Medical School Environments and Physician Treatment Styles*

Shirley Cai† Ian McCarthy‡

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Abstract

We examine the role of medical school environments in shaping physicians' later treatment decisions, focusing on a specific subset of cardiology in which physician discretion is particularly salient and separate from patient need. Using a year-matched measure of cath lab availability in the hospital referral region of each cardiologist's medical school, we estimate that a 10-percentage-point increase in training-period availability raises later catheterization rates by 0.58 percentage points, identified across graduation cohorts within medical school HRR. The imprint is concentrated among interventional cardiologists and operates through measurable features of the training environment rather than ranking or prestige. Combining this training imprint with effects from their peers or general practice environments, identified from mid-career movers, implies a long-run multiplier of roughly 1.5 on per-cardiologist cath rates. The findings suggest that training-side interventions, if pursued at scale, would propagate through cohort transition into a meaningful reduction in place-based variation in physician treatment decisions.

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†Emory University. shirley.cai@emory.edu

‡Emory University & NBER. ian.mccarthy@emory.edu

1 Introduction

Physicians exercise meaningful discretion in their treatment decisions, and individual physicians vary substantially in how they exercise that discretion across clinically similar patients. This variation in physician treatment decisions is a well-documented contributor to geographic dispersion in health care utilization and spending, with as much as 60% of regional variation in spending attributable to such 'place-based' variation rather than to differences in patient need (Finkelstein et al., 2016; Molitor, 2018; Cutler et al., 2019; Badinski et al., 2023). These patterns are not arbitrary. They are shaped over the course of a long training pipeline, from medical school through residency and fellowship and into practice, and they continue to evolve through peer interactions and accumulated experience once physicians enter practice. Understanding which features of these environments shape later treatment style, and how those features propagate over a physician's career, is essential for designing supply-side interventions that aim to reduce inefficient variation in care.

In this paper, we exploit rich claims data in a care setting in which physician discretion is particularly salient, and we combine this with historic variation in clinically relevant technologies when physicians attended medical school. This allows us to credibly identify the effects of physicians' training environments on future practice patterns, separate from other concurrent place-based factors such as peers, arrangement with hospitals, and many others. Existing work has examined the post-training practice environment in some detail, while the medical school and residency environments have received less direct empirical attention. Part of the reason is measurement. The most common proxy in this literature, medical school rank (Schnell and Currie, 2018; Doyle Jr et al., 2010), bundles research intensity, faculty composition, student selectivity, and prestige, and it does not directly capture features of the medical school environment that would directly shape practice style. A more direct measure of the training environment, one that varies both across institutions and across graduation cohorts within institution, allows us to identify the medical school imprint on a specific clinical margin and quantify how it propagates through a physician's career.

Our analysis focuses on cardiologists treating non-ST-elevation myocardial infarction (NSTEMI) patients in Medicare claims data. NSTEMI is a useful empirical setting because the catheterization decision is meaningfully discretionary. Treatment guidelines support catheterization for many but not all NSTEMI patients, leaving substantial gray-zone cases in which physician practice style drives the decision (Chan et al., 2011; Amsterdam et al., 2014). We measure the training environment a medical student was exposed to as the share of hospitals in the medical school's hospital referral region (HRR) with a cardiac catheterization laboratory ("cath lab") in the year the student matriculated, drawn from the American Hospital Association's Annual Survey. This measure varies both across HRRs (some markets had cath labs earlier than others) and within HRR across graduation cohorts (cath labs proliferated steadily from 1980 to 2003), and the variation is plausibly independent of any individual medical student's future behavior or choice of medical school itself.[1]

We combine this training-side measure with a Medicare claims panel of cardiologists treating NSTEMI patients between 2008 and 2018. Our identification effectively rests on a mover design, albeit a mover from training to final practice rather than mid-career moves. Specifically, around 87% of cardiologists in our sample currently practice in a different HRR from the one in which they attended medical school, which generates the variation we exploit. Conditional on current practice HRR and year, cardiologists who trained in different HRRs were exposed to different training-period cath lab availability, and we estimate the imprint coefficient under a conditional-independence assumption that we defend with descriptive evidence on mover characteristics and origin-destination flows.[2] We further tighten the identification by adding fixed effects for the medical school HRR. The medical school imprint is then identified from cardiologists who attended medical school in the same HRR but in different graduation cohorts and thus encountered different cath lab availability during their clinical rotations.

We find that training-environment exposure has a causal effect on later catheterization rates. The cross-sectional mover specification produces an imprint coefficient of 0.035 (SE 0.011), which strengthens to 0.058 (SE 0.021) once we add medical school HRR fixed effects and identify the coefficient via cross-cohort variation within origin HRRs. The within-origin specification rules out fixed characteristics of medical school HRRs that might correlate with the type of physicians they produce. The effect is concentrated in interventional cardiologists, where the imprint coefficient is 0.058 (SE 0.019), compared to 0.013 (SE 0.019) for general cardiologists. The pattern is consistent with the procedural orientation a medical student observes during clinical rotations being most consequential for the subspecialty most directly engaged in catheterization. The estimates imply that a 10 percentage point increase in the training-period cath lab share, roughly the gap between the 25th and 75th percentile HRR in the mid-1990s, translates into a 0.58 percentage point increase in risk-adjusted catheterization rates (or about 0.04 standard deviations) when those same physicians are ultimately practicing cardiologists.

Subsequent analysis suggests that the medical school imprint operates through training-

[1] We consider questions of selection in more detail throughout our analysis as well as the supplemental appendix.

[2] The original move from medical school to first practice location precedes our 2008–2018 panel, so the identifying variation is cross-sectional rather than within-physician. We discuss the implications for our identification strategy in Section 3.

environment features rather than simply reflecting medical school prestige. To examine this, we replace cath lab availability with a year-matched measure of NIH research-funding rank, computed from the NIH ExPORTER bulk files. This analysis shows effectively a null result for ranking during medical school on future catheterization rates. The cath lab availability measure retains its predictive power once rank is controlled, and the rank coefficient remains small and statistically insignificant across alternative parameterizations of rank (continuous, tiered, and binary top-25). These results affirm that our analysis identifies effects from procedurally rich training environments, separate from a medical school's overall ranking or prestige.

We further estimate how cardiologists adapt to their current practice environment after training. A within-physician event study around mid-career moves yields a sharp jump in catheterizations at the year of move, with no evidence of pre-trends, and a pooled post-move adaptation rate of roughly 35% of the destination gap. Combining the destination response with our training imprint in a cohort-transition calibration implies a long-run multiplier of roughly 1.5 on per-physician practice intensity. This magnifier arises from spillovers of the training environment effect onto future peers, as cohorts replace one another and the peer environment evolves. Incorporating such spillovers, our estimates suggest that a 10 percentage point increase in cath lab shares during training translates into a 0.05 standard deviation in risk-adjusted catheterization rates. This magnitude aligns with existing literature on other more targeted interventions, including audit-and-feedback and peer-comparisons (Ivers et al., 2012; Doctor et al., 2018; Barnett et al., 2023), but operates through a slower channel that compounds across cohorts.

Our analysis contributes to three distinct areas of economics and health policy. First, we contribute to the literature on sources of supply-side variation in health care utilization. Finkelstein et al. (2016) estimate that 50–60% of geographic variation in Medicare spending is attributable to supply-side factors rather than patient demand, with subsequent work attributing much of that share to physician practice style (Molitor, 2018; Cutler et al., 2019; Badinski et al., 2023). This literature has documented the magnitude of practice-style variation and traced its post-training evolution, but the upstream determinants of practice style at the start of a physician's career have received less direct attention. Our analysis identifies one such determinant, the procedural environment at the medical school during clinical rotations, and shows that the imprint persists into practice and is concentrated in the subspecialty most exposed to the procedural margin in question.

Second, we contribute to the literature on training as a determinant of physician behavior. Existing work has primarily relied on rank as a proxy for training quality (Schnell and Currie, 2018; Doyle Jr et al., 2010), with a related literature examining specific features of residency training (Epstein and Nicholson, 2009). Our analysis remains distinct from this literature in three key ways: 1) we replace rank with a direct measure of the procedural environment a medical student was exposed to, allowing us to identify a specific channel rather than a composite; 2) we exploit within-HRR variation in the procedural environment across graduation cohorts, which lets us rule out fixed characteristics of medical school markets that might correlate with the type of physicians they produce; and 3) we directly compare the procedural-exposure measure against a year-matched NIH-rank measure on the same sample and outcome, which allows us to adjudicate between the two channels rather than test them in isolation.

Third, we contribute to the literature on physician adaptation to current practice environments. Molitor (2018) shows that cardiologists who relocate adopt a substantial share of the gap between their old and new market's catheterization intensity. We complement this evidence using a within-physician event study that traces the adaptation trajectory in event time around mid-career moves, with sharp adjustment at the move year and parallel pre-trends. Prior work further documents that physician treatment patterns respond to changes in reimbursement (Clemens and Gottlieb, 2014) and to evolving clinical evidence (DeCicca et al., 2024). We build on this work by separately identifying a training imprint and a destination response, then combining the two in a calibration that translates training-side effects into a long-run change in place-based practice intensity.

Our findings are particularly salient given renewed policy interest in shaping the geographic distribution of physician practice through the medical training pipeline, including state-level loan-repayment and residency-expansion programs targeting underserved areas. If the medical school environment imprints durable practice-style features that persist into practice and propagate through peer environments via cohort turnover, then training-side interventions provide a slow but compounding lever on practice-style variation. The lever is partial. Training imprints are one input into practice style, and the within-physician adaptation we document indicates that cardiologists do continue to update in response to current peer behavior. Even so, the long-run multiplier implied by our calibration suggests that training-side equalization, if pursued at scale, would propagate through cohort transition into a meaningful reduction in place-based variation in cardiac catheterization rates over the medium- to long-term.

2 Setting and Data

2.1 NSTEMI Catheterization and Cardiologist Training

Non-ST-elevation myocardial infarction (NSTEMI) is a heart attack characterized by partial occlusion of a coronary artery without persistent ST-segment elevation on the electrocardiogram.[3] NSTEMI patients are typically less acutely unstable than STEMI patients (for whom rapid catheterization is standard) but face elevated short-term mortality risk. Treatment guidelines support catheterization for many but not all NSTEMI patients, with the decision turning on a clinical judgment about the patient's risk profile, comorbidities, and likely benefit from invasive intervention. Substantial gray-zone cases exist in which the catheterization decision reflects clinical discretion rather than a firm clinical guideline, which is what makes NSTEMI a useful setting for studying physician practice style. Variation in catheterization across cardiologists treating similar NSTEMI patients therefore plausibly reflects a physician's discretionary practice intensity rather than differential clinical indication or patient mix.

Cardiologists in the United States enter practice through a long, sequential training pipeline. Allopathic medical schools grant the MD degree over four years, with the final two years spent in clinical rotations at affiliated teaching hospitals.[4] Cardiology training continues with three years of internal medicine residency followed by three or more years of cardiology fellowship, with longer fellowships for interventional cardiology, electrophysiology, and advanced heart failure subspecialties. The procedural environment a medical student observes during clinical rotations is the foundation we have in mind when we measure training-period cath lab availability. Cath lab availability serves as a proxy for the procedural intensity of this environment, standing in for the broader orientation of a region's cardiology practice during training rather than an effect specific to cath labs alone. The measure may therefore also capture related features of how a region treats cardiac patients. We measure this environment at the level of the medical school's hospital referral region rather than at a single hospital. Clinical training is rarely tied to one institution, as students typically rotate across a school's affiliated network of hospitals in the surrounding market, and the professional norms a trainee absorbs plausibly reflect the broader regional

[3]The ST segment refers to the portion of the electrocardiogram between the S and T waves. Persistent elevation in this segment typically indicates complete coronary occlusion and identifies an ST-elevation myocardial infarction (STEMI), which warrants immediate revascularization. The absence of persistent ST-segment elevation distinguishes NSTEMI cases, which present a wider range of underlying severity and a correspondingly wider range of appropriate treatment strategies (Amsterdam et al., 2014).

[4]In the U.S., there are both allopathic medical schools, which grant MDs, and osteopathic medical schools, which grant DOs. We focus on MDs because only roughly 11% of U.S. medical school graduates are DOs, with an even smaller share among cardiologists (AAMC, U.S. Physician Workforce Data Dashboard).

medical community as much as any single site. Measuring at the HRR captures this regional environment without requiring us to identify the particular hospitals at which each student rotated. For example, take a cardiologist for which we observe treating NSTEMI patients in 2010. Working backward from four years of medical school, three years of internal medicine residency, and three years of cardiology fellowship, that cardiologist matriculated medical school around 2000. For interventional cardiologists and advanced heart failure subspecialists, the additional fellowship year shifts the matriculation year to 1999, and for electrophysiologists, the two-year fellowship shifts it to 1998. Ultimately, the cath lab share we attribute to their training period is the share that prevailed in their medical school HRR in the implied year of matriculation.

2.2 Data Sources

Medicare claims. Our analytical sample derives from 100% Medicare fee-for-service (FFS) data for inpatient and carrier claims from 2008 through 2018, accessed via the Centers for Medicare and Medicaid Services (CMS) Virtual Research Data Center (VRDC). NSTEMI admissions are identified by ICD-9 (410.71) and ICD-10 (I21.4) diagnosis codes on inpatient claims, retaining new episodes only. Cardiac catheterization, percutaneous coronary intervention, and coronary artery bypass graft procedures are identified from procedure codes within 90 days of the index NSTEMI admission. Carrier claims link each NSTEMI episode to the treating cardiologist, which we use to assign a single focal cardiologist per episode following the procedure described in Section 2.3. Beneficiary summary files provide demographics, fee-for-service coverage status, and the inputs to construct the 31 Elixhauser comorbidity flags from ICD diagnosis codes in the year prior to the NSTEMI episode.

MD-PPAS and Physician Compare. We identify cardiologists in the Medicare Data on Provider Practice and Specialty (MD-PPAS) file using primary-specialty fields for cardiology, interventional cardiology, clinical cardiac electrophysiology, and advanced heart failure and transplant cardiology. MD-PPAS also reports each cardiologist's primary practice ZIP code based on Medicare claim volume. We obtain medical school name, graduation year, and gender from the CMS Physician Compare National Downloadable File. We map medical schools to ZIP codes using a hand-curated crosswalk restricted to LCME-accredited U.S. allopathic schools, then assign each ZIP to a hospital referral region (HRR) using the Dartmouth Atlas ZIP-to-HRR crosswalk. We exclude cardiologists for whom the medical school field is missing or coded as "OTHER" (which captures most foreign-trained physicians and a small number of unmatched U.S. schools).

AHA Annual Survey. The AHA Annual Survey provides a rich set of hospital characteristics for essentially all non-federal general acute care hospitals from 1980 onward. We use the AHA to construct cath lab availability at the medical school HRR level.[5] We measure cath lab availability using a simple binary indicator of direct hospital provision of cardiac catheterization, and we aggregate to the HRR-year level by computing the share of hospitals for which the indicator is one.

NIH ExPORTER. To distinguish procedural exposure from medical school prestige, we construct a year-matched panel of medical school NIH research funding from the NIH ExPORTER bulk files. We aggregate annual project-level awards (1985–2025) to the medical school level and rank schools by total NIH funding within each year. The constructed series is validated against published Blue Ridge Institute for Medical Research (BRIMR) rankings, with correlation exceeding 0.99 in the overlap years.

Doximity physician profiles. We obtain each cardiologist's residency and fellowship program from publicly available physician profiles on Doximity (doximity.com), an online directory used by U.S. physicians. Each profile reports the institution name and graduation year for medical school, residency, and fellowship training. We link cardiologists in our Medicare panel to Doximity profiles via normalized name, graduation year, and state, with tie-break details given in the supplemental appendix. Approximately 75% of cardiologists in our panel resolve to a Doximity profile, and 70% to an identifiable residency hospital that we map to the AHA Annual Survey via a hand-curated lookup for the most common residency programs supplemented by exact and substring matching for the long tail.

2.3 Sample Construction and Key Variables

Cardiologist assignment and volume restriction. For each NSTEMI episode, we assign a single attending cardiologist following the procedure of Molitor (2018), prioritizing the first cardiologist who delivers a consultation, then the first cardiologist of record for inpatient care, and finally the first cardiologist seen by the patient on the carrier line. We exclude episodes for which no cardiologist could be assigned and patient-years for which Medicare FFS coverage was not present for the entire year. We restrict to cardiologist-years with at least 11 NSTEMI patients, which provides stable per-physician estimates of catheterization rates and aligns with the CMS cell-size requirements for data export. The

[5]Cath lab availability derives from the AHA variable 'CCLABHOS' from 1994 onward, with the predecessor 'CCLAB82' covering 1980–1993.

trade-off of the volume restriction is that established, higher-volume cardiologists are over-represented in our sample relative to the broader cardiologist population. We discuss the implications for our event-study identification in Section 4.

Residualized catheterization rate. Our patient-level outcome is an indicator equal to one if the patient received a catheterization within two days of admission. We then residualize this indicator against the 31 Elixhauser comorbidities and year fixed effects in a linear probability model, retain the patient-level residual, and aggregate to the cardiologist-year as a volume-weighted mean. The residualization removes mechanical variation across cardiologists that would arise from differences in patient comorbidity mix, isolating the practice-style component.

Training-period cath lab share. For each cardiologist, we match the AHA HRR-year cath lab share at the start of medical school, defined as graduation year minus three. AHA cath lab data are available from 1980 through 2003, so the year-matching produces clean assignments for cardiologists with graduation years from 1983 through 2006. We restrict our analytical sample to this graduation-year window. Cardiologists who attended medical school in the same HRR but in different cohorts therefore receive different training-period values, which is the variation we exploit in our preferred within-origin specification.

Mover status and current practice environment. We assign each cardiologist's current-practice HRR using the Dartmouth ZIP-to-HRR crosswalk applied to the MD-PPAS practice ZIP. Movers are defined as cardiologists whose current practice HRR differs from their medical school HRR. To measure the current peer environment, we construct a leave-one-out HRR-year cath rate, defined as the volume-weighted mean residualized cath rate of all other cardiologists practicing in the cardiologist's HRR-year cell, excluding the focal cardiologist.

Practice characteristics. Cardiologists in our sample work in varied settings, ranging from large hospital-affiliated cardiology groups to smaller office-based practices, and these settings may themselves shape catheterization behavior independently of the training environment we are estimating. We construct two practice-setting characteristics from MD-PPAS to capture this dimension of the cardiologist's current work environment. The first is the share of the cardiologist's Medicare claims rendered at inpatient or hospital-outpatient places of service, which proxies for whether the practice is predominantly hospital-based versus office-based or ambulatory. The second is the log of the cardiologist's primary TIN-level

Medicare patient volume, which proxies for the size of the practice group the cardiologist works within. Both vary at the cardiologist-year level. We use them as covariates in our preferred specifications to test whether the training imprint is sensitive to differences in current practice setting beyond what practice HRR fixed effects absorb. Additional detail on cardiologist assignment, residualization, the medical school crosswalk, and the GME-duration filter appears in the supplemental appendix.

2.4 Descriptive Statistics

The final analytical panel contains roughly 10,800 cardiologist-year observations covering about 3,200 unique cardiologists with non-missing training-period exposure, restricted to the 1983–2006 graduation-year window. Table 1 reports summary statistics at both the cardiologist-year and cardiologist levels. The mean residualized cath rate is approximately zero by construction, with a standard deviation of roughly 0.16. Average NSTEMI volume is 16 patients per cardiologist-year. Roughly three-quarters of the cardiologists in our sample are general cardiologists, with another 20% in interventional cardiology and the remainder split among electrophysiology and advanced heart failure.

Most cardiologists in our sample are cross-sectional movers in the sense that their current practice HRR differs from their medical school HRR. The mover share is roughly 87% by cardiologist-year. Table 2 compares movers and stayers on a set of pre-treatment characteristics. Movers come from medical school HRRs with somewhat lower mean cath lab share than stayers' medical school HRRs, suggesting that selection on training-environment intensity is at work. Movers also differ slightly on graduation cohort and subspecialty composition. We address selection via inverse probability weighting in Section 3.5 and report the comparison stratified by subspecialty in the supplemental appendix.

Two features of the data help to inform our identification strategy. First, training-period cath lab availability varies substantially across HRRs, as do realized cath rates. Figure 1 maps the average residualized cath rate across HRRs in our sample. Clusters of high-cath and low-cath markets persist across years, consistent with the place-based variation in practice style that motivates the paper more generally. Second, movers face meaningful variation in the gap between their training environment and their current peer environment, which is the source of identifying variation in our destination event study. Figure 3 plots the distribution of this gap, which is roughly symmetric around zero with substantial mass in both tails, giving us variation to identify the destination response in the event study (Section 4). We discuss details of these analyses and identification strategies in their respective sections below.

3 Medical School Environments and Physician Treatment Styles

The summary statistics in Section 2.4 document substantial variation along the two dimensions central to our analysis. Across cardiologists, the residualized cath rate has a standard deviation of 0.16 (Table 1), so cardiologists treating clinically similar NSTEMI patients differ meaningfully in their catheterization decisions. Across medical school HRRs, training-period cath lab availability ranges from 0 to 83% of hospitals, with a standard deviation of 0.17. Figure 2 plots a binscatter of the residualized cath rate against training-period cath lab share at the cardiologist level. The fitted line is weakly positive, with a slope of about 0.006 per unit of training-cath share, though the ventile means scatter substantially around the line. The cross-cardiologist noise is consistent with many other determinants of practice style operating alongside the training environment, and the unconditional slope is too small and too noisy to identify a causal effect on its own. Figure 1 further shows that residualized cath rates cluster geographically, with the same regions persistently above or below the national mean. The descriptive picture is therefore consistent with the medical school environment shaping later practice style. It is equally consistent, however, with cardiologists trained in cath-rich HRRs subsequently settling in cath-rich practice destinations, with stronger procedural orientation that influenced their school choice in the first place, or with rank-related sorting that we have not yet ruled out. The rest of this section uses our mover-design framework to separate these explanations and isolate the medical school imprint on cardiologist catheterization decisions. We first lay out our identification strategy and present the main estimates, then assess whether the imprint operates through procedural exposure rather than medical school ranking, examine subspecialty heterogeneity, and close with a series of robustness checks.

3.1 Identification Strategy

Our initial identification strategy is a cross-sectional mover design that compares cardiologists who now practice in the same HRR but were trained in different medical school HRRs. If medical school training environments shape later practice intensity, we should observe that cardiologists trained in cath-rich HRRs catheterize at higher rates than cardiologists trained in cath-poor HRRs, even after we condition on where the cardiologist now practices. The condition on current practice HRR is essential. Without it, we would conflate the training imprint with the destination effect documented in Molitor (2018), since cardiologists who trained in cath-rich markets are also more likely to settle in cath-rich destinations. The estimating equation is

$$y_{it} = \beta_{\text{train}}\tau_i + \delta_{d(i,t)} + \gamma_t + \varepsilon_{it}, \tag{1}$$

where y_{it} is the volume-weighted mean residualized cath rate of cardiologist i in year t, τ_i is the training-period cath lab share in cardiologist i's medical school HRR (year-matched), $\delta_{d(i,t)}$ is a current-practice HRR fixed effect, and γ_t is a year fixed effect. We weight by NSTEMI volume and cluster standard errors at the medical school HRR level.

Under the assumption that cardiologists do not select their practicing HRR based on procedural exposure during their medical school years, this design aims to remove correlation between training-period cath lab share and unobserved determinants of current practice intensity. A violation would require cardiologists to sort into destinations whose unobserved characteristics correlate with their own training-period cath lab exposure. If such selection were present, it would likely bias our estimates upward, as cardiologists with higher procedural orientation would settle in markets with characteristics that further reinforce that orientation. To assess the reasonableness of this assumption, Figure 4 shows that cardiologists move to a wide spread of destinations rather than concentrating on one or two. Movers from the median origin HRR are observed in 23 distinct destination HRRs, with a destination-share HHI of 0.066, supporting the view that destinations are not driven by training-side composition.[6]

One issue with this strategy is that it leaves untouched any time-invariant feature of the medical school HRR that might generate the imprint we estimate. Two medical schools could differ in cath lab availability and also differ in the prestige of their teaching hospitals, the patient case mix during clerkship rotations, the typical career path of their graduates, the local professional culture, or the financial incentives faced by faculty mentors. Any of these other features could be what shapes later practice intensity, with cath lab availability simply correlated with the true mechanism. We therefore also consider a cross-cohort identification strategy that adds fixed effects for the medical school HRR:

$$y_{it} = \beta_{\text{train}}\tau_i + \rho_{m(i)} + \delta_{d(i,t)} + \gamma_t + \varepsilon_{it}, \tag{2}$$

where $\rho_{m(i)}$ is a medical school HRR fixed effect. Under this strategy, β_{train} is identified from cardiologists who attended medical school in the same HRR but in different graduation cohorts and thus encountered different cath lab availability during their clinical rotations. The national mean cath lab share rose from roughly 0.14 in 1980 to roughly 0.39 in 2003, with

[6]As a more direct check, we regress the cardiologist's current peer cath rate on training-period cath lab share and find a small and statistically insignificant coefficient (-0.012, SE 0.016, $n = 10{,}736$), with a pairwise correlation of -0.03. Training-period cath lab availability does not predict where cardiologists end up. Details are in the supplemental appendix.

substantial variation across HRRs in the timing of the rollout. The identifying assumption embedded in equation (2) is that within-HRR cath lab adoption is uncorrelated with cohort-level shifts in other determinants of later practice intensity. We caution that cohorts entering medical school in the early 1980s and the early 2000s differ on margins beyond local cath lab proliferation, including managed care diffusion, the introduction of stenting and drug-eluting stents, and curriculum shifts. We revisit this concern in the robustness analysis below.

Results from both strategies are reported in Table 3. Panel A reports the cross-sectional design from equation (1), with destination HRR and year fixed effects. Panel B adds medical school HRR fixed effects per equation (2). Within each panel, column (1) is the baseline, column (2) adds physician characteristics (gender and years since graduation), and column (3) further adds practice characteristics (hospital-based share of Medicare claims and log of TIN-level patient volume). We deliberately exclude subspecialty from the set of controls, as subspecialty selection is itself a downstream outcome of the training environment we are estimating. We instead consider subspecialty as a dimension of heterogeneity in Section 3.3.

From column (1) of Panel A, the training-imprint coefficient is 0.035 (SE 0.011) and statistically distinguishable from zero at the 1% level. A cardiologist who trained in an HRR where every hospital had a cath lab catheterizes about 3.5 percentage points more often than a cardiologist trained in an HRR with no cath labs, holding current practice HRR and year fixed. Incorporating medical school HRR fixed effects in column (1) of Panel B increases our estimate of $\hat{\beta}_{\text{train}}$ to 0.058 (SE 0.021), suggesting that fixed origin-HRR features were attenuating the cross-sectional estimate. The training imprint is essentially stable across columns within each panel. Adding physician characteristics in column (2) and practice characteristics in column (3) leaves the coefficient in the same range, with the Panel B estimate increasing from 0.058 to 0.071 across the three columns. The pattern indicates that the imprint is not driven purely by sorting on observable cardiologist or practice characteristics. Ultimately, we treat the within-origin baseline in column (1) of Panel B as our preferred specification. For this estimate, the identifying variation is the difference in cath lab exposure between cardiologists from the same medical school but different graduation cohorts, which is plausibly orthogonal to cardiologist-level unobservables in a way that cross-sectional variation alone is not.

3.2 Training Environment vs. Medical School Ranking

While Table 3 suggests that medical school training environment has an economically meaningful effect on future treatment patterns, an alternative interpretation is that what really matters is the prestige of the medical school, with cath lab availability simply serving as a proxy for overall school quality. Indeed, several papers in the practice-style literature use medical school rank as a proxy for training quality (Schnell and Currie, 2018; Doyle Jr et al., 2010). While rank conceptually captures potentially different dimensions of medical school characteristics (e.g., research intensity, faculty composition, student selectivity, and prestige), the two channels could in principle both matter, or the effects of one could be absorbed by the other. We test this by replacing τ_i in equation (2) with the cardiologist's NIH-funding rank tier from our year-matched ExPORTER panel.

Table 4 reports the rank specifications. Panel A enters rank as $-\log(\text{rank})$, and Panel B enters tier indicators with unranked schools as the reference. Within each panel, column (1) is the rank-only specification, column (2) adds the training-period cath lab share, and column (3) further adds physician and practice characteristics. The continuous rank coefficient in Panel A is small in magnitude (around 0.005 to 0.006 per unit of $-\log(\text{rank})$), borderline statistically significant in columns (1) and (2), and small and insignificant once controls are added in column (3). The tier indicators in Panel B do not exhibit a monotone gradient and are again economically small and statistically insignificant in all three columns. The training cath share, by contrast, remains positive and statistically significant, with point estimates between 0.058 and 0.066. While rank may ultimately affect physician behaviors in other ways, it has limited explanatory power for NSTEMI catheterization rates once we condition on the training-period cath lab availability of the medical school HRR.

A natural follow-up is whether the training imprint operates similarly within rank tiers, or whether it is concentrated at either end of the rank distribution. Table 5 estimates the training-imprint coefficient separately for cardiologists trained at Top 25 NIH-ranked schools (Panel A) and at below-Top-25 schools (Panel B), under the same three-column progression of controls as our main specifications. The Below-Top-25 panel produces an imprint of 0.038 at baseline and 0.033 with physician and practice controls, both statistically distinguishable from zero. The Top-25 panel has only 1,754 cardiologist-year observations and produces a small, statistically insignificant coefficient that flips sign once controls are added, reflecting the limited within-tier variation that remains after fixed-effect absorption. The imprint is therefore identifiable in the much larger below-Top-25 sample and not concentrated at the top of the rank distribution.

The evidence is therefore consistent with the medical school environment shaping later cath behavior through training-environment features rather than through the prestige or research orientation of the school itself. A cardiologist trained at a non-elite medical school in a cath-rich HRR carries the imprint as cleanly as one trained at an elite school in a cath-rich HRR, while training at a top-ranked school in a cath-poor HRR does not produce an imprint of comparable magnitude. We do not attempt to disentangle the specific channel through which a procedurally rich training environment imprints on later practice style, since our setting cannot separately identify direct-observation channels (e.g., medical students observing catheterization decisions during clinical rotations) from broader training-environment channels (e.g., regional norms among teaching faculty or peer-effect spillovers within the cardiology workforce a graduate later joins). Additional rank specifications, including continuous and tier-based forms estimated on the full and mover subsamples, appear in the supplemental appendix and yield similar conclusions.

3.3 Subspecialty Heterogeneity

The training-environment interpretation makes a sharp prediction about subspecialty heterogeneity. If exposure to a procedurally rich training environment imprints a procedural orientation that persists into practice, then the imprint should manifest most strongly in cardiologists who later select into the most procedurally focused subspecialty. Interventional cardiologists perform catheterizations themselves, general cardiologists primarily make referral and management decisions, and electrophysiologists and advanced heart failure cardiologists perform other types of procedures and rarely catheterize NSTEMI patients directly. We test the prediction by stratifying the within-origin specification by cardiology subspecialty.

Table 6 reports the training-imprint coefficient stratified by subspecialty under the same three-column progression of controls as our main specifications. We restrict the table to general cardiology and interventional cardiology, since the electrophysiology and advanced-heart-failure subsamples are too small (358 and 65 cardiologist-years respectively) for the controls-augmented specifications to be informative. Among interventional cardiologists, the imprint is 0.058 in the baseline (Panel A), 0.047 with physician characteristics (Panel B), and 0.041 with practice characteristics (Panel C), each statistically distinguishable from zero. Among general cardiologists, the point estimate is 0.013 at baseline and essentially zero with controls, in all cases statistically indistinguishable from zero.[7] The interventional concentration is consistent with the training-environment interpretation. Cardiologists who selected into the most procedurally oriented subspecialty bear the strongest imprint, while generalists, whose role is less procedurally focused, do not.

We caution that subspecialty selection is endogenous. Cardiologists with strong procedural orientation may sort into interventional cardiology, in which case the subspecialty heterogeneity reflects both a within-subspecialty practice-style effect and a between-subspecialty selection effect. Both interpretations are consistent with the broader claim that the imprint

[7] The corresponding minimum detectable effect at 80% power in the general-cardiology baseline is approximately 0.053, so the general-cardiology null is informative against effects of magnitude similar to the interventional coefficient.

operates through procedural orientation rather than through generic medical school quality.

3.4 The Training Pipeline

The medical school imprint identified in Section 3.1 may operate as a direct exposure effect or as the first stage of a training-pipeline selection chain. Cardiologists train at one medical school but then complete three to five additional years of residency and fellowship before entering practice. If procedural exposure during medical school shapes later catheterization behavior primarily by sorting trainees into procedurally rich residency programs, then conditioning on residency exposure should attenuate the medical school coefficient. If the imprint operates directly, residency exposure should add little once medical school exposure is in the regression.

We combine our medical school cath share with two residency-stage measures constructed from the Doximity-to-AHA mapping described in Section 2. The first is a binary indicator for whether the trainee's residency hospital had a cardiac catheterization laboratory during their first three years of post-graduate training. The second is the share of cath-equipped hospitals in the residency program's same-HRR system, capturing the broader procedural environment available through within-system rotations. The two measures coincide for solo programs. Residency is conceptually at the hospital level rather than the HRR level, since residents are tied to a single program with affiliated rotations rather than rotating across an entire region. The Doximity-linked subsample restricts to cardiologists with a mappable Doximity profile and a resolvable residency hospital, which covers roughly 45% of the analytical sample of Section 3.1. The results in this subsection therefore corroborate the medical school imprint identified on the broader sample, and we treat the within-origin estimate of $\hat{\beta}_{\text{train}} = 0.058$ in Table 3 as our main finding.

Table 7 reports joint estimates of the within-origin specification with both medical school and residency exposure. In the full matched sample, the medical school coefficient is 0.105 (SE 0.029), statistically distinguishable from zero at the 1% level, while the residency own-hospital coefficient is 0.012 (SE 0.009) and indistinguishable from zero. Replacing the residency own-hospital binary with the same-HRR-system share leaves the conclusion unchanged. Columns (3) and (4) restrict to the cleanest subset of residency matches (hand-curated and exact normalized-name matches only). The medical school coefficient strengthens to 0.130–0.134, and the residency coefficient remains at most marginally distinguishable from zero. The medical school imprint is not absorbed by residency hospital exposure.

We caution that hospital- and system-level cath lab availability is a coarse proxy for a trainee's actual exposure to procedural cardiology during residency. A sharper measure would be the residency hospital's realized catheterization rate during the trainee's training years, constructed directly from claims data. Such a measure is feasible for cardiologists whose residency overlaps our 2008–2018 claims panel, but the subsample is small (cardiologists with graduation year 2006 or later, who fall outside our medical school sample window because AHA cath lab data ends in 2003). We therefore treat the present analysis as a coarse-grained pipeline check that the medical school imprint survives the addition of a residency-stage control, rather than as a direct test of residency exposure on a more granular margin. An analysis of recent graduates (2006 or later) using contemporaneous NSTEMI catheterization rates at the hospital of residency as the exposure measure yields similar results for the effect of residency on future NSTEMI catheterization. These results are presented in the supplemental appendix.

A within-residency-hospital cohort specification adds residency-hospital fixed effects on top of the medical school HRR and practice HRR fixed effects, so that the residency coefficient identifies off across-cohort differences in cath lab status for cardiologists at the same residency program. The residency coefficient is -0.004 (SE 0.018), again indistinguishable from zero, while the medical school coefficient remains positive at 0.067 (SE 0.034).

We also test whether medical school exposure predicts residency placement. Regressing a cardiologist's residency-hospital cath lab status on their medical school cath share with medical school HRR and graduation-year fixed effects yields a coefficient of 0.14 (SE 0.19), indistinguishable from zero. Within-school cohort variation in medical school cath exposure does not predict whether a graduate's residency program has a cath lab, consistent with the medical school imprint operating through direct exposure rather than through sorting into procedurally similar residency programs.

The fellowship-stage analog points in the same direction. Fellowship hospital cath lab exposure, whether measured as the own-hospital binary or the same-HRR-system share, is statistically indistinguishable from zero in standalone and joint specifications, and we do not report it in detail. Most cardiology fellowships are housed at major teaching hospitals with cath labs, leaving little cross-program variation to identify against.

Taken together, the medical school cath share is the singular training-environment measure that produces a detectable, durable imprint on later catheterization behavior in our data. We therefore focus the remainder of the paper on the medical school stage and do not develop separate identification strategies for residency or fellowship environments.

3.5 Robustness

We assess two threats to the within-origin training-imprint estimate, with results reported alongside the baseline in Table 8. The first threat is selection into being a mover, where we define a mover as a cardiologist whose current practice HRR differs from their medical school HRR (about 87% of our analytical sample). Table 2 shows that movers and stayers differ on observable characteristics, including graduation cohort, gender, subspecialty composition, and training-period cath lab share. If the same characteristics also correlate with unobserved practice-style propensities, our cross-sectional mover variation reflects selection rather than a causal training effect. Column (2) addresses this with an inverse-probability-weighted (IPW) version of the within-origin specification. We estimate a logit propensity score predicting mover status from observable cardiologist characteristics, then weight each cardiologist by the inverse of their predicted probability of being in their observed mover-or-stayer group. This procedure re-balances the sample so that movers and stayers have the same distribution of observable characteristics. The IPW-weighted training-imprint coefficient is 0.057 (SE 0.021), essentially identical to the baseline of 0.058. Observable selection on mover status does not drive the imprint.

The second threat, raised in Section 3.1, is that the within-origin estimate could reflect national changes over the training-cohort window rather than the local training environment. As noted in Section 2, we read cath lab availability as a marker for that local environment rather than a cath-lab-specific channel, so the concern is not that the measure captures other local features of a region's cardiology practice, but that estimated effects could be driven by national secular trends. To guard against that, we add a linear graduation-year trend to the within-origin specification, isolating within-HRR variation across cohorts net of the national trend (column (3) of Table 8). The training coefficient is essentially unchanged, at 0.058 (SE 0.034). That said, the estimate is less precise than the baseline, since the trend absorbs part of the variation in training-period intensity. The point estimate remains stable across additional cohort controls, including a quadratic trend and a control for the national cath lab share in the matriculation year, reported in the supplemental appendix.

4 Amplification of Training Effects via Peer Effects

Section 3 establishes that medical school environments leave a durable imprint on a cardiologist's later catheterization behavior. The full effect of medical training on place-based practice intensity, however, depends not only on this direct imprint but also on how the peer environment responds to and propagates it. A cardiologist whose training environment shifted their practice intensity becomes part of the peer environment that shapes subsequent entrants, so a portion of the training effect spills over onto cardiologists who themselves never trained in that environment.[8] To characterize the full effect of medical training, we therefore need to separately identify the direct training effect from the response of cardiologists to their current peer environment. Molitor (2018) provides the closest existing evidence on the latter through cardiologist relocation, finding that catheterization rates substantially adjust toward the destination market. We revisit this question within our NSTEMI sample using a within-physician event study around mid-career moves, and further examine whether the response is symmetric in direction, which speaks to whether the training imprint and the current peer environment act as substitutes or complements.

4.1 Event Study of Mid-Career Movers

A clean within-physician estimate of the destination response requires cardiologists who change practice HRRs during our panel. We define mid-career movers as cardiologists with at least two distinct practice HRRs in the 2008–2018 panel. Roughly 580 cardiologists in our analytical sample meet this criterion. Compared with the non-movers, mid-career movers are disproportionately interventional cardiologists (29% of movers vs. 22% of non-movers), have somewhat higher NSTEMI volume per year, are slightly younger by graduation cohort, and come from training HRRs with marginally higher cath lab share. Table 9 reports the comparison. Across the destinations they go to, mid-career movers do not exhibit strong sorting on training intensity. A cross-sectional regression of the destination peer cath rate on training-period cath lab share yields a statistically insignificant coefficient. High-trained and low-trained movers go to similar mixes of destinations, so the destination response we estimate below is not confounded by destination-type selection that varies with the cardiologist's own training environment.

For each mid-career mover, define the move year as the first year in which their practice HRR differs from their initial-panel HRR. Define event time τ as calendar year minus move year. The event-study specification is

$$y_{it} = \alpha_i + \gamma_t + \sum_{\tau \neq -1} \beta_\tau \cdot \mathbf{1}[\tau_{it} = \tau] \cdot \Delta_i + \varepsilon_{it}, \tag{3}$$

[8] Importantly, this spillover does not threaten SUTVA in our training-imprint estimates in Section 3. The destination HRR fixed effects in that specification absorb the peer environment, so peer-mediated influences from other cardiologists' training are captured by the fixed effects rather than attributed to a cardiologist's own training. The training-imprint coefficient β_{train} therefore identifies the direct effect of own training on own catheterization, and the destination response β_{dest} estimated below captures the peer channel separately.

where α_i is a cardiologist fixed effect, γ_t is a calendar-year fixed effect, Δ_i is the gap between the leave-one-out destination peer cath rate at the move year and the corresponding origin peer cath rate the year before the move, and β_τ traces the share of Δ_i reflected in cardiologist i's cath rate at event time τ, normalized to zero at $\tau = -1$. We restrict to the event-time window $[-3, +5]$ to retain a balanced panel of physician-years, weight by NSTEMI volume, and cluster standard errors at the cardiologist level.

Figure 5 plots the event-study coefficients with 95% confidence intervals. Pre-move coefficients ($\tau = -3, -2$) are nearly 0 and statistically insignificant, such that mid-career movers and stayers do not appear to exhibit differential trends in catheterization rates prior to the move. At the move year, $\hat{\beta}_0 = 0.443$ (95% CI [0.25, 0.63]), indicating immediate adaptation of roughly 44% of the peer-environment gap. Post-move coefficients persist, with the pooled post-move coefficient at 0.350. The full coefficient table appears in the supplemental appendix.

The point estimates are smaller than the roughly 0.6 reported in Molitor (2018) for cardiologists generally, though the comparison is not apples-to-apples. Molitor's outcome is a broader practice-intensity index built from the cardiologist's procedure mix, while ours is a narrower measure specifically of residualized NSTEMI catheterization rates. Our sample is also restricted to high-volume cardiologists, as discussed in Section 2. Within these restrictions, the event-study estimate is comparable in identification logic to the analysis of pooled adaptation rates in Molitor (2018).

4.2 Long-Run Multiplier

The training imprint in Section 3 and the destination response above jointly identify two parameters governing how training-side shifts propagate to current cath behavior. The training imprint $\beta_{\text{train}} = 0.058$ measures how a marginal increase in training-period cath lab share translates into an increase in own cath rate, identified within-origin across cohorts. The destination response $\beta_{\text{dest}} = 0.35$ measures how an increase in current peer-environment cath rate translates into an increase in own cath rate, identified within-physician. The destination effect, however, also serves as a multiplier to training effects. For example, suppose training-period cath lab share is uniformly raised by $\Delta\tau$ for all new cohorts of cardiologists entering an HRR. Each new cohort enters with practice intensity raised by $\beta_{\text{train}} \cdot \Delta\tau$ relative to baseline. As new cohorts enter and old cohorts retire, the HRR's peer-environment cath rate gradually shifts upward, and existing cardiologists adjust toward the new peer mean at rate β_{dest}. Their adjustment in turn contributes to further shifts in the peer mean for the next cohort. In steady state, the per-cardiologist long-run effect of the uniform training shift is

$$\Delta y^* = \frac{\beta_{\text{train}} \cdot \Delta\tau}{1 - \beta_{\text{dest}}}. \tag{4}$$

With $\beta_{\text{train}} = 0.058$ and the within-physician estimate $\beta_{\text{dest}} = 0.35$, the amplification multiplier $1/(1 - \beta_{\text{dest}})$ is approximately 1.54. A uniform 10-percentage-point shift in training-period cath lab share therefore produces a long-run shift of roughly 0.89 percentage points in per-cardiologist cath rate, decomposing into 0.58 percentage points of direct training effect on the new cohorts and 0.31 percentage points of cross-cardiologist spillover that accumulates as new cohorts displace old ones and the peer environment evolves.

Peer effects, identified in prior work and confirmed in our setting as a feature of how individual cardiologists respond to their current environment, also serve as the mechanism through which training-side shifts propagate across cohorts over time. The training imprint and the peer-effect channel are complementary rather than competing, with peer-effect spillovers contributing roughly half to one and a half times as much to the long-run effect as the direct training imprint alone. We caution that the cross-cardiologist amplification embedded in the multiplier assumes incumbents adjust to peer-environment shifts at the same rate as the mid-career movers from whom we identify β_{dest}, which is most defensible at long horizons since incumbents eventually become the peer environment for newly arriving cohorts. The supplemental appendix traces the full cohort-transition path under a 5% annual replacement rate.

5 Conclusion

This paper examines whether the medical school environment in which a cardiologist trained leaves a causal imprint on their later treatment decisions, and how that imprint interacts with the current peer environment to shape practice style over a career. We focus on cardiac catheterization for non-ST-elevation myocardial infarction patients, a clinical setting where guideline-supported treatment leaves meaningful room for physician discretion and where practice style varies substantially across cardiologists treating clinically similar patients. Using a year-matched measure of cath lab availability in the cardiologist's medical school hospital referral region, drawn from the AHA Annual Survey, we identify the training imprint within-origin across graduation cohorts. We further estimate the destination response through a within-physician event study around mid-career moves and combine the two parameters in a cohort-transition calibration.

We find that training-environment exposure has a causal effect on later catheterization rates, with a within-origin coefficient of 0.058 (SE 0.021). The imprint operates through training-environment features rather than through medical school prestige or ranking, and it is concentrated in interventional cardiology, the subspecialty most directly engaged in the procedural margin we study. To quantify how the training imprint propagates onto cardiologists who never trained in the same environment, we further estimate a within-physician destination response, an analog to the parameter identified by Molitor (2018). The destination-response estimate is roughly 0.35, with a sharp jump at the move year and parallel pre-trends. Combining the training imprint and destination response in a cohort-transition calibration implies a long-run multiplier on per-cardiologist practice intensity of approximately 1.5, with the bulk of the effect compounding through cohort turnover.

Taken together, our findings highlight that place-based variation in physician practice style is shaped not only by the current peer environment, where most of the supply-side literature has focused, but also by the training environment decades earlier. Medical school environments leave durable imprints on physician practice style, and these imprints propagate through peer effects across cohorts. Where a cardiologist trained therefore matters for the variation in care that motivates the broader supply-side literature.

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Tables and Figures

Table 1. **Summary Statistics**[a]

	Mean	SD	Min	Max	N
Cardiologist-year level					
Residualized cath rate	0.013	0.161	-0.680	0.514	31,235
NSTEMI volume per year	15.9	5.8	11.0	133.0	31,235
Training-HRR cath lab share	0.282	0.167	0.000	0.833	15,306
Current-HRR peer cath rate (LOO)	0.015	0.079	-0.511	0.422	31,022
Hospital-based share of claims	0.554	0.219	0.000	1.000	31,235
Log TIN-level patient volume	7.248	0.536	3.989	9.592	31,235
Cardiologist level (per NPI)					
Graduation year	1989.8	10.7	1947.0	2012.0	9,495
Years observed in panel	3.3	2.5	1.0	10.0	9,568
Female	0.077				9,568
General Cardiology	0.756				9,568
Interventional Cardiology	0.201				9,568
Electrophysiology	0.036				9,568
Adv. Heart Failure	0.007				9,568

[a]Cardiologist-year observations from the 2008–2018 Medicare fee-for-service panel, restricted to cardiologists treating at least 11 NSTEMI patients in a given year and to graduation cohorts 1983–2006. The residualized cath rate is the volume-weighted mean of patient-level residuals from a linear probability model regressing an indicator for catheterization within two days of NSTEMI admission on the 31 Elixhauser comorbidities and year fixed effects.

Table 2. **Movers vs. Stayers**[a]

	Movers	Stayers	Diff.	p-value
Graduation year	1989.4	1990.0	-0.6	0.003
Female (%)	7.5	7.9	-0.3	0.530
General Cardiology (%)	74.1	76.8	-2.7	0.002
Interventional Cardiology (%)	21.1	19.3	1.8	0.035
Electrophysiology (%)	4.2	3.1	1.1	0.006
Adv. Heart Failure (%)	0.6	0.8	-0.1	0.474
Training-HRR cath lab share	0.299	0.257	0.042	0.000
Years in panel	3.2	3.3	-0.1	0.087
Mean NSTEMI volume per year	14.2	14.6	-0.4	0.000
First observation year	2011.5	2011.8	-0.3	0.000
Cardiologists	4,121	5,447		

[a]Cardiologist-level comparison of movers (whose current practice HRR differs from their medical school HRR) and stayers. Means are reported by group, with the difference in means and a p-value from a two-sample t-test. The training cath share is the share of hospitals in the cardiologist's medical school HRR with a cardiac catheterization laboratory in the year of matriculation, drawn from the AHA Annual Survey.

Table 3. **Effect of Training Environment on Residualized Catheterization Rate**[a]

	(1)	(2)	(3)
Panel A. Destination FE			
Training-HRR cath lab share	0.035***	0.025*	0.025*
	(0.011)	(0.013)	(0.014)
Current-HRR cath culture (LOO)	0.047	0.046	0.050
	(0.030)	(0.031)	(0.031)
Panel B. Origin + Destination FE			
Training-HRR cath lab share	0.058***	0.062*	0.071**
	(0.021)	(0.034)	(0.034)
Current-HRR cath culture (LOO)	0.049	0.048	0.054*
	(0.030)	(0.031)	(0.030)
Physician characteristics	No	Yes	Yes
Practice characteristics	No	No	Yes
Practice HRR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	10,729	10,729	10,729

[a]The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. Panel A reports the cross-sectional mover specification with destination HRR and year fixed effects (equation 1). Panel B adds medical school HRR fixed effects (equation 2). Column (1) is the baseline. Column (2) adds physician characteristics (gender and years since graduation). Column (3) further adds practice characteristics (hospital-based share of Medicare claims and log of TIN-level Medicare patient volume). All specifications weight by NSTEMI volume and cluster standard errors at the medical school HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4. **Effect of School Rank on Residualized Catheterization Rate**[a]

	(1)	(2)	(3)
Panel A. $-\log$*(NIH rank)*			
$-\log$(NIH rank)	0.006**	0.005*	0.005
	(0.003)	(0.003)	(0.003)
Training cath lab share		0.058***	0.066*
		(0.022)	(0.035)
Panel B. NIH rank tier indicators (ref. = unranked)			
Top 51-100	0.001	0.003	0.000
	(0.012)	(0.012)	(0.011)
Top 26-50	-0.003	-0.002	-0.005
	(0.015)	(0.015)	(0.015)
Top 11-25	0.013	0.015	0.012
	(0.013)	(0.012)	(0.013)
Top 10	0.014	0.015	0.011
	(0.015)	(0.015)	(0.015)
Training cath lab share		0.059***	0.066*
		(0.021)	(0.035)
Physician characteristics	No	No	Yes
Practice characteristics	No	No	Yes
Med school HRR FE	Yes	Yes	Yes
Practice HRR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	10,609	10,609	10,609

[a]The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. NIH rank is the year-matched ranking of the cardiologist's medical school by total NIH research funding, constructed from the NIH ExPORTER bulk files. Panel A enters rank as $-\log$(rank). Panel B enters tier indicators with unranked schools as the reference. Column (1) is the rank-only specification. Column (2) adds the training-HRR cath lab share. Column (3) further adds physician characteristics (gender and years since graduation) and practice characteristics (hospital-based share of Medicare claims and log of TIN-level Medicare patient volume). All specifications weight by NSTEMI volume and cluster standard errors at the medical school HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5. **Effect of Training Environment by Rank Tier**[a]

	(1)	(2)	(3)
Panel A. Top 25 schools			
Cath lab share, training HRR	0.027	-0.029	-0.028
	(0.042)	(0.046)	(0.042)
Panel B. Below Top 25 schools			
Cath lab share, training HRR	0.038***	0.033**	0.033*
	(0.013)	(0.016)	(0.016)
Physician characteristics	No	Yes	Yes
Practice characteristics	No	No	Yes
Practice HRR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	8,831	8,831	8,831

[a]The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. Panels stratify by the NIH-rank tier of the cardiologist's medical school in the matriculation year. Panel A restricts to cardiologists who attended a medical school ranked in the top 25 by NIH research funding. Panel B restricts to those who attended any other ranked or unranked school. Within each panel, column (1) is the baseline, column (2) adds physician characteristics (gender and years since graduation), and column (3) further adds practice characteristics (hospital-based share of Medicare claims and log of TIN-level Medicare patient volume). All specifications include practice HRR and year fixed effects, weight by NSTEMI volume, and cluster standard errors at the medical school HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6. **Effect of Training Environment by Cardiology Subspecialty**[a]

	General Cards	Interventional
Panel A. Baseline		
Cath lab share, training HRR	0.013	0.058***
	(0.019)	(0.019)
Observations	7,570	2,717
Panel B. + Physician characteristics		
Cath lab share, training HRR	-0.004	0.047**
	(0.019)	(0.019)
Observations	7,570	2,717
Panel C. + Practice characteristics		
Cath lab share, training HRR	-0.001	0.041**
	(0.020)	(0.020)
Observations	7,570	2,717

[a]The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. Columns report the training-imprint specification stratified by cardiology subspecialty as recorded in MD-PPAS. General Cards covers cardiologists with the Cardiology primary specialty, and Interventional covers cardiologists with the Interventional Cardiology primary specialty. Panel A is the baseline. Panel B adds physician characteristics (gender and years since graduation). Panel C further adds practice characteristics (hospital-based share of Medicare claims and log of TIN-level Medicare patient volume). Electrophysiology and advanced-heart-failure subspecialties are omitted because their small samples (358 and 65 cardiologist-years respectively) produce unstable coefficients once controls are added. All specifications include practice HRR and year fixed effects, weight by NSTEMI volume, and cluster standard errors at the medical school HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7. **Effect of Medical School and Residency Cath Lab Exposure on Residualized Catheterization Rate**[a]

	Full sample		Manual+exact only	
	Own hospital	System share	Own hospital	System share
Medical school cath share	0.105***	0.107***	0.130***	0.134***
	(0.029)	(0.030)	(0.034)	(0.034)
Residency exposure	0.012	0.009	0.015	0.018*
	(0.009)	(0.009)	(0.012)	(0.010)
Cardiologist-years	4,916	4,974	3,944	3,999
Cardiologists	1,451	1,470	1,177	1,194
Med-school HRR FE	Yes	Yes	Yes	Yes
Practice HRR FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

[a]The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. The medical school cath share is the share of hospitals in the cardiologist's medical school HRR with a cardiac catheterization laboratory in the year of matriculation. "Own hospital" is a binary indicator for whether the trainee's residency hospital had a cardiac catheterization laboratory during their first three years of post-graduate training. "System share" is the share of cath-equipped hospitals in the same-HRR system as the residency program, equal to the own-hospital binary for solo programs. The full sample includes all cardiologists with a Doximity-mapped residency hospital. The manual+exact only subsample drops cardiologists whose residency program matched only via a substring-fuzzy procedure. All specifications include medical school HRR, practice HRR, and year fixed effects, weight by NSTEMI volume, and cluster standard errors at the medical school HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8. **Robustness of the Training Imprint**[a]

	(1)	(2)	(3)
Training-HRR cath lab share	0.058***	0.057***	0.058*
	(0.021)	(0.021)	(0.034)
IPW	No	Yes	No
Linear cohort trend	No	No	Yes
Med school HRR FE	Yes	Yes	Yes
Practice HRR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	10,729	10,729	10,729

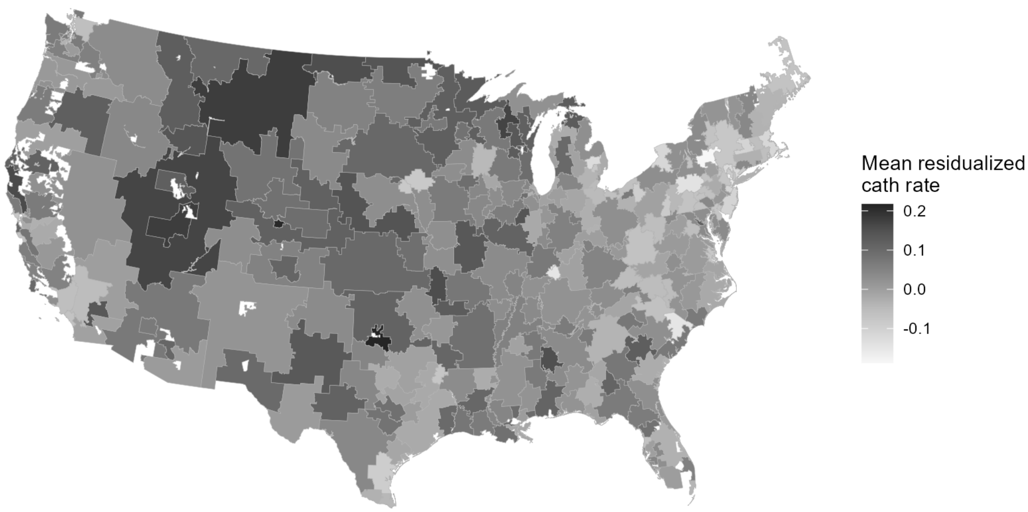
[a]The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. Column (1) is the within-origin baseline (equation 2). Column (2) re-weights cardiologists by the inverse of their estimated propensity to be a mover, where the propensity score is estimated as a function of graduation cohort, gender, subspecialty, and training-period cath lab share. Column (3) adds a linear graduation-year trend, isolating within-HRR variation across cohorts net of the national cohort trend. All specifications include medical school HRR, practice HRR, and year fixed effects, weight by NSTEMI volume (column 2 weights additionally by the inverse propensity), and cluster standard errors at the medical school HRR level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9. **Mid-Career Movers vs. Non-Movers**[a]

	Movers	Non-movers	Diff.	p-value
Training cath share	0.341	0.317	0.024	0.056
Graduation year	1994.4	1993.8	0.7	0.020
Female (%)	7.2	9.1	-1.9	0.101
General Cardiology (%)	67.3	72.9	-5.6	0.006
Interventional (%)	29.3	21.6	7.6	0.000
Electrophysiology (%)	2.4	4.6	-2.2	0.002
Adv. Heart Failure (%)	1.0	0.9	0.2	0.723
Years observed in panel	4.7	3.2	1.5	0.000
Mean NSTEMI volume / year	15.6	14.4	1.3	0.000
Cardiologists	581	5,924		

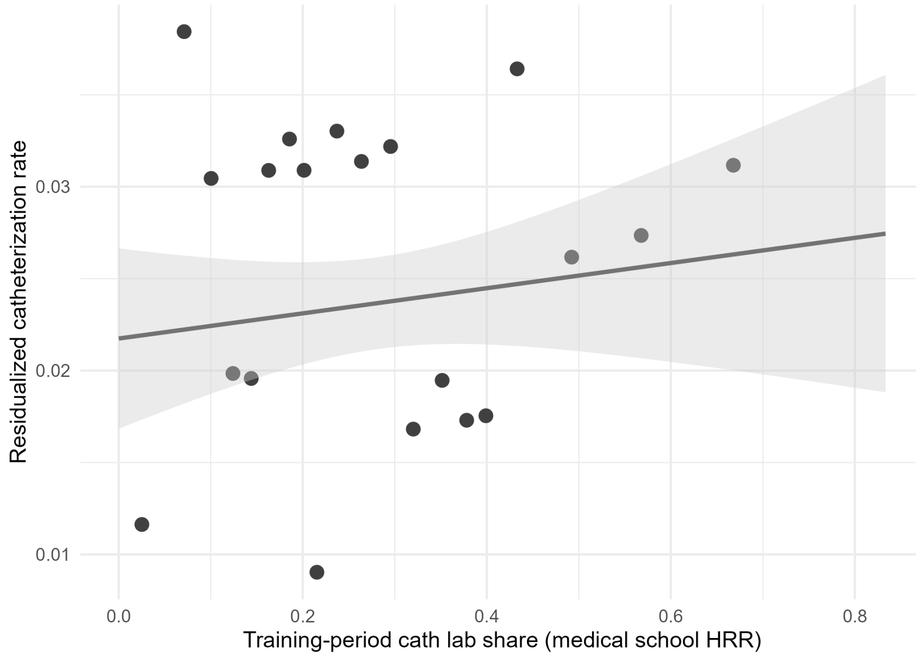
[a]Cardiologist-level comparison of mid-career movers (cardiologists with at least two distinct practice HRRs over the 2008–2018 panel) and non-movers. Means are reported by group, with the difference in means and a p-value from a two-sample t-test. The training cath share is the AHA HRR-year cath lab share at the cardiologist's medical school HRR in the year of matriculation.

Figure 1. **HRR-level Mean Residualized Cath Rate**[a]



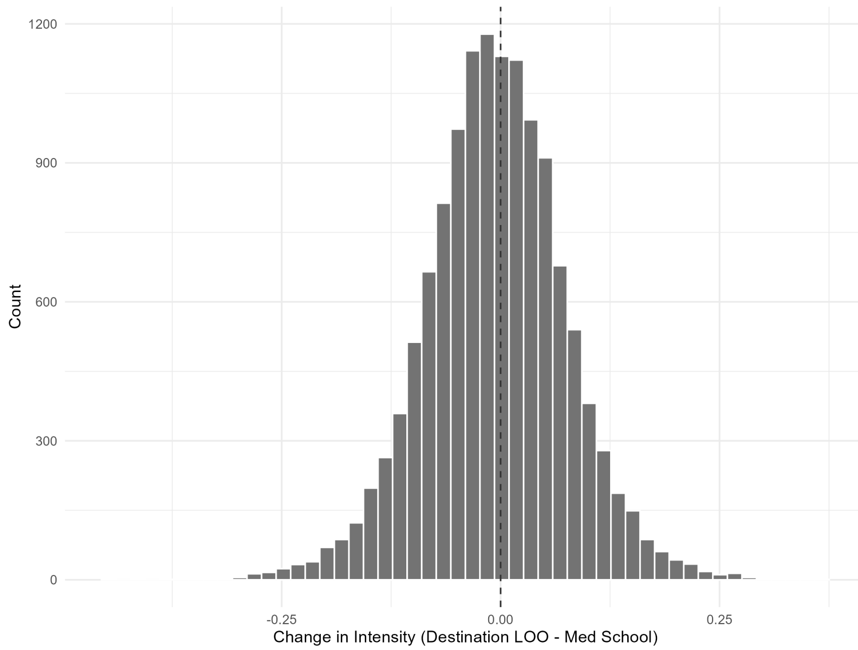
[a]Each polygon is a hospital referral region (HRR). HRRs are shaded by the mean residualized cath rate across cardiologist-years in the analytical sample, with darker shading indicating higher residualized cath rates. The residualized cath rate is the volume-weighted mean of patient-level residuals from a linear probability model regressing an indicator for catheterization within two days of NSTEMI admission on the 31 Elixhauser comorbidities and year fixed effects.

Figure 2. **Training-Period Cath Lab Share vs. Residualized Cath Rate**[a]



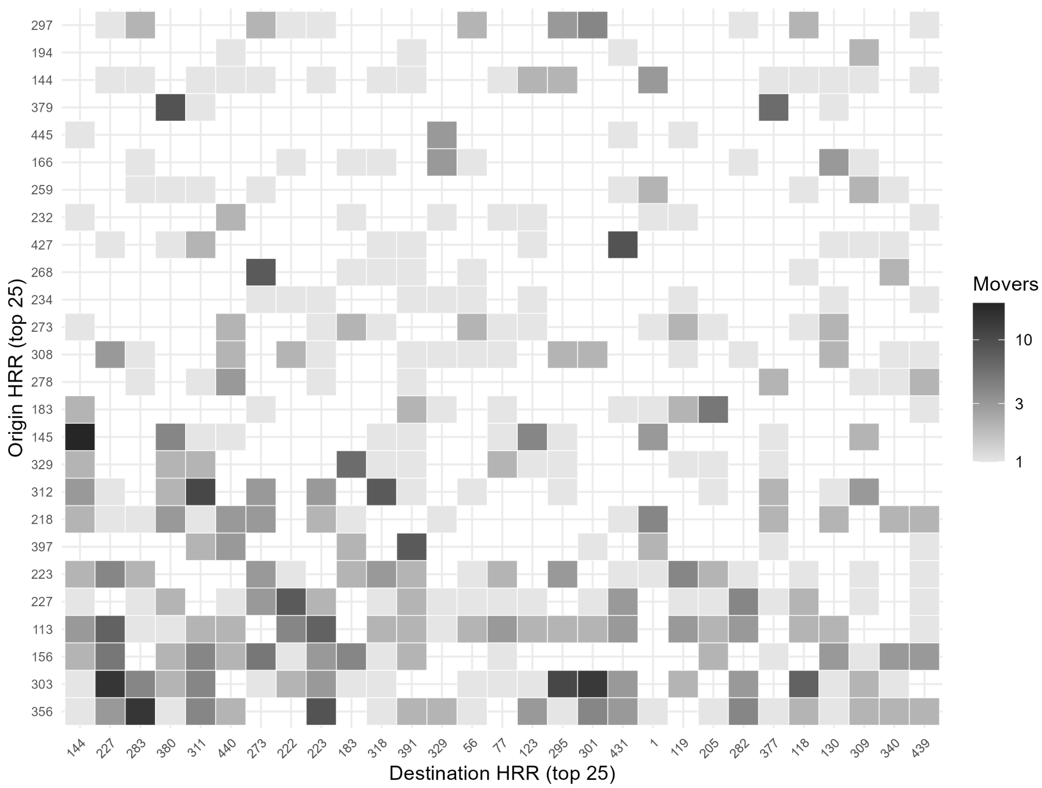
[a]Binscatter of training-period cath lab share at the cardiologist's medical school HRR (x-axis) against the volume-weighted mean residualized catheterization rate at the cardiologist-year level (y-axis). Each point represents the volume-weighted mean within a ventile of the training cath share distribution. The fitted line is from an OLS regression on the underlying cardiologist-year observations, with 95% confidence interval shaded. The descriptive relationship is unadjusted and does not condition on current practice HRR.

Figure 3. **Distribution of Intensity Change for Movers**[a]



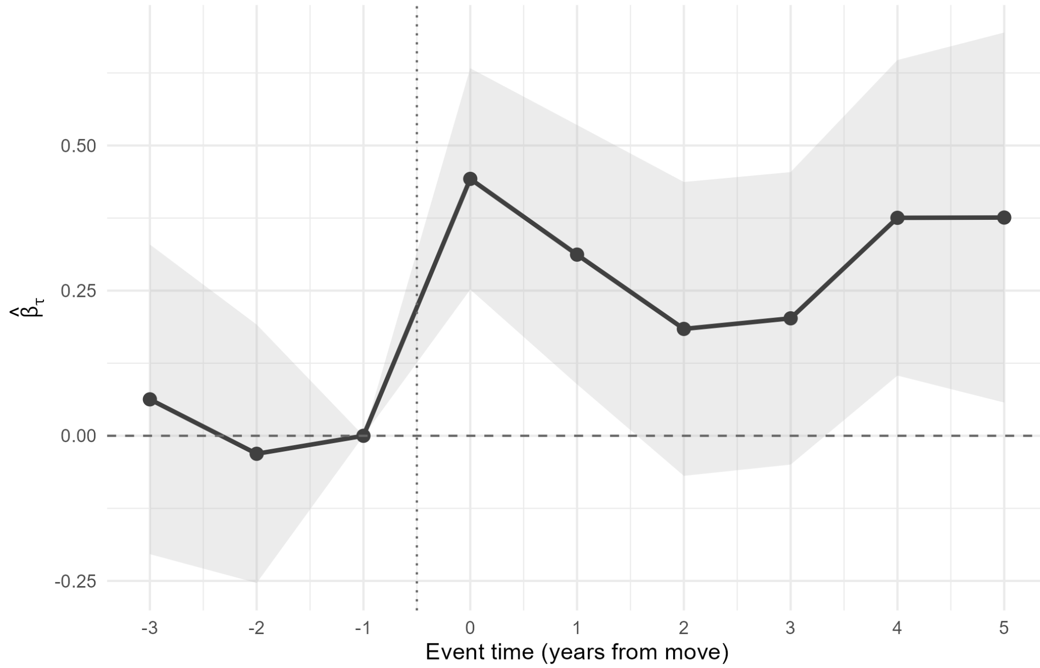
[a]Histogram of the gap, for movers, between the destination peer cath rate (the leave-one-out mean residualized cath rate of other cardiologists in the current practice HRR-year) and the training-period cath lab share at the cardiologist's medical school HRR in the year of matriculation. Movers are cardiologists whose current practice HRR differs from their medical school HRR.

Figure 4. **Origin-Destination Flows, Top 25 Origins and Destinations**[a]



[a]Heatmap of mover counts by medical school HRR (rows) and current practice HRR (columns), restricted to the top 25 origins and top 25 destinations by mover count. Shading intensity indicates the number of movers from each origin HRR to each destination HRR.

Figure 5. **Event Study Around Mid-Career Moves**[a]



[a]Event-study coefficients with 95% confidence intervals from a within-physician specification of the destination response (equation 3). The outcome is the volume-weighted mean residualized cath rate at the cardiologist-year level. Event time τ is measured in years relative to the move year, with the coefficient at $\tau = -1$ normalized to zero. The specification includes cardiologist and calendar-year fixed effects, weights by NSTEMI volume, and clusters standard errors at the cardiologist level.