peers influence focal physicians to adjust their radiation output, we next focus on whether these spillovers impact patient outcomes. We conjecture that the peer effects may be transmitted through two main channels: first, they may convey suggestions on how to improve quality of care through improved adherence to a range of acceptable dosages

[18] For comparison, this value corresponds approximately to the dose received from exposure to one chest x-ray procedure in the US. See https://www.epa.gov/radiation/radiation-sources-and-doses.

defined as DRLs (Diagnostic Reference Levels). As explained in Section 2.1, DRLs is a benchmark used to determine whether the radiation dose applied during routine procedures is unusually high or low and is not a formal trial-based clinical guideline. Second, they could merely be a simple reaction prompted by more aggressive peer radiation behavior from treating more emergency cases. To disentangle the two mechanisms, we argue that we should observe an increase in focal physicians' applied radiation doses within the recommended dose range if peer spillovers primarily mediated information about adherence to radiation guidelines. On the other hand, if peers mainly projected a more aggressive radiation practice style onto the focal physicians, we would observe a monotonically higher radiation output for the latter also above the upper threshold for the recommended dose range.

To this end, we define radiation dose categories in accordance with the recommended DRLs for the related interventional procedures (see, e.g., Vassileva and Rehani, 2015). Specifically, we assess whether radiation dosage is considered "insufficient", "appropriate", or "excessive" with respect to the DRL classification. Table 3 reports the results from estimating peer influence on focal physicians' share of radiation doses in each of the three DRL categories using our preferred 2SLS specification. We use the standardized share of patients in each group as dependent variable, to align with the coefficient interpretation in Table 2.

The first two columns show that the share of insufficient doses among focal physicians decreased significantly due to peer exposure. The effect size of 0.678 in the specification with controls translates into a decrease of 21 percentage points (0.678 $\times$ 0.312) reduction in the proportion of patients with insufficient dosage on average, or a decrease of almost 60 percent with respect to the mean. Using the example from the previous section, exposure to one more emergency case per peer translates into a 1.3 percentage points (3 percent) drop in the share of patients with insufficient radiation dose. Turning to the results for the share of appropriate doses in columns (3) and (4) present, we observe positive coefficient estimates implying an improvement in the overall share of patients that were treated with guideline-adhering radiation dosages. The point estimate from our preferred specification in column (4), 0.371 can be translated into an increase of 11 percentage points (20 percent) of patients in this category, or a 0.7 percentage point increase per additional peer emergency case.

Finally, the last two columns report results for the share of cases with excessive radiation doses. The positive point estimates imply that the peer influence leads to an increase in this category, lending support to the "monotonicity" mechanism rather than the guideline adherence mechanism. Specifically, the point estimate from column (6) suggests that the average share of patients treated with excessive radiation doses increased by 10 percentage points (0.533 $\times$ 0.189), or almost doubled with respect to the baseline sample mean. In terms of the impact per additional emergency case treated by each peer, the effect size is similar to the change in the share of appropriate doses, 0.7 percentage points. Thus, the reduction in the share of patients with insufficient radiation doses is redistributed equally across the appropriate and excessive radiation categories, indicating a general increase in the use of radiation among focal physicians from peer influence.

5.2.2 Treatment intensity

We next explore whether focal physicians' increased use of radiation also impacted the intensity of therapeutic treatments. We first study whether higher radiation doses led to the detection of additional and/or more complex lesions during the CA procedure. This may occur if higher radiation doses improve physicians' ability to detect lesions when analyzing medical imaging scans.[19] We also analyze whether any such increased detection rates prompted focal physicians to treat their patients more intensively on the extensive (i.e., perform more PTCA procedures) and intensive (i.e., treat additional lesions) margins.

To evaluate the link between radiation dose and detection, we study three additional diagnostic outcomes from the CA procedure: the total fluoroscopic time used in the procedure, whether the case is regarded as complex, and the total number of blocked artery segments. Columns (1)-(3) of Table 4 display the results from estimating our preferred 2SLS model for standardized versions of these outcomes. Column (1) shows a positive and statistically significant impact on the total fluoroscopic time used in the diagnostic phase. In particular, the point estimate of 0.330 implies that focal physicians increase the total diagnostic time by around 97 seconds (0.330×294), or 17 percent, for each SD increase in peers' radiation output. This is equivalent to 5.7 seconds for each additional weekly emergency case treated per peer. Point estimates for the prevalence of a complex case and for the number of segments are also positive and statistically significant, with magnitudes corresponding to 1.2 percentage points (five percent) greater likelihood of classifying a case as complex, and 0.1 (14 percent) additional detected lesions per SD change in peer radiation dose (0.1 percentage points and 0.01 additional lesions per emergency case). Hence, the peer influences led focal physicians to both increase their total duration spent in the diagnostic phase and to increase lesion detection rates.[20]

The effects of peer influence on focal physicians' treatment intensity are reported in the

[19] The total radiation output from fluoroscopy is a function of the product of the applied dose and the continuous duration of x-ray exposure. Thus, a higher total radiation dose suggests longer fluoroscopic time, which should be weakly positively related to increased detection rates.

[20] Since complex lesions are often treated with CABG surgery, we also study whether a greater detection rate of complex cases led focal physicians to change their treatment recommendation from PCI to CABG. Column (4) of Table 4 reports the results, showing that peer influences did not significantly change the share of patients assigned to CABG. Following Avdic et al. (2024), we also examine whether peer effects on treatment intensity vary by type of hospital. Local hospitals, typically a single technology hospitals (i.e. PTCA-only) also face a financial obligation to cover referral costs when transferring patients to other hospitals. Hence, we expect peer-induced treatment intensity to be stronger at the extensive margin (i.e. the probability to perform PTCA) in the local hospitals. Indeed the results in Table C.3 of Appendix C support this expectation. Conversely, the effect in academic hospitals shown in Table C.4 is muted, likely due to the presence of cardio-thoracic surgeons.

last two columns of Table 4. Specifically, column (5) shows the results for the probability that a case was treated with PTCA after the diagnostic phase (extensive margin), while column (6) refers to the total number of stents inserted given that PTCA was performed on the patient (intensive margin). Our results show that both outcomes were positively impacted, with magnitudes corresponding to a 4.9 percentage points (10 percent) increase in the probability of PTCA and a 0.11 percentage point (16 percent) increase in the number of inserted stents, respectively.These effect sizes correspond to 0.01 additional stents and 0.2 percentage points increased PTCA probability per additional peer emergency case, respectively. Hence, peer-induced increases in radiation output led focal physicians to treat patients more intensively.

5.2.3 Patient health outcomes

Given our findings from the last subsection, we now turn to study the impact of peer influences on patient health outcomes. We consider relevant clinical endpoints, including: restenosis (re-occlusion of the artery); reinfarction (subsequent heart attack); revascularization (subsequent PTCA); and all-cause mortality (patient death). These outcomes are all measured within one year after the initial intervention and are standard in the medical literature when evaluating the effectiveness of treatments in cardiovascular care.

Estimation results are presented in Table 5, suggesting significant improvements in the quality of care in terms of lower prevalence rates (in rates of 1 per 1,000 patients) for all four outcomes. The magnitudes range between reductions of 0.25 to 0.91, or, equivalently, from 80 to 108 percent from baseline levels for each SD change in peers' radiation output. However, given that this change is an extreme extrapolation of our results based on the identifying variation we use to estimate these effects[21], the more appropriate comparison of another emergency case per peer suggests reductions of between 0.01 (for restenosis) and 0.05 (for one-year mortality) adverse outcomes per 1,000 patients, corresponding to reductions of between four and six percent from baseline levels.

To sum up the results from this section, the spillover effects derived from peer group exposure to emergency cases led focal physicians to apply radiation more aggressively to their patients in the diagnostic phase. In turn, the increased use of radiation is associated with higher lesion detection rates, more intensive therapeutic case management, and, importantly, significant reductions in adverse health outcomes for this patient population. While our approach precludes us from directly link these outcomes in a causal chain, our findings are nevertheless consistent with such a mechanism.

[21]Specifically, the first-stage estimate suggests that each additional emergency case treated by peers increases their radiation output by around 0.02 standard deviations. Since our instrument (peers' total on-call emergency cases treated per week) has an SD of 4.78, the identifying variation we use in our analysis is substantially lower (roughly one-tenth) than the overall variation in the endogenous variable.

5.3 Extensions

5.3.1 Physician heterogeneity

The conventional instrumental variables model assumes that the spillover effects we estimate are homogeneous across physicians. However, previous research has suggested that peer effects typically vary by sex and age (see, e.g., Han and Li, 2009; Lavy and Schlosser, 2011; Beugnot et al., 2019). In the presence of effect heterogeneity and given the assumption of instrument monotonicity, the 2SLS estimator is only informative about the subgroup of compliers for whom our instrument changed behavior. To characterize cardiologist compliers in our data, we proceed by estimating our models for different sample subsets.

The first two columns in Table 6 report separate 2SLS estimates when restricting the sample to only male and only female focal physicians, respectively. The results suggest that male cardiologists respond more to input from peers, while female physicians have both a smaller effect size and a weaker first stage. While the latter can be related to the relatively small number of female physicians (17 out of 175) in our data, the lower point estimate could also indicate stronger resistance to peer influence. The next three columns report the estimates from different age groups, partitioned into groups of junior (age 31-44), mid-career (age 45-58), and senior (over 58 years of age) physicians. Estimates for the two younger groups are broadly similar and correspond to our pooled results, while the result for senior physicians is far from significant and based on a very weak first stage. This result echoes findings from similar contexts, including Molitor (2018) and Avdic et al. (2023), and is perhaps not surprising if more senior physicians have already acquired an established practice style and are therefore less malleable relative to less experienced clinicians.

The final set of columns reports estimates by hospital type. Specifically, we compare results for district (non-teaching) and academic (teaching) hospitals where we hypothesize that the latter, through their capacity as learning centers, may have more advanced infrastructure for enabling peer interactions and harnessing workplace spillovers. Moreover, if more distinguished cardiologists are more likely to work in academic hospitals, we should expect that junior physicians in these hospitals would have additional avenues for feedback and exchange compared to physicians employed in the less prestigious district hospitals. However, although the results reported in columns (6) and (7) indicate a slightly larger point estimate for the sample of academic hospitals, the difference is not large enough to statistically reject the hypothesis of effect homogeneity.

5.3.2 Effect persistence

Understanding whether the effects we estimate permanently change behavior via some form of learning through an information transfer mechanism or whether it constitutes a more behavioral transitory response from focal physicians' is crucial for contextualizing the benefits of harnessing peer spillovers. Thus far we have only considered spillover effects across two consecutive weeks. However, the peer influences we identify may persist over longer time horizons.

To investigate the persistence of peer influences in our context, we estimate dynamic event study versions of Equation (1) where the dependent variable is defined as leads and lags of the original outcome (i.e., $Y_{\sim ig_{t+k}}$ for $k = \{k_{min}, k_{min}+1, ..., k_{max}-1, k_{max}\}$). In this specification, we estimate the model for different outcomes while keeping the right-hand side fixed, including the instrumented peer exposure variable, $\bar{Y}_{\sim ig}$. To control for potential peer influences from other periods, we also successively include (instrumented) past peer exposure variables for the other time periods, $\bar{Y}_{\sim ig_{t+m}}$ for $m = \{k_{min}, ..., k \mid 0 \notin m\}$, in the model. Hence, we estimate the following model separately for each $k \in \{k_{min}, k_{max}\}$:

$$Y_{ig_{t+k}} = \alpha_i + \gamma_t + \lambda_h \times t + \beta_k \bar{Y}_{\sim ig} + \sum_{m=k_{min}|m\neq 0}^{k} \gamma_m \bar{Y}_{\sim ig_{t+m}} + \delta X_{ig} + \tau \bar{X}_{\sim ig} + \varepsilon_{ig} \tag{4}$$

where the β_k coefficients across all $K \ni k$ regressions measure the peer influence centered around period t at time k, while the γ_m coefficients control for dynamic peer exposure in previous time periods. As focal doctors are exposed to different peer groups each week, this specification allows us to assess the lasting effects of peer group g during week t.

Figure 3 displays the $\hat{\beta}_k$ estimates from estimating Equation (4) for $k \in \{-3, 3\}$. Two important patterns can be discerned from the figure: first, we do not observe any anticipatory effects in the weeks leading up to the focal time period at $k = 0$. This is a reassuring finding since we do not expect spillover effects to impact focal physicians' past outcomes. Second, while the strong positive spillover effect in period $k = 0$ is consistent with the results previously reported in Table 2, we also see a tapering off in subsequent periods indicating a highly transitory impact of peers on physician behavior. Specifically, the point estimate drops by about one-half between the initial week and the next and has essentially disappeared after three weeks.

The temporary nature of the response depicted in Figure 3 is consistent with a peer pressure or a framing effect mechanism in contrast to a persistent behavioral adaptation from learning or updating of professional beliefs (see, e.g., Mas and Moretti, 2009; DellaVigna, 2009). This result is perhaps not entirely surprising for several reasons. First, focal doctors' responses show a behavioral alignment with the peers they encounter in a given week. However, being exposed to different peers in different weeks may diffuse the feedback received, especially when professional uncertainty is high as in the current setting. These findings are consistent with those of Molitor (2018), Avdic et al. (2023), and Doyle Jr and Staiger (2024) where doctors' practice styles adjust to those of their peers after a change in their practice environment.

Moreover, since the effects we estimate are identified from quasi-random peer feedback, it is possible that focal physicians may not be as receptive to advice from peers that they themselves did not choose or were self-selected into. Finally, the paucity of clinical guidelines on radiation dose for interventional procedures may compound the disregard of peer feedback since it is not based on research evidence or established norms. While these reasons suggest a limited scope for peer knowledge transfer in our setting, it is still relevant for understanding which factors may inhibit learning and malleability of physician practice styles.

5.4 Robustness checks

In this section, we conduct a series of robustness checks to assess the sensitivity of our empirical findings. Columns (2) to (4) of Table 7 report estimation results from a set of alternative specifications of our main instrumental variables model, while our preferred 2SLS estimate is reproduced in column (1) for comparison. First, while our baseline model controls for hospital linear time trends, there could still exist week-to-week variation that our fixed effects may not account for. Motivated by Nicoletti et al. (2018), we therefore control for weekly hospital case volumes to adjust for time-varying workplace dynamics within hospitals that may be related to the allocation of cases to physicians and possibly violating the instrument exclusion restriction. The reported 2SLS estimate in column (2) is virtually equal to our main estimate and suggests that any correlated effects may have been properly accounted for by the combination of fixed effects and the instrument we apply. In column (3), we report results from including focal physicians' own radiation output in the previous week as an additional control to address the potential issue that such behavior might in some cases be directly related to their current radiation output. Again, this alteration only marginally changes the point estimate. Finally, since the distribution of our radiation variable includes some extreme outliers, we study whether removing these has an impact on our results. Column (4) presents the 2SLS estimate when excluding observations above the 97.5 percentile of the radiation dose distribution from our sample (567 observations), showing a slight, but not statistically significant, attenuation of the point estimate from column (1).[22]

Another remaining concern with our baseline estimates is potential autocorrelation in the instrument. If the number of emergency cases treated by physicians in one week is systematically linked to the total emergency cases in the following week, then the instrument will be invalid. This could happen if, for example, the hospital planner changes shift rotation to relieve on-duty physicians following a high-load emergency shift in the previous week. We address this by augmenting our main specification by controlling for contemporaneous peers' emergency cases. If there is negative autocorrelation, we expect the estimates to tend towards

[22]We have also tested the sensitivity of our results to various combinations of fixed effects. Results from these are provided in Table C.5 of Appendix C, showing small and statistically insignificant variations across the board.

zero. Columns (1) and (2) of Table 8 report these results, showing, if anything, larger point estimates compared with our preferred 2SLS specification. In addition, columns (3) and (4) present estimates from controlling for focal doctors' emergency cases in both the current and previous weeks. Our result remain robust also to these inclusions.

Finally, we study whether our results vary with the type of patients focal doctors see. Specifically, we examine peer influences of focal doctors for emergency and elective cases and across CA and PTCA procedures. Table 9 presents results from this exercise, showing that peer effects are consistent across both case types and procedures.[23]

6 Conclusion

Social interactions in the workplace are ubiquitous in almost all professions. The healthcare sector is no exception: physicians and other healthcare professionals continuously interact to exchange ideas on patient care, provide feedback on clinical decisions, and share opinions about new medical technology (see, e.g., Coleman et al., 1957). Understanding and quantifying the role and potential benefits of team-based learning and the influence of peers on health system functionality and efficiency should, therefore, be a priority for policymakers and administrators. However, despite the vast scope for identifying and utilizing such sources of productivity, it has been largely overlooked in the debate over healthcare reform.

This paper shows that peer influences in the specific context of the use of ionizing radiation in the diagnosis and treatment of heart attacks in Sweden are both salient and consequential. Using an instrumental variables approach where we exploit the plausibly random arrivals of emergency cases for on-call physicians to account for endogenous peer formation, we show that focal physicians strongly align their applied radiation doses to changes in their peer groups' radiation outputs. These peer effects have downstream implications for the quality and appropriateness of care provided by physicians in our sample. Specifically, we provide evidence that the higher radiation output relayed by peers prompted focal physicians to employ a more aggressive treatment practice style, presumably through a higher detection rate of arterial blockages, and is associated with a lower risk of adverse clinical events, including patient death and subsequent heart attacks. However, the peer effects are transient and fade out quickly after the initial peer exposure, suggesting that they are channeled by peer pressure and or framing effect rather than a peer learning behavioral mechanism. This is contextually important as it allows us to expand our understanding of the factors that may encourage peer

[23] We also conduct a more systematic bounding exercise on our main 2SLS estimates based on Conley et al. (2012) presented in Figure C.1 of Appendix C. This method enables inference on the 2SLS estimates by accounting for the possibility of a direct effect of the instrument on the outcomes. The graph shows that peer effects remain positive and statistically significant even if almost the entire reduced form estimate would be attributed to a direct impact of the instrument on the radiation dose outcome.

learning among medical doctors.

In conclusion, our results provide important policy implications as well as contribute to the scant academic literature on social spillovers in healthcare. Even in the Swedish context where competition and profit motives among healthcare providers and professionals are minimal, there exist glaring quality differences in care across hospitals and geographical regions. Understanding the role of positive and negative social multiplier effects is one important venue to explain such quality variations. Moreover, harnessing the former and weeding out the latter elements is key for improving efficiency and sustainability to prepare for growing future healthcare needs. While our analysis provides important insights on the prevalence and the consequences of peer influence in healthcare, future research could focus on the specific behavioral mechanisms (see e.g. DellaVigna, 2009; Bursztyn et al., 2014; Bordalo et al., 2020) at play in the interactions between healthcare professionals that precipitate these outcomes.

References

Abaluck, Jason, Leila Agha, Chris Kabrhel, Ali Raja, and Arjun Venkatesh, "The determinants of productivity in medical testing: Intensity and allocation of care," *American Economic Review*, 2016, *106* (12), 3730–3764.

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

Andrews, Isaiah, James H Stock, and Liyang Sun, "Weak instruments in instrumental variables regression: Theory and practice," *Annual Review of Economics*, 2019, *11*, 727–753.

Angrist, Joshua D, "The perils of peer effects," *Labour Economics*, 2014, *30*, 98–108.

_ , Guido W Imbens, and Donald B Rubin, "Identification of causal effects using instrumental variables," *Journal of the American statistical Association*, 1996, *91* (434), 444–455.

Arcidiacono, Peter and Sean Nicholson, "Peer effects in medical school," *Journal of Public Economics*, 2005, *89* (2-3), 327–350.

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

Arnold, David, Will Dobbie, and Crystal S Yang, "Racial bias in bail decisions," *The Quarterly Journal of Economics*, 2018, *133* (4), 1885–1932.

Avdic, Daniel, Maryna Ivets, Bo Lagerqvist, and Ieva Sriubaite, "Providers, peers and patients. How do physicians' practice environments affect patient outcomes?," *Journal of Health Economics*, 2023, *89*, 102741.

_ , Nils Gutacker, Giovanni van Empel, and Johan Vikström, "Provider responses to market entry under competing health technologies," Unpublished Manuscript 2024.

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

_ , _ , and _ , "Social incentives in the workplace," *The Review of Economic Studies*, 2010, *77* (2), 417–458.

Barrenho, Eliana, Eric Gautier, Marisa Miraldo, Carol Propper, and Christiern D Rose, "Innovation diffusion and physician networks: Keyhole surgery for cancer in the English NHS," CEPR Discussion Paper No. DP15515, Centre for Economic Policy Research 2020.

_ , Marisa Miraldo, Carol Propper, and Brendan Walsh, "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*, 2021, *272*, 113715.

Barro, Jason R, Robert S Huckman, and Daniel P Kessler, "The effects of cardiac specialty hospitals on the cost and quality of medical care," *Journal of health economics*, 2006, *25* (4), 702–721.

Bayer, Patrick, Stephen L Ross, and Giorgio Topa, "Place of work and place of residence: Informal hiring networks and labor market outcomes," *Journal of Political Economy*, 2008, *116* (6), 1150–1196.

Bergmark, Brian A, Njambi Mathenge, Piera A Merlini, Marilyn B Lawrence-Wright, and Robert P Giugliano, "Acute coronary syndromes," *The Lancet*, 2022, *399* (10332), 1347–1358.

Beugnot, Julie, Bernard Fortin, Guy Lacroix, and Marie Claire Villeval, "Gender and peer effects on performance in social networks," *European Economic Review*, 2019, *113*, 207–224.

Bhuller, Manudeep, Gordon B Dahl, Katrine V Løken, and Magne Mogstad, "Incarceration, recidivism, and employment," *Journal of Political Economy*, 2020, *128* (4), 1269–1324.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Memory, attention, and choice," *The Quarterly journal of economics*, 2020, *135* (3), 1399–1442.

Bragard, Isabelle, Gilles Dupuis, and Richard Fleet, "Quality of work life, burnout, and stress in emergency department physicians: A qualitative review," *European Journal of Emergency Medicine*, 2015, *22* (4), 227–234.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin, "Identification of peer effects through social networks," *Journal of Econometrics*, 2009, *150* (1), 41–55.

Bursztyn, Leonardo, Florian Ederer, Bruno Ferman, and Noam Yuchtman, "Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions," *Econometrica*, 2014, *82* (4), 1273–1301.

Caeyers, Bet and Marcel Fafchamps, "Exclusion bias in the estimation of peer effects," NBER Working Paper 22565, National Bureau of Economic Research 2016.

Card, David, Carlos Dobkin, and Nicole Maestas, "The impact of nearly universal insurance coverage on health care utilization: Evidence from Medicare," *American Economic Review*, 2008, *98* (5), 2242–58.

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

Catalano, Carlo, Marco Francone, Adriano Ascarelli, Matteo Mangia, Ilaria Iacucci, and Roberto Passariello, "Optimizing radiation dose and image quality," *European Radiology Supplements*, 2007, *17*, 26–32.

Chambers, Charles E, Kenneth A Fetterly, Ralf Holzer, Pei-Jan Paul Lin, James C Blankenship, Stephen Balter, and Warren K Laskey, "Radiation safety program for the cardiac catheterization laboratory," *Catheterization and Cardiovascular Interventions*, 2011, *77* (4), 546–556.

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

— , **Matthew Gentzkow, and Chuan Yu**, “Selection with variation in diagnostic skill: Evidence from radiologists,” *The Quarterly Journal of Economics*, 2022, *137* (2), 729–783.

Chandra, Amitabh, Amy Finkelstein, Adam Sacarny, and Chad Syverson, “Health care exceptionalism? Performance and allocation in the US health care sector,” *American Economic Review*, 2016, *106* (8), 2110–44.

— , **David Cutler, and Zirui Song**, “Who ordered that? The economics of treatment choices in medical care,” in Mark V. Pauly, Thomas G. Mcguire, and Pedro Barros, eds., *Handbook of Health Economics*, Vol. 2, Elsevier, 2011, chapter 6, pp. 397–432.

Chen, Yiqun, “Team-specific human capital and team performance: evidence from doctors,” *American Economic Review*, 2021, *111* (12), 3923–3962.

Chodick, Gabriel, Yoav Goldstein, Ity Shurtz, and Dan Zeltzer, “Challenging encounters and within-physician practice variability,” *Review of Economics and Statistics*, 2024, *Forthcoming.*

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

Coleman, James, Elihu Katz, and Herbert Menzel, “The diffusion of an innovation among physicians,” *Sociometry*, 1957, *20* (4), 253–270.

Conley, Timothy G, Christian B Hansen, and Peter E Rossi, “Plausibly exogenous,” *Review of Economics and Statistics*, 2012, *94* (1), 260–272.

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

— , — , **and Jessica Van Parys**, “Provider practice style and patient health outcomes: The case of heart attacks,” *Journal of Health Economics*, 2016, *47*, 64–80.

Cutler, David M and Mark McClellan, “Is technological change in medicine worth it?,” *Health Affairs*, 2001, *20* (5), 11–29.

— , **Robert S Huckman, and Jonathan T Kolstad**, “Input constraints and the efficiency of entry: Lessons from cardiac surgery,” *American Economic Journal: Economic Policy*, 2010, *2* (1), 51–76.

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

DellaVigna, Stefano, “Psychology and economics: Evidence from the field,” *Journal of Economic literature*, 2009, *47* (2), 315–372.

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

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

European Commission: Directorate-General for Energy, "Medical radiation exposure of the European population," Radiation Protection 180, European Commission 2015.

Georges, Jean-Louis, Loic Belle, Cécile Etard, Jean-Baptiste Azowa, Franck Albert, Michel Pansieri, Jacques Monsegu, Franck Barbou, Charlotte Trouillet, Pierre Leddet et al., "Radiation doses to patients in interventional coronary procedures—estimation of updated national reference levels by dose audit," *Radiation protection dosimetry*, 2017, *175* (1), 17–25.

Giorgi, Giacomo De, Anders Frederiksen, and Luigi Pistaferri, "Consumption network effects," *The Review of Economic Studies*, 2020, *87* (1), 130–163.

_, Michele Pellizzari, and Silvia Redaelli, "Identification of social interactions through partially overlapping peer groups," *American Economic Journal: Applied Economics*, 2010, *2* (2), 241–275.

Godøy, Anna and Harald Dale-Olsen, "Spillovers from gatekeeping–Peer effects in absenteeism," *Journal of Public Economics*, 2018, *167*, 190–204.

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

Hall, Marlous, Lesley Smith, Jianhua Wu, Chris Hayward, Jonathan A Batty, Paul C Lambert, Harry Hemingway, and Chris P Gale, "Health outcomes after myocardial infarction: A population study of 56 million people in England," *Plos Medicine*, 2024, *21* (2), e1004343.

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

Harmon, Nikolaj, Raymond Fisman, and Emir Kamenica, "Peer effects in legislative voting," *American Economic Journal: Applied Economics*, 2019, *11* (4), 156–80.

Haynes, Alex B, Thomas G Weiser, William R Berry, Stuart R Lipsitz, Abdel-Hadi S Breizat, E Patchen Dellinger, Teodoro Herbosa, Sudhir Joseph, Pascience L Kibatala, Marie Carmela M Lapitan et al., "A surgical safety checklist to reduce morbidity and mortality in a global population," *New England journal of medicine*, 2009, *360* (5), 491–499.

Herkenhoff, Kyle, Jeremy Lise, Guido Menzio, and Gordon M. Phillips, "Production and Learning in Teams," *Econometrica*, 2024, *92* (2), 467–504.

Hirshfeld, JW, JA Brinker, and MJ Kern, "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*, 2005, *111* (4), 511–532.

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

ICRP (International Commission on Radiation Protection), "Radiological protection in cardiology," *Annals of the ICRP*, 2013, *42* (1).

James, Stefan, Bo Lagerqvist, Petter Lundborg, and Johan Vikström, "Learning-by-doing and productivity growth among high-skilled workers: evidence from the treatment of heart attacks," Technical Report, Working Paper 2022.

Jaravel, Xavier, Neviana Petkova, and Alex Bell, "Team-specific capital and innovation," *American Economic Review*, 2018, *108* (4-5), 1034–73.

Jin, Lawrence, Rui Tang, Han Ye, Junjian Yi, and Songfa Zhong, "Path dependency in physician decisions," *Review of Economic Studies*, 2024, *91* (5), 2916–2953.

Jochmans, Koen, "Testing random assignment to peer groups," *Journal of Applied Econometrics*, 2023, *38* (3), 321–333.

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

Jr, Fred A Mettler, Walter Huda, Terry T Yoshizumi, and Mahadevappa Mahesh, "Effective doses in radiology and diagnostic nuclear medicine: a catalog," *Radiology*, 2008, *248* (1), 254–263.

Jr, Joseph J Doyle and Becky Staiger, "Physician group influences on treatment intensity and health: Evidence from physician switchers," *American Economic Journal : Economic Policy*, 2024, *Forthcoming.*

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

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

Keane, Michael and Timothy Neal, "Instrument strength in IV estimation and inference: A guide to theory and practice," *Journal of Econometrics*, 2023.

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

Kobayashi, Taisei and John W Hirshfeld Jr, "Radiation exposure in cardiac catheterization: operator behavior matters," 2017.

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

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

Li, Xinhua, Joshua A Hirsch, Madan M Rehani, Kai Yang, and Bob Liu, "Effective dose assessment for patients undergoing contemporary fluoroscopically guided interventional procedures," *American Journal of Roentgenology*, 2020, *214* (1), 158–170.

Luo, Feijun, Grace Chapel, Zhiqiu Ye, Sandra L Jackson, and Kakoli Roy, "Labor income losses associated with heart disease and stroke from the 2019 panel study of income dynamics," *JAMA Network Open*, 2023, *6* (3), e232658–e232658.

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

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

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

McWilliams, J Michael, "Pay for Performance: When Slogans Overtake Science in Health Policy," *JAMA*, 2022, *328* (21), 2114–2116.

Meeker, Daniella, Jeffrey A Linder, Craig R Fox, Mark W Friedberg, Stephen D Persell, Noah J Goldstein, Tara K Knight, Joel W Hay, and Jason N Doctor, "Effect of behavioral interventions on inappropriate antibiotic prescribing among primary care practices: a randomized clinical trial," *Journal of the American Medical Association*, 2016, *315* (6), 562–570.

Miraldo, Marisa, Carol Propper, and Christiern D. Rose, "Identification of Peer Effects using Panel Data," *SSRN Electronic Journal*, 2021, pp. 1–31.

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

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

Picano, Eugenio, Eliseo Vano, Madan M Rehani, Alberto Cuocolo, Lluis Mont, Vicente Bodi, Olivier Bar, Carlo Maccia, Luc Pierard, Rosa Sicari et al., "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*, 2014, *35* (10), 665–672.

Pope, J Hector, Tom P Aufderheide, Robin Ruthazer, Robert H Woolard, James A Feldman, Joni R Beshansky, John L Griffith, and Harry P Selker, "Missed diagnoses of acute cardiac ischemia in the emergency department," *New England Journal of Medicine*, 2000, *342* (16), 1163–1170.

Richardson, David B, Klervi Leuraud, Dominique Laurier, Michael Gillies, Richard Haylock, Kaitlin Kelly-Reif, Stephen Bertke, Robert D Daniels, Isabelle Thierry-Chef, Monika Moissonnier, Ausrele Kesminiene, and Mary K Schubauer-Berigan, "Cancer mortality after low dose exposure to ionising radiation in workers in France, the United Kingdom, and the United States (INWORKS): cohort study," *BMJ*, 2023, *382.*

Roth, Gregory A, George A Mensah, Catherine O Johnson, Giovanni Addolorato, Enrico Ammirati, Larry M Baddour, Noël C Barengo, Andrea Z Beaton, Emelia J Benjamin, Catherine P Benziger et al., "Global burden of cardiovascular diseases and risk factors, 1990–2019: update from the GBD 2019 study," *Journal of the American College of Cardiology*, 2020, *76* (25), 2982–3021.

Sacerdote, Bruce, "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, 2011, pp. 249–277.

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

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

Vassileva, Jenia and Madan Rehani, "Diagnostic reference levels," *American Journal of Roentgenology*, 2015, *204* (1), W1–W3.

Waldinger, Fabian, "Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany," *The review of economic studies*, 2012, *79* (2), 838–861.

WHO (World Health Organization), "Enhancing radiation safety culture in health care : guidance for health care providers.," Technical Report, World Health Organization 2024.

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

Zwarenstein, Merrick and Wendy Bryant, "Interventions to promote collaboration between nurses and doctors," *Cochrane database of systematic reviews*, 2000, *2*, CD000072.

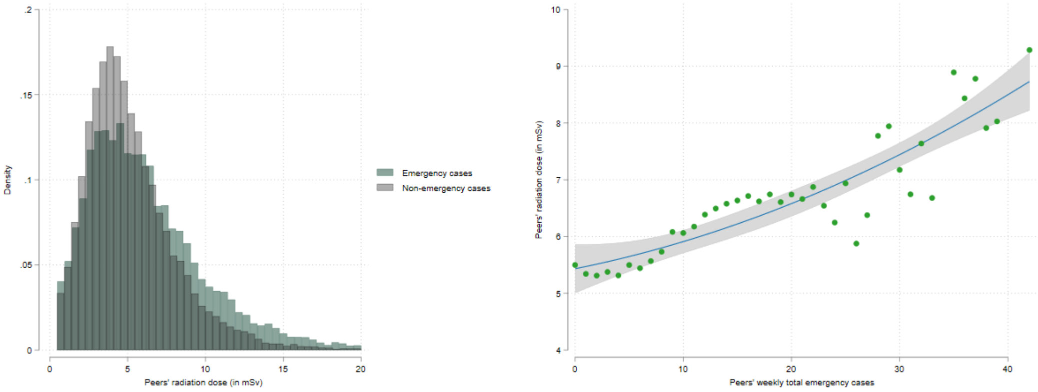
Tables and Figures

TABLE 1.
Summary statistics

	Mean	SD
Physicians' output (weekly averages)		
Radiation dose (mSv)	5.56	2.98
Peers' radiation dose (mSv)	5.55	2.15
Share of patients - excessive dosage	0.11	0.19
Share of patients - insufficient dosage	0.35	0.31
Share of patients - appropriate dosage	0.54	0.30
Fluoroscopic time (sec)	553.57	293.90
Workplace		
Weekly cases (focal)	6.82	4.78
On-call emergency cases (focal)	1.00	1.59
Peer's total on-call emergency cases	3.81	4.78
Number of peers	3.30	1.80
Physicians' characteristics		
Age	48.97	7.47
Female doctors (share)	0.10	0.30
Peers' age	48.21	6.14
Junior (30-44)	0.32	0.47
Mid-level (45-58)	0.57	0.50
Senior (> 58)	0.11	0.31
Patients' characteristics		
Patients' age	66.50	6.19
Female (share)	0.33	0.47
Complex cases	0.23	0.23
PTCA/PCI performed	0.50	0.28
Diabetes (share)	0.20	0.21
Hypertension (share)	0.60	0.28
Previous infarction (share)	0.25	0.23
Previous PCI (share)	0.22	0.22
Previous bypass (share)	0.10	0.16
Smoker/ex-smoker (share)	0.58	0.28
Weight (kg)	81.46	7.86
Quality (rate per 1,000 procedures)		
Mortality - 1 year post	1.13	2.56
Revascularization - 1 year post	0.90	2.25
Restenosis - 1 year post	0.30	1.31
Infarction - 1 year post	0.69	1.94
Observations	28,467	

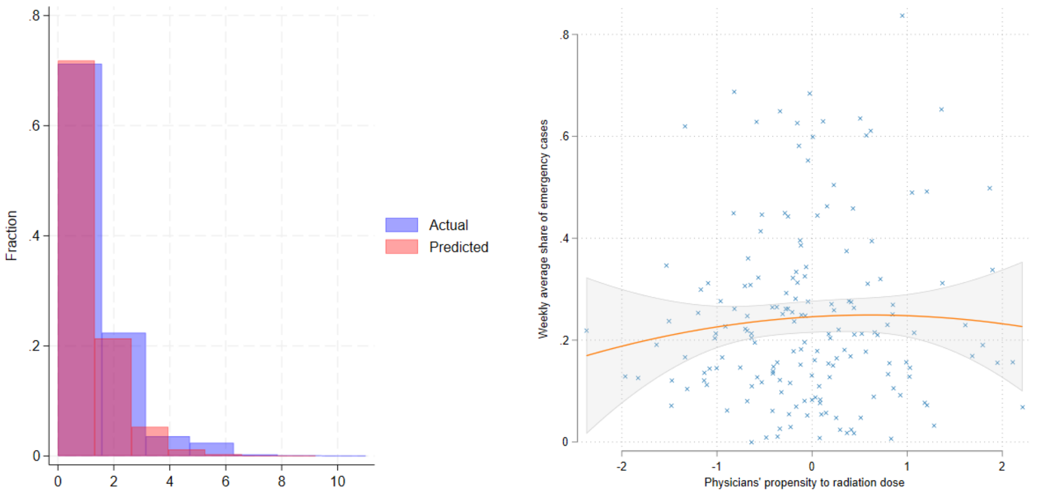
NOTE. Data from Swedish Coronary Angiography and Angioplasty Registry (SCAAR) pooled across years 2008-2013. Radiation dose is defined as Effective Dose (mSv), see Appendix B for detailed explanation on the calculation. Share of patients receiving range of reference levels in radiation dose are classified based on the European Diagnostic Reference Levels (DRLs) as specified in Section 3. Peer's total on-call emergency cases are derived from cases the peer's treated during on-call shifts (outside working hours). Quality outcomes are calculated at the rate per 1,000 procedures in 1-year post intervention date.

Figure 1.
IV Relevance



Note. Data from Swedish Coronary Angiography and Angioplasty Registry (SCAAR) pooled across years 2008-2013. Left panel plots the distributions of average radiation dose (in mSv) in : 1. Emergency cases (green) and 2. Non-emergency cases (grey). The green dots on the right panel plots the total weekly on-call emergency cases the peers' treated (x-axis) on the average peers' radiation dose (y-axis, in mSv). Green line on the right panel is the linear fit with the corresponding 95% CIs (in grey).

Figure 2.
IV Validity



Note. Data from Swedish Coronary Angiography and Angioplasty (SCAAR) pooled across years. The left panel shows the actual data distribution of the weekly arrival of emergency cases (blue) and the distribution of the predicted weekly arrival of emergency cases (red) from the estimated Poisson model controlling for hospital and week-by-year fixed effects. The right panel plots the mixed-model estimated physician-specific random intercepts as a measure of physicians' underlying preference for radiation (x-axis) on the average weekly share of emergency cases (y-axis) treated by the corresponding physician.

TABLE 2.
Main results

	(1)	(2)	(3)
Panel A. OLS		Outcome : Focal radiation output	
Peers' radiation output	0.372***	0.168***	0.171***
	(0.014)	(0.011)	(0.011)
Effect size	[19.9%]	[9%]	[9.1%]
Panel B. First-stage		Outcome : Peers' radiation output	
Peer's total on-call emergency cases	0.031***	0.018***	0.018***
	(0.004)	(0.003)	(0.003)
Montiel-Pflueger F-stats	72.5	35.1	35.2
Panel C. Reduced form		Outcome : Focal radiation output	
Peer's total on-call emergency cases	0.025***	0.014***	0.013***
	(0.003)	(0.002)	(0.002)
Panel D. 2SLS : Second-stage		Outcome : Focal radiation output	
Peers' radiation output	0.834***	0.804***	0.710***
	(0.031)	(0.065)	(0.065)
Effect size	[44.7%]	[43%]	[38%]
Mean outcome	5.56	5.56	5.56
SD outcome	2.98	2.98	2.98
Specification	No control	Baseline w/o Risk-adjusters	Baseline
Anderson-Rubin p-value	0.00	0.00	0.00
Observations	28,467	28,467	28,467

NOTE. Own calculations based on the SCAAR registry pooled across years 2008–2013. Panel A present the OLS estimates, Panel B-D present the first-stage, reduced form, and second-stage estimates, respectively. Focal doctors and peer's average radiation output are standardized.The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level and are in parentheses. Effect size (in brackets) is calculated with respect to the mean outcome. Baseline model controls for doctors, hospital linear time trend, month-by-year FEs; the focal physician's emergency cases in the previous week (*t-1*); and various risk-adjuster measures : average age of the patients and share of patients with co-morbidities (diabetes, hypertension, smoking status, past history of infarction/PTCA/bypass).

Table 3.
Appropriateness of care

	Share of patients receiving [...]					
	Insufficient dosage		Appropriate dosage		Excessive dosage	
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' radiation output	-0.752***	-0.678***	0.403***	0.371***	0.606***	0.533***
	(0.114)	(0.113)	(0.136)	(0.135)	(0.090)	(0.093)
Average cases	6.8	6.8	6.8	6.8	6.8	6.8
Mean outcome	0.353	0.353	0.539	0.539	0.108	0.108
SD outcome	0.312	0.312	0.298	0.298	0.189	0.189
Montiel-Pflueger F-stats	35.1	35.2	35.1	35.2	35.1	35.2
Anderson-Rubin p-value	0.00	0.00	0.00	0.00	0.00	0.00
Risk-adjusters	-	✓	-	✓	-	✓
Observations	28,467	28,467	28,467	28,467	28,467	28,467

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcomes are defined as share of cases receiving the corresponding range of Diagnostic Reference Levels (DRLs) as specified in Section 3. Peer's average radiation output is standardized. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). Average cases refer to the total (weekly) that the focal physician's treated. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Baseline model controls for doctors, hospital linear time trend, month-by-year FEs, and the focal physician's emergency cases in the previous week (*t-1*) and various risk-adjuster measures (patient's characteristics and co-morbidities).

Table 4.
Treatment intensity

	Diagnostic intensity				Treatment intensity	
	Time	Complex	Segments	CABG	PTCA	Stents
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' radiation output	0.330***	0.053**	0.193*	-0.007	0.171*	0.192*
	(0.100)	(0.027)	(0.115)	(0.016)	(0.102)	(0.115)
Mean outcome	554	0.233	0.727	0.090	0.498	0.634
SD outcome	294	0.228	0.520	0.153	0.284	0.547
Montiel-Pflueger F-stats	35.2	35.2	35.2	35.2	35.2	35.2
Anderson-Rubin p-value	0.01	0.04	0.12	0.636	0.12	0.12
Observations	28,467	28,467	28,467	28,467	28,467	28,467

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcomes are defined as standardized fluoroscopic time (in seconds) (1); ; share of patients diagnosed as "Complex" (3); standardized weekly number of segments or the coronary artery treated (3); share of patients recommended for heart bypass surgery (CABG - Coronary Artery Bypass Graft) (4); share of patients receiving PTCA (5) and standardized number of stents used (5). Peer's average radiation output is standardized. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

TABLE 5.
Quality implication

	Restenosis (1)	Infarction (2)	Revascularization (3)	Mortality (4)
Peers' radiation output	-0.188	-0.380***	-0.280**	-0.356***
	(0.116)	(0.129)	(0.129)	(0.133)
Mean outcome	0.304	0.687	0.900	1.129
SD outcome	1.311	1.945	2.255	2.559
Montiel-Pflueger F-stats	35.1	35.1	35.1	35.1
Anderson-Rubin p-value	0.09	0.00	0.02	0.00
Observations	28,467	28,467	28,467	28,467

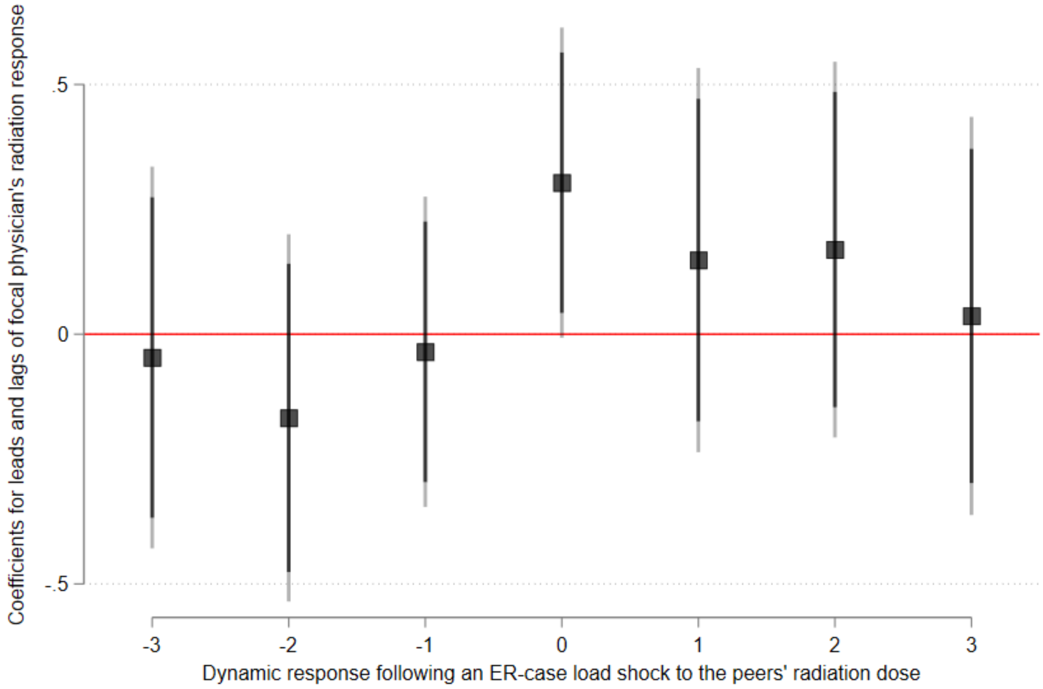
NOTE. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcomes are (standardized) number of corresponding adverse events occurred within 1-year post intervention date. Restenosis is reduction in artery diameter post-intervention; Re-infarction is recurrence of clinical signs and symptoms of ischemia in patients with previously diagnosed of heart attacks; Revascularization is re-intervention following initial interventional procedure given. Peer's average radiation output is standardized. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

Table 6.
Heterogeneity analysis

	(1) Female	(2) Male	(3) Junior	(4) Mid	(5) Senior	(6) Local hospital	(7) Academic hospital
Peers' radiation output	0.357	0.740***	0.602***	0.657***	1.022	0.602***	0.654***
	(0.273)	(0.081)	(0.143)	(0.137)	(0.746)	(0.133)	(0.083)
Mean outcome	6.43	5.46	5.72	5.53	5.22	5.55	5.61
SD outcome	3.39	2.91	3.02	2.98	2.81	2.96	3.02
Montiel-Pflueger F-stats	10.4	31.0	22.4	25.7	2.0	17.3	18.7
Anderson-Rubin p-value	0.18	0.00	0.00	0.00	0.06	0.00	0.00
Observations	2,892	25,575	9,192	16,153	3,122	17,565	10,902

Note. . The table presents the 2SLS estimates based on focal doctors' characteristics. Outcome is focal doctors (standardized) radiation output and the instrumented (standardized) peer's average radiation output. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). Columns (1)-(2) control for peer's emergency cases at t; Columns (3)-(4) control for focal emergency cases at t. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (t-1), and various risk-adjuster measures (patient's characteristics and co-morbidities).

FIGURE 3.
Event study



NOTE. Own calculations based on the SCAAR registry pooled across years 2008–2013. The graph plots the 2SLS estimates (solid point) and the corresponding 95% confidence intervals (black lines) and 90% confidence intervals (grey lines) from the model specification in Equation (4). The model vary the outcome variable at various *t* (the focal physicians' radiation output at various lag and lead). Model controls for (instrumented) current peer exposure, (non-instrumented) past peer exposures, doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

TABLE 7.
Sensitivity analysis

	(1)	(2)	(3)	(4)
Peers' radiation output	0.710***	0.707***	0.693***	0.611***
	(0.065)	(0.063)	(0.069)	(0.082)
Mean outcome	5.56	5.56	5.56	5.47
SD outcome	2.98	2.98	2.98	2.65
Montiel-Pflueger F-stats	35.2	36.0	32.0	34.5
Anderson-Rubin p-value	0.000	0.000	0.000	0.000
Specifications	Baseline	Hospitals volume	Own (lagged) outcome	Excluding outliers
Observations	28,467	28,467	28,467	27,900

NOTE. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcome is focal doctors (standardized) radiation output and the instrumented (standardized) peer's average radiation output. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

Table 8.
Robustness check : Autocorrelation

	(1)	(2)	(3)	(4)
Peers' radiation output	0.901***	0.802***	0.815***	0.724***
	(0.089)	(0.086)	(0.065)	(0.066)
Mean outcome	5.56	5.56	5.56	5.56
SD outcome	2.98	2.98	2.98	2.98
Montiel-Pflueger F-stats	23.7	23.8	35.4	35.5
Anderson-Rubin p-value	0.00	0.00	0.00	0.00
Model	w/o Risk-adjusters	Baseline	w/o Risk-adjusters	Baseline
Control	Peer's emergency cases	Peer's emergency cases	Focal's emergency cases	Focal's emergency cases
Observations	28,467	28,467	28,467	28,467

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcome is focal doctors (standardized) radiation output and the instrumented (standardized) peer's average radiation output. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). Columns (1)-(2) control for peer's emergency cases at *t*; Columns (3)-(4) control for focal emergency cases at *t*. * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

Table 9.
Robustness : Types of cases

	Emergency (1)	Elective (2)	Angiography (CA) (3)	PTCA (4)
Peers' radiation output	0.480***	0.550***	0.548***	0.529***
	(0.126)	(0.104)	(0.111)	(0.079)
Mean outcome	6.33	5.23	3.46	7.61
SD outcome	3.97	2.98	2.08	3.93
Montiel-Pflueger F-stats	21.3	34.9	37.7	34.9
Anderson-Rubin p-value	0.00	0.00	0.00	0.00
Observations	17,983	25,898	25,007	25,455

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates based on types of cases treated by the focal doctors. Outcome is focal doctors' (standardized) radiation output across case types (Emergency and Elective) and procedures (angiography and PTCA). Peers' radiation output is standardized. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures such as patient's characteristics and co-morbidities.

Appendix A Coronary Angiography Procedure

The coronary arteries provide the pathway for blood to flow and supply oxygen to the heart muscle (myocardium). In some cases, these arteries can become narrowed or blocked by fatty deposits called plaque, leading to conditions such as coronary artery disease (CAD). In these conditions, the passage for blood flow is restricted, and consequently, the heart muscle doesn't receive enough oxygen, leading to permanent damage. A coronary angiography (CA) is a diagnostic procedure that allows doctors to examine the coronary arteries, especially in the event of a heart attack. Its primary use is to detect blockages and map areas of narrowing (stenosis) in these arteries, which helps cardiologists determine the appropriate treatment (e.g., ballooning or stents) to maintain patency of the affected blood vessels.

There are preparation steps to consider before undergoing the procedure. In a non-emergency situation, the patient typically has a consultation with their doctor and undergoes some tests, such as blood work, an electrocardiogram (ECG), or a chest x-ray. The patient is also advised to avoid eating or drinking for 6 to 8 hours before the procedure. If the patient takes medications like blood thinners (e.g., warfarin or aspirin), they may need to temporarily stop these under their doctor's guidance. The medical team will also check for any allergies to iodine or contrast dye, as this dye is crucial for visualizing the arteries during the angiography.

A coronary angiography is generally a safe procedure, but as with any medical intervention, there are potential risks. Common side effects include bruising or bleeding at the access site, as well as mild discomfort. Rarely, more serious complications like allergic reactions to the dye, arrhythmias (irregular heartbeats), or damage to the blood vessels may occur. In extremely rare cases, a heart attack or stroke can happen during the procedure. However, for most patients, the benefits outweigh these risks.

The angiography typically involves the following steps:

1. Locating and accessing the artery: The procedure begins with the cardiologist selecting an access point to reach the coronary arteries. The two common access points are the radial artery (located in the forearm) or the femoral artery (in the groin). The radial approach is increasingly favored due to its lower complication rates and quicker recovery; however, it requires more precision than the femoral artery as it is smaller. Patients are given a local anesthetic around the puncture site, and the cardiologist inserts a thin tube called a catheter into the artery using a needle.

2. Guiding the catheter to the heart: Once the catheter is in the artery, the cardiologist carefully guides it up to the coronary arteries. The movement of the catheter is tracked using continuous x-ray imaging called fluoroscopy, which helps the clinician navigate the blood vessels safely. Radiation exposure occurs throughout the fluoroscopy procedure. The catheter is steered through the blood vessels toward the heart, similar to

threading a wire through a winding tube.

3. Use of contrast agent: Once the catheter reaches the coronary arteries, a contrast dye or contrast agent is injected through the catheter. This dye contains iodine, which makes the coronary arteries visible on x-ray images. The dye allows the cardiologist to see how blood is flowing through the arteries and to detect any areas of narrowing or blockage.

4. Capturing x-ray images: As the dye moves through the arteries, x-ray images are taken in real time. The images provide a clear view of the coronary arteries, showing whether the blood flow is normal or obstructed. If a significant blockage (usually more than 70% narrowing) is found, the cardiologist may perform further treatment, such as PTCA (Percutaneous Transluminal Coronary Angioplasty), by inserting a balloon or stent to open the artery. In complex cases, a coronary bypass surgery may be recommended.

The procedure usually takes 30-45 minutes to complete. Once the angiography is finished, the catheter is carefully removed, and pressure is applied to the access site to prevent bleeding. If the procedure was done via the radial artery, the patient can often sit up and walk shortly afterward. For those with femoral access, a few hours of lying flat may be required to ensure the artery heals properly. Most patients are discharged on the same day but may be advised to avoid heavy lifting or strenuous activities for a few days. Patients are prescribed appropriate medications and will be re-evaluated in the following week to monitor improvements and check for any side effects.

Appendix B Calculation of Effective dose (mSv)

Dose Area Product (DAP) is a measure of the total radiation dose delivered to a patient during radiological procedures (including Coronary Angiography), taking account of both the dose and the area exposed to the radiation (Li et al., 2020). Intuitively, DAP represents the total radiation dose multiplied by the exposed area during a radiological procedure. The common unit of measurements are Gray centimetres squared ($Gy.cm^2$) or milligray centimetres squared ($mGy.cm^2$).

Effective dose, on the other hand, represents the overall risk of radiation exposure by accounting the type of radiation and sensitivity of different body tissues exposed to ionizing radiation. DAP is informative to the overall radiation is absorbed per unit mass, Effective dose accounts for how vulnerable certain tissues to radiation-induced damage. For instance, breast, lungs, and bone marrow are relatively more susceptible to radiation damage. In other words, Effective dose is a risk-adjusted measure of ionizing radiation.

Effective dose is important to determine the stochastic risk (i.e. risk of cancer), effects that occur randomly yet is positively correlated with the amount of radiation dose. The higher the effective dose, the risk of developing stochastic effects is increased. There is no known 'threshold' exists below which the risk is zero, as even small doses pose a small probability of stochastic effects. Deterministic risk from ionizing radiation, such as skin burns, on the other hand is more relevant for DAP as it measures directly the absorbed radiation dose to the body tissues. As such, there is a 'threshold' in which the effects would occur if it exceeded a specific range of dose.

Our data records DAP in μGray meters squared ($\mu Gy.m^2$). We first convert this measure to the typical DAP unit, in Gray centimeters squared ($Gy.cm^2$) simply by dividing 100 (as detailed in the website https://www.dosewizard.com/2011/06/dap-converter.html). We then convert DAP into Effective dose, measured in millisieverts (mSv) by multiplying DAP with a dose conversion factors (derived from studies and/or clinical guidelines for specific procedures). We assume dose conversion factor for Coronary Angiography is 0.1 $mSv/Gy.cm^2$. Formally, the conversion steps is the following :

1. Convert radiation dose to DAP ($\mu Gy.m^2$ to $Gy.cm^2$)

$$\text{Radiation dose } (\mu\text{Gy.m2})/100 = \text{DAP } (\text{Gy.cm}^2)$$

2. DAP to Effective dose

$$\text{Effective Dose (mSv)=DAP } (\text{Gy.cm}^2)\times\text{Conversion Factor } (\text{mSv/Gy.cm}^2)$$

Taking an example of the average radiation dose of 5,500 $\mu Gy.m^2$, this means that the Effective dose is simply 5,500/1,000 = 5.5 mSv

Appendix C Additional Figures and Tables

Table C.1.
Conditional random assignment test

Group	No. of groups	T-statistics	
		Observable	Non-observable
Hospital-by-week	6,002	*1.03E-07*	*-8.14E-08*
Hospital-by-month	1,917	*5.32E-08*	*2.87E-09*
Hospital-by-quarter	663	-0.00330	0.00622

Note. Table presents the t-statistics from the random assignment test of peer groups following (Jochmans, 2023). The method builds on a regression approach similar to (Sacerdote, 2011), that checks for correlations between individual and peer's characteristics, conditional on the group fixed (at the urn level). If correlations exist, it then suggests a non-random assignment and hence the null hypothesis in this test is random assignment. The test are based on both observables (age, gender) and unobservables (the estimated random intercepts from mixed-model as shown in Figure 2, right panel. The independent variable is the average observable and unobservables characteristics of the peers (age and the average preference for radiation). The test controls for fixed effects at the urn level (i.e. peer group).

Table C.2.
IV Monotonicity

	Sex		Age group		
	Male	Female	Junior	Mid	Senior
	(1)	(2)	(3)	(4)	(5)
Peer's total on-call emergency cases	0.017***	0.020***	0.017***	0.017***	0.009*
	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)
Observations	25,575	2,892	9,192	16,153	3,122

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the OLS estimates from the first-stage specification in Equation (3) across sub-groups of the focal doctors. Outcome variable is (standardized) average peer's radiation dose. The IV is Peer's total on-call emergency cases and this is defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer group level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures such as patient's characteristics and co-morbidities.

Table C.3.
Treatment intensity : Local hospitals

	Diagnostic intensity				Treatment intensity	
	Time	Complex	Segments	CABG	PTCA	Stents
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' radiation output	0.459***	0.038	0.317*	-0.021	0.359**	0.377**
	(0.150)	(0.034)	(0.180)	(0.023)	(0.168)	(0.183)
Mean outcome	546.970	0.228	0.717	0.089	0.484	0.619
SD outcome	283.250	0.218	0.503	0.150	0.270	0.524
Montiel-Pflueger F-stats	17.3	17.3	17.3	17.3	17.3	17.3
Anderson-Rubin p-value	0.00	0.26	0.09	0.34	0.04	0.04
Observations	17,565	17,565	17,565	17,565	17,565	17,565

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcomes are defined as standardized fluoroscopic time (1); ; share of patients diagnosed as "Complex" (3); standardized weekly number of segments or the coronary artery treated (3); share of patients recommended for heart bypass surgery (CABG - Coronary Artery Bypass Graft) (4); share of patients receiving PTCA (5) and standardized number of stents used (5). Peer's average radiation output is standardized. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

Table C.4.
Treatment intensity : Academic hospitals

	Diagnostic intensity				Treatment intensity	
	Time	Complex	Segments	CABG	PTCA	Stents
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' radiation output	0.348**	0.067*	0.237	-0.005	0.141	0.179
	(0.136)	(0.040)	(0.154)	(0.022)	(0.139)	(0.162)
Mean outcome	564.217	0.242	0.743	0.09	0.520	0.659
SD outcome	310.015	0.244	0.546	0.158	0.304	0.581
Montiel-Pflueger F-stats	18.7	18.7	18.7	18.7	18.7	18.7
Anderson-Rubin p-value	0.05	0.09	0.17	0.82	0.35	0.31
Observations	10,902	10,902	10,902	10,902	10,902	10,902

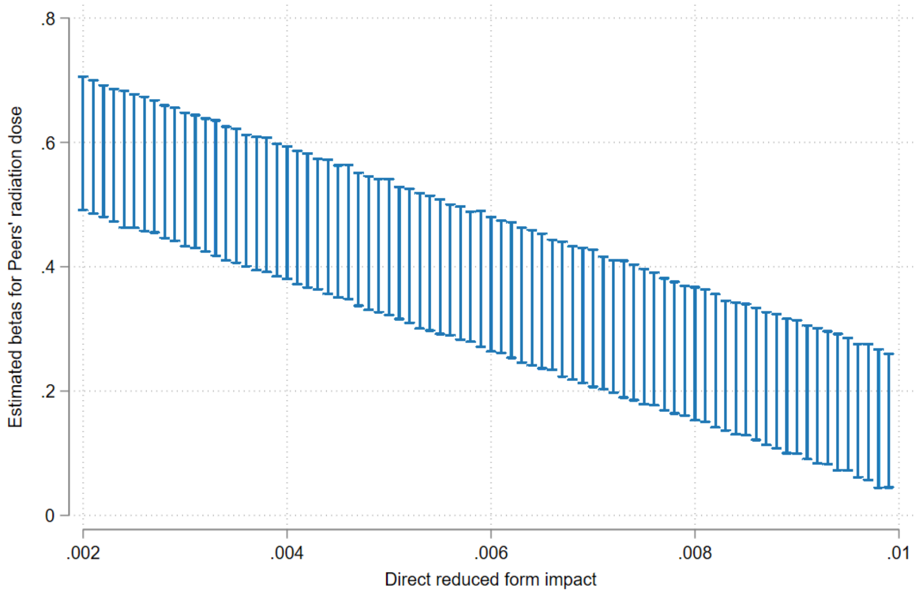
Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcomes are defined as standardized fluoroscopic time (1); ; share of patients diagnosed as "Complex" (3); standardized weekly number of segments or the coronary artery treated (3); share of patients recommended for heart bypass surgery (CABG - Coronary Artery Bypass Graft) (4); share of patients receiving PTCA (5) and standardized number of stents used (5). Peer's average radiation output is standardized. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures (patient's characteristics and co-morbidities).

Table C.5.
Robustness check : Various FEs combinations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peers' radiation output	0.710***	0.722***	0.694***	0.703***	0.677***	0.686***	0.696***	0.862***	0.805***	0.724***
	(0.065)	(0.068)	(0.061)	(0.064)	(0.061)	(0.064)	(0.062)	(0.113)	(0.058)	(0.070)
Mean outcome	5.56	5.56	5.56	5.56	5.56	5.56	5.56	5.56	5.56	5.56
SD outcome	2.98	2.98	2.98	2.98	2.98	2.98	2.98	2.98	2.98	2.98
Montiel-Pflueger F-stats	35.2	32.9	36.9	34.6	36.7	34.5	36.3	36.7	38.7	33.5
Anderson-Rubin p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Doctor's FE	✓	✓	✓	✓	-	-	-	✓	-	✓
Hospital linear trend FE	✓	✓	-	-	-	-	✓	-	-	-
Hospital polynomial trend FE	-	-	-	-	-	-	-	-	-	✓
Month-by-year FE	✓	-	✓	-	✓	-	✓	✓	✓	✓
Week-by-year FE	-	✓	-	✓	-	✓	-	-	-	-
Doctor linear trend FE	-	-	-	-	✓	✓	✓	-	-	-
Hospital FE	-	-	✓	✓	✓	✓	-	-	✓	-
Observations	28,467	28,467	28,467	2,8467	28,467	28,467	28,467	28,467	28,467	28,467

Note. Own calculations based on the SCAAR registry pooled across years 2008–2013. The table presents the 2SLS estimates. Outcome is focal doctors (standardized) radiation output and the instrumented (standardized) peer's average radiation output. The instrument variable, peer's total on-call emergency cases are defined in counts as specified in Equation (2). * p <0.1 ; ** p<0.05; *** p<0.01. Standard errors are clustered at unique peer groups level. Model controls for doctors, hospital linear time trend, month-by-year FEs, the focal physician's emergency cases in the previous week (*t-1*), and various risk-adjuster measures such as patient's characteristics and co-morbidities.

Figure C.1.
Bounding exercise



Note. The figure plots the 2SLS estimates of the peers' average radiation output on focal doctors' radiation output across a range bounds for the instrument to impact the focal doctors directly (i.e. relaxing the exclusion criterion) following (Conley et al., 2012). Range of the bounds (direct reduced form effects) is guided by the reduced form estimates on Table 2.