The Effects of Switching Electronic Health Record Developer on PCP-to-Specialist Patient Sharing

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Abstract: We use national physician-pair panel data to examine how switching electronic health record (EHR) developers affects out-of-network patient sharing between primary care physicians (PCPs) and specialists. We estimate a difference-in-differences model, exploiting changes in EHR developer adoption by physicians' affiliated hospitals. After a change in the PCP's EHR developer, patient sharing with same-developer specialists increases by 5.8%, and patient sharing with specialists using the PCP's prior EHR decreases by 4.2%. Our theoretical model indicates that PCP preferences for convenience may reduce referrals to the highest-quality specialists and lead to EHR market agglomeration, presenting a possible economic rationale for antitrust regulation of information blocking.

Keywords: electronic health record; physician referral; physician homophily; information blocking

JEL codes: C25; I11; I18; L41

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1. Introduction

As new digital technologies such as artificial intelligence (AI) become increasingly integrated into healthcare delivery, a key question for economists is how these innovations reshape provider interactions and influence the coordination of care. Although systematic evidence on the effects of AI remains limited, the earlier diffusion of electronic health records (EHRs)—digital systems that store, manage, and exchange patient health information—offers a useful precedent for studying how digital technologies affect information flows, patient sharing and market structure.

We study how switching EHR developers by primary care physicians (PCPs) affects patient sharing with specialists, focusing on the critical period of rapid EHR adoption from 2011 to 2015. This period coincided with the implementation of the Centers for Medicare and Medicaid Services (CMS) Promoting Interoperability Program, which provided financial incentives for adopting certified EHR systems that met specific "Meaningful Use" (MU) criteria. These criteria, which governed system capabilities in the domains of quality, safety, efficiency, health disparities, privacy and security, were implemented in three stages. Starting in 2015 adoption incentives transitioned to penalties for the failure to adequately implement EHR systems and CMS reduced Medicare payments to providers that failed to meet certain criteria (CMS 2024).[1] As a result, progress towards MU criteria is a frequently cited reason for switching EHR developers (Edsall and Adler 2015).

These policy incentives contributed to a sharp increase in EHR adoption. In 2004, only 20% of office-based physicians used EHRs, but by 2021, 88% of physician offices had EHR systems (Office of the National Coordinator for Health Information Technology [ONC] 2024a). EHR adoption by acute care hospitals was even higher, reaching 96% in 2021 (ONC 2024b). Because they contain patient health information from a multitude of sources, EHRs facilitate information transfer across providers, which is particularly important when patients are referred from primary care physicians (PCPs) to specialists (Menachemi et al. 2018). However, lack of interoperability

[1] In 2011, MU Stage 1 established preliminary requirements for the electronic recording of clinical data and reporting of health information. Stage 2 expanded the set of measures and focused on advancing clinical processes, achieving quality improvement, and the exchange of information among providers. For example, MU Core Measures 12-1, 12-2 and 12-3 contain specific benchmarks for the transmission of summary of care records using certified EHR technology. In October 2015, CMS released a final rule focusing Stage 3 requirements on improving measured health outcomes.

limits the potential benefits of EHRs for information sharing (Kataria and Ravindran 2020; Li et al. 2023). To address this shortcoming, U.S. states and community organizations developed health information exchanges (HIEs). Despite early successes, the number of HIEs has declined and many geographic areas are not covered by exchanges (Adler-Milstein, Lin, and Jha 2016). As an alternative to publicly supported HIEs, EHR developers created proprietary networks that have become the predominant means of sharing patient data. Due to competitive pressures in the EHR market, researchers and policy makers have raised concerns over whether EHR developers use information and referral exchanges as a mechanism to concentrate patient sharing among providers that adopt their product and block access by competitors (Adler-Milstein and Pfeifer 2017; Pylypchuk et al. 2022).

The term *information blocking* refers to intentional and unreasonable interference with the exchange or use of electronic health information (HealthIT.gov 2022). Although emphasizing exchange within the same developer's network and impeding the connectivity to other developers is financially beneficial to EHR developers, it can be detrimental to patient outcomes (Dix, Moran, and Nguyen 2025; Eastaugh 2013; Everson and Adler-Milstein 2016; ONC 2015). One quarter of respondents in a 2015 – 2016 national survey of HIE leaders reported information blocking by EHR developers and health systems, with the former typically limiting product interoperability (Adler-Milstein and Pfeifer 2017). Despite ongoing policy efforts to curtail information blocking, such as the 21st Century Cures Act, Everson, Patel, and Adler-Milstein (2021) found in a 2019 – 2020 national survey that EHR developers still regularly engaged in information blocking. Common mechanisms for limiting access to patients by competitors are referral systems and developer information exchanges that facilitate patient referrals to other providers with the same developer. For example, Pylypchuk et al. (2022) found that switching to a new EHR developer increased same-developer hospital patient sharing by 4% - 19%.

While changes in patient sharing after providers switch to a new EHR developer can occur for multiple reasons, large and immediate shifts of referrals to other providers using the newly adopted EHR may indicate information blocking. This is especially true for out-of-network patient sharing not influenced by network referral policies. Using a difference-in-differences (DiD) framework and data from 2011 – 2015 on Medicare patient sharing, we present causal evidence that EHR developer switches significantly affect PCP out-of-network patient sharing. We show that when a PCP switches to the same developer as a specialist, a larger number of patients are shared between

the two physicians. In most cases, shared patients between PCPs and specialists represent referrals from the former to the latter physicians (Agha et al. 2018). Although there is a sizable literature on homophily in physician patient sharing, this is the first paper to demonstrate homophily over health information technology (IT). In contrast, previous studies consider how patient, physician, and healthcare system structure influence referral behavior (Barnett et al. 2012; Dunlea and Lenert 2015; Forrest et al. 2006; Kinchen et al. 2004; Linde 2019). Characterizing physician referral preference based on EHR developer is important because health systems commonly switch EHR developers to improve system functionality, lower their costs or meet federal requirements, and physician referrals significantly influence patient outcomes (Blease et al. 2021; Coustasse et al. 2018; Freedman et al. 2018; Kossman and Scheidenhelm 2008; Mehrotra, Forrest, and Lin 2011; Seth Joseph et al. 2014).[2] Moreover, EHR system designs that exploit physicians' preferences for convenience to increase referrals to other physicians using the same EHR developer are a form of information blocking that may violate antitrust regulations.

Non-random assignment of physicians to EHR developers makes it challenging to identify the causal relationship between developer switching and referrals. We are particularly concerned that a referral-initiating physician may intentionally switch to the same EHR developer as a set of referred-to physicians to increase cooperation, or that referral-initiating physicians who are less likely to switch developers because they are resistant to change are the most likely to have stable referral networks. To reduce the potential for selection into developer switching, we subset our sample to physicians affiliated with healthcare systems, and model EHR decisions made by the physician's affiliated hospital. Since hospital decisions over EHR adoption require significant planning, coordination and financial investments they are unlikely to be affected by an individual physician's preferences.[3] We consider only a PCP's shared patients outside the hospital system to rule out the effect of vertical integration on patient sharing across physicians within the same system, and subset to physicians who did not change hospital affiliation or practice location during the sample period to ensure physicians did not join a new practice due to a change in EHR

[2] The pace of innovation in the EHR market has contributed to high rates of switching across EHR systems. From 2010 to 2016, disclosed deals and equity funding in U.S. EHR developers increased from 36 million to over 320 million, and as of 2016, 186 certified health IT developers supplied certified health IT to 4,520 non-federal acute care hospitals (CB Insights 2021; HealthIT.gov 2017).

[3] Hospitals typically solicit input over EHR developer choices through a committee that includes providers and administrative staff from multiple departments (Bartley and Daiker 2022).

developer (Arah, Ogbu, and Okeke 2008; Brot-Goldberg and de Vaan 2018; Carlin, Dowd, and Feldman 2015). The treatment group in our DiD framework includes PCPs whose affiliated hospitals switched to the same EHR developer as a referred-to specialist, while the control group includes PCPs who hospitals either did not switch developers or switched to a different EHR developer than the specialist.

Our DiD results indicate that switching primary EHR developers results in more shared patients between PCPs and specialists that use the same developer. On average, when a PCP's hospital adopts a new EHR, the proportion of out-of-healthcare-system patient sharing from a PCP to a same-developer specialist increases by 5.8%. This change is at the expense of a 4.2% decrease in patient sharing with specialists who had the same EHR developer as the PCP before the switch. However, there is no change in patient-sharing with specialists who used a different developer prior to the switch. We also examine other types of patient sharing and find no significant change in PCP-to-PCP, specialist-to-specialist, or specialist-to-PCP patient sharing. A key question that we cannot answer directly from our data is whether the quality of referrals increases after the hospital switches EHR. However, predictions from a discrete choice model suggest PCPs are less likely to refer patients to the highest-quality specialist after switching EHRs if that specialist uses a different EHR.

By demonstrating that switching EHR providers leads to an increase in the concentration of patients with specialists using the same EHR, we provide evidence of an important mechanism driving EHR agglomeration, with implications for innovation and regulations governing information blocking and antitrust (Behrens and Robert-Nicoud 2015; Carlino and Kerr 2015; Freedman, Lin, and Prince (2018). Our discrete choice model predicts that specialists can maximize their probability of receiving referrals by choosing the EHR developer used by most PCPs, and Freedman, Lin, and Prince (2018) found EHR agglomeration increased in more competitive markets, indicating a preference for coordination. Both results suggest policies increasing competition among hospitals could lead to less competition among EHR developers, implying the assessment of changes in competition across multiple markets is useful when evaluating regulatory policies.

2. Data

2.1. Patient sharing, physician and hospital data

Our analysis combines data from several sources. We used the 2011– 2015 CMS Physician Shared Patient Patterns 30-day data file (PSPP) to measure patient referrals and other types of patient sharing from each focal physician to other physicians. The PSPP is a panel dataset that contains the annual number of shared Medicare patients among all healthcare providers in the United States, based on the National Claims History (NCH) database, as well as each physician's National Provider Identifier (NPI).[4] Shared patients are defined as those receiving health services by two providers within 30 days. For privacy reasons, CMS only reports physician pairs with at least 11 distinct shared patients during the calendar year. We excluded patient sharing directly by organizational health care providers, which are those with a Type 2 NPI. We determined the type of NPI by merging data from the CMS National Plan and Provider Enumeration System (NPPES).[5] The NPPES also contains information on each physician's primary practice address and the associated zip code that we used to exclude physicians who changed their primary practice address (relocated) during the sample period.[6] This exclusion precludes simultaneous changes in patient sharing patterns and EHR systems resulting from relocation.

Next, we identified patient sharing most likely to represent referrals using information on Medicare claim date and physician characteristics. The latter are from the Physician Compare National Downloadable File (PC), which we merged with the PSPP using NPI.[7] The PC data contain information on the physician's primary hospital affiliation, specialty, experience and demographic characteristics.[8] The first year of the PC database is 2013, so we extrapolated each physician's hospital affiliation to 2011 and 2012 under the assumption that physicians who

[4] The National Plan and Provider Enumeration System (NPPES) assigns National Provider Identifiers (NPI) – a 10-digit unique identification number – to covered healthcare providers under the Health Insurance Portability and Accountability Act (HIPAA). Since Medicare is a HIPAA-covered entity, physicians must have an NPI to enroll in Medicare.

[5] NPPES assigns a Type 1 NPI to individual healthcare providers, including physicians, dentists and all sole proprietors, and a Type 2 NPI to organizations.

[6] We used both business mailing address postal code and practice location address postal code to determine relocation.

[7] The Physician Compare National Downloadable File was renamed as Doctors and Clinicians National Downloadable File in 2019. To be consistent with the literature, we use the PC abbreviation in this paper.

[8] If a physician reports more than one affiliation in the PC database, we use the first reported affiliation as the physician's primary hospital affiliation.

remained at the same primary practice addresses from 2011 – 2015 did not change their primary hospital affiliation during 2011 – 2013. We categorized referrals as patient sharing where the physician with the earlier Medicare claim date is a primary care physician (PCP) and the physician with the later claim date is a specialist, based on conventional PCP gatekeeper models (Garrido, Zentner, and Busse 2011). By our definition, PCPs have specialties that include family practice, internal medicine, pediatric medicine, geriatric medicine, and general practice, and specialists are physicians practicing in all other areas. Using the panel dimension of our data, we categorized "long-term referral relationships" as those where the PCP-specialist pair shared patients for at least three consecutive years.[9] While our main results are based on PCP-specialist patient sharing, we examine other types of patient sharing in Section 5.3.

Using the hospital identifiers on the PC file, we merged hospital characteristics from the Dartmouth Atlas Project and from the CMS Hospital Compare data archives. The former includes the number of hospital beds, healthcare system designation, Hospital Service Area (HSA) code, and Hospital Referral Region (HRR), while the latter includes type of hospital, whether the hospital had an emergency center, and four categorical measures indicating the hospital's 30-day mortality rate and 30-day readmission rate of heart failure and pneumonia patients relative to the national means.[10]

Finally, we removed physicians (both referring PCPs and referred-to specialists) from the sample whose primary hospital affiliation changed between 2011 and 2015 to rule out cases where EHR systems changed simultaneously with a hospital acquisition. We also excluded from our analysis physician pairs affiliated with the same hospital or hospital system because physicians face strong incentives to refer patients within the same hospital system, so we prefer to focus on out-of-system patient sharing to isolate the effect of EHR developer change on referral decisions.

[9] Our use of three years to define these categorizations is based primarily on data availability in that we have only two years of prior PSPP data to define long-term relationships in the first year of our analysis sample.

[10] HSAs are local health care markets for hospital care defined by the Dartmouth Atlas Project as the collections of zip codes in which resident Medicare fee-for-service enrollees are hospitalized primarily in hospitals in the defined area. Similarly, HRRs are regional markets for tertiary medical care that contain at least one hospital that provides major cardiovascular care and performs neurosurgery. These geographic delineations are updated yearly (Dartmouth Atlas Project 2024).

2.2. Primary EHR developer of affiliated hospitals

We used two additional data sources to identify the primary EHR developer of each hospital in our physician-pair dataset. First, we merged a CMS ID from the CMS Eligible Hospitals Public Use File. The ID is a unique identifier assigned by the CMS PI program to hospitals that successfully attested to the EHR incentive payment program.[11] Second, we obtained a complete list of Certified-EHR products and developers associated with each attestation from the Certified Health IT Product List attached to the CMS ID. Following Pylypchuk et al. (2022), we defined the primary EHR developer in each year as the company providing the largest number of products on the hospital's Certified Health IT Product List.[12] We then calculated the market share of each referral-initiating PCP's EHR developer within the HRR to measure EHR marketplace dominance (Sorace et al., 2020).

2.3. Summary of sample exclusions and construction of treatment variable

The full 2011 – 2015 PSPP contains 222,755 unique physicians (PCPs and specialists). We retained 120,849 physicians (54.3% of the full sample) after exclusions for change of practice location or primary hospital affiliation and then retained 65% of this smaller sample after excluding patient sharing among providers in the same hospital system and cases in which hospitals failed to report EHR developers to the Certified Health IT Product List. The resulting 2011 – 2015 panel dataset contains 1,856,374 physician-pair-year observations after expanding the dataset to physician pairs across years.[13] The majority of these observations (64.1%, N=1,189,635) represent cases where two specialists shared patients, which we excluded from our main sample because we focus on PCP-specialist patient sharing. We also excluded 316,876 referrals from specialists back to PCPs because they are largely a consequence of the PCP's initial referral and 40,338 cases where

[11] Hospitals eligible for PI program incentive payments include (1) Subsection (d) hospitals in the 50 states, DC, and Puerto Rico that are paid under the Inpatient Prospective Payment System (IPPS); (2) Critical Access Hospitals; (3) Medicare Advantage (MA-Affiliated) Hospitals.

[12] In most cases there is no ambiguity in the determination of primary EHR developer. Even if we consider any of the hospital's developers, 83% shared patients are through the primary developer.

[13] During database construction, we first created a balanced panel with missing values indicating censored observations for the purpose of determining the year PCPs switched EHR developers and then dropped these censored observations when constructing the estimation sample. In our robustness checks, we estimate models using the balanced paper where we input 5 shared patients for all censored observations.

patients were shared by two PCPs, leaving 309,527 physician-pair-year observations in our main sample representing PCP-to-specialists referrals between 120,878 unique PCP-to-specialist pairs.[14] All hospital referral regions (HRRs) are represented in this sample, except Provo, UT. We analyze other types of patient sharing than PCP-specialist referrals in a supplementary analysis.

Our primary treatment variable indicates whether the PCP and specialist switched to the same EHR developer, including cases of simultaneous switching. We set the treatment equal to one in the year when the PCP's EHR developer switch occurred and all subsequent years for which the PCP and specialist continued to use the same developer. We refer to this treatment as "*Switch-to-same*". Because we model PCP referrals, cases where a referred-to specialist switches to the same EHR developer as the PCP are included in the control group rather than the treatment group, although we conduct a robustness check where we eliminate these cases from the control group. In subsequent analyses, we also consider cases where PCPs with the same EHR developer as the specialist switched to a different EHR developer (*Switch-to-different*) and where PCPs with a different EHR developer switched to another different developer (*Different-to-different*). In all cases, the treatment variable is coded to zero for PCPs and specialists with the same EHR developer at the beginning of the sample period.

Figure 1 displays the relative proportions of different categories of PCP EHR developer switching during our sample period. The largest category of switching, which accounts for over 99% of cases in 2012, includes PCPs whose affiliated hospitals switched to a different EHR developer than the specialist's affiliated hospital (the blue bar). Over time, PCPs' affiliated hospitals more frequently switched to the same developer as specialists (the red and green bars), accounting for 14% of EHR developer switches by 2015. In most cases, the *Switch-to-same* treatment captures unilateral switching by the PCP's hospital, with the number of cases where PCPs and specialists switched simultaneously to the same EHR developer increasing over time. The increase in the proportion of PCPs switching to the same EHR developer as the specialists' affiliated hospital is consistent with consolidation in the EHR industry and agglomeration of EHR developers (Freedman, Lin, and Price 2018; Sorace et al. 2020).

[14] The number of observations representing referrals from specialists back to PCPs and patient sharing by multiple PCPs do not account for exclusions imposed on our main sample for missing covariates.

The average number of referred-to specialists among PCPs that ever switched to the same EHR developer as a specialist is 11.2, while PCPs that never switched to the same developer as specialists referred patients to 13.6 different specialists. There were 1,084 annual referrals among the former PCPs and 1,549 annual referrals among the latter PCPs, on average.

2.4. Summary statistics

Figure 2 shows the variation in total shared Medicare patients and the number of PCP-to-specialist referrals across HRRs during our sample period. The geographic distributions for both measures are similar, with more total shared patients and a higher volume of PCP-to-specialist referrals in the Middle and South-Atlantic, West and East North-Central, and West South-Central regions. This spatial pattern coincides with the distribution of Medicare beneficiaries who have multiple chronic conditions (Lochner and Shoff 2015).

Table 1 contains descriptive statistics for our main sample, divided into PCP-specialist pairs that switched to the same EHR at any point during the sample period, and those that never switched to the same EHR. In addition to means and standard deviations for all variables, we report the normalized difference between the means of the two groups. Values greater than 0.25 generally indicate problematic imbalance (Imbens and Rubin 2015; Baker et al. 2025). The only normalized difference in that range is for the market share of the primary EHR developer. Not surprisingly, primary EHR developers have a larger market share (35%) for physician pairs where the PCP switched to the same developer as the specialist than for physician pairs that never switched to the same developer (22%).

3. Empirical framework

Consider a static bipartite physician referral network where patients are only referred from PCPs to specialists, and PCP decisions over specialty referrals depend on the specialists' EHR developers and other physician-pair characteristics. Let $\mathcal{J}$ denote the set of PCPs, $\mathcal{K}$ denote the set of specialists and $\mathcal{H}$ denote the set of EHR developers in an HRR. If h_j and h_k are the EHR developers used by PCP j and specialist k, then $\mathcal{H} = \{h_j : j \in \mathcal{J}\} \cup \{h_k : k \in \mathcal{K}\}$. Given a choice set $\mathcal{K}$, a PCP's utility maximizing choice of specialist is:

$$(1) \qquad arg \max_{k \in \mathcal{K}} U_j(k) = \beta \mathbb{1}\{h_j = h_k\} + \boldsymbol{X}_{jk}\boldsymbol{\gamma} + \epsilon_{jk},$$

where $\boldsymbol{X_{jk}}$ is a vector of characteristics of either the PCP, specialist or the PCP-specialist pair and $\mathbb{1}\{h_j = h_k\}$ indicates whether PCP j and the specialist k use the same primary EHR developer. If $\beta > 0$, the PCP has a preference to make referrals to same-developer specialists. Given sufficient controls for specialist quality in the vector $\boldsymbol{X_{jk}}$, we assume the preference for a same-developer specialist is largely driven by convenience. Letting ϵ_{jk} be an independently and identically distributed Gumbel extreme value, equation (1) corresponds to a conditional logit model with probability function:

$$p_{jk} \equiv \Pr(k|j) = \frac{\exp(V_{jk})}{\sum_{\kappa \in \mathcal{K}} \exp(V_{j\kappa})} \tag{2}$$

where $V_{jk} \equiv E[U_j(k)] = \beta\mathbb{1}\{h_j = h_k\} + \boldsymbol{X_{jk}\gamma}$ is the expected utility of PCP j's patient referral to specialist k.

Direct estimation of equation (2) requires observations on individual referrals, but our sample contains counts of referrals between each pair of physicians. We, therefore, derive an alternative specification by first applying the natural logarithm to both sides of equation (2):

$$ln(p_{jk}) = \beta\mathbb{1}\{h_j = h_k\} + \boldsymbol{X_{jk}\gamma} - ln(\textstyle\sum_{\kappa \in \mathcal{K}} \exp(V_{j\kappa})). \tag{3}$$

The last term in equation (3) is a measure of PCP j's total utility from referring patients to all specialists. Because this term is PCP-specific, we can rewrite equation (3) as:

$$ln(p_{jk}) = \beta\mathbb{1}\{h_j = h_k\} + \boldsymbol{X_{jk}\gamma} + \alpha_j.^{15} \tag{4}$$

To account for sampling uncertainty, we replace the true referral probability p_{jk} with its sample estimate: the proportion of PCP j's referrals to specialist k:

$$\widehat{p_{jk}} \equiv \frac{\text{Number of patients shared from PCP j to specialist k}}{\text{Total number of shared patients by PCP j}}, \tag{5}$$

where $\widehat{p_{jk}}$ converges to p_{jk} by the law of large numbers. Applying the conditional expectation function decomposition, we have

$$ln(\widehat{p_{jk}}) = E[ln(\widehat{p_{jk}})] + u_{jk}. \tag{6}$$

[15] Note that α_j implicitly captures PCP characteristics formerly contained in $\boldsymbol{X_{jk}}$.

Following Teh, Newman, and Welling (2006), we can then use a second-order Taylor series expansion to approximate equation (6) and substitute in equation (4):

$$(7) \qquad \approx \ln\left(E\left[\widehat{p_{jk}}\right]\right) - \frac{Var(\widehat{p_{jk}})}{2E[\widehat{p_{jk}}]} + u_{jk}.$$

$$(8) \qquad = \beta \mathbb{1}\{h_j = h_k\} + \boldsymbol{X_{jk}\gamma} + \alpha_j - \frac{Var(\widehat{p_{jk}})}{2E[\widehat{p_{jk}}]} + u_{jk}.$$

Finally, we extend this static equation to multiple time periods and apply the model specifically to changes in the probability of referral after switching EHR developers. Assuming β and γ do not vary over time, and the time variation of $\alpha_j - Var(\widehat{p_{jk}})/(2E\left[\widehat{p_{jk}}\right])$ is additive, we arrive at the following two-way fixed effect (TWFE) specification:

$$(9) \qquad ln\left(\widehat{p_{jkt}}\right) = \beta \times Switch - to - same_{jkt} + \boldsymbol{X}_{jkt}\gamma + \alpha_{jk} + \tau_t + v_{jkt},$$[16,17]

where $Switch - to - same_{jkt}$ indicates whether PCP j switched to the same developer as specialist k during or prior to time t. In the case of PCPs switching EHR developers multiple times during the sample period, this indicator is set to one while the PCP continues to use the same EHR developer as specialist k. The vector $\boldsymbol{X}_{jkt}$ contains time-varying physician characteristics that include the market share of the EHR developer used by the PCP's affiliated hospital, an indicator for whether the PCP and specialist practice in the same HSA and an indicator for PCP-specialist pairs that have shared patients at least three years. The vector also contains the following characteristics of the PCP's and the specialist's affiliated hospital: the number of beds, whether the hospital has an emergency unit, and eight readmission and mortality measures for heart failure and pneumonia. In all models we cluster the standard errors at the level of the PCP's affiliated hospital. Using the wild bootstrap method with 1,000 replications clustered at the affiliated hospital level

[16] Our empirical specification, which uses the log share of referrals as the outcome, is closely related to the demand estimation framework developed by Berry (1994). In his model of differentiated product demand, market shares are derived from an underlying random utility function and then log-linearized to estimate choice parameters using aggregate data. Similarly, we model physician referral behavior as arising from a discrete choice process and approximate the log of observed referral shares as a function of referral determinants and fixed effects.

[17] We do not use the notion *Same-Developer* in this dynamic setting for two reasons: (1) we make clear that physician pairs that consistently used the same EHR developer throughout the study period are not part of the treatment group; and (2) we will separately examine the effects of both switching to the same developer ("phase-in" stage) and switching from the same to a different developer ("phase-out" stage) in Section 4.1.

does not change levels of statistical significance relative to standard cluster adjustments to the covariance matrix.

The log transformation of the dependent variable in equation (9) reduces skewness. Appendix Figure A1 shows that the empirical distribution of the proportion of specialist referrals is right skewed with a mass point at 100%. Identification of the structural parameters in equation (9) requires several assumptions. To control for time-invariant unobserved characteristics of PCP-specialist pairs, we include fixed effects, α_{jk}, in the model, which fully absorb the PCP fixed effect, α_j, in equation (8). We also include year fixed effects, τ_t. Both α_{jk} and τ_t will absorb some of the variation in $Var(\widehat{p_{jk}})/(2E[\widehat{p_{jk}}])$, and we assume that any remaining variation is additively separable across physician pairs and time, such that it is captured in the error term v_{jkt}. This separability assumption could be violated if a PCP intentionally switched to the same EHR developer as the specialist to achieve an increase in utility (from, for example, the expansion of their referral network). We support the separability assumption by modeling EHR developer adoptions by the physician's affiliated hospital, which are largely beyond the control of any individual physician.

The TWFE specification in equation (9) is commonly known as a generalized difference-in-differences (DiD) model with variable treatment timing (Goodman-Bacon 2021). The treatment group is composed of PCP-specialist pairs with affiliated hospitals that use the same EHR developer, and the control group includes PCP-specialist pairs with different EHR developers. The parameter β is identified by comparing changes in the proportion of referrals by PCPs to specialists with the same EHR following the adoption (or de-adoption) of the common EHR to changes in the proportion of the focal PCP's referrals to specialists with a different EHR *and* changes in the proportion of referrals by other PCPs who do not share an EHR with the given specialist. The latter group includes PCP-specialist pairs that never shared an EHR, those that have not yet shared an EHR and those that once shared an EHR. This last group is created by default when a PCP switches to a new EHR, as PCP-specialist pairs that previously shared an EHR become controls. Estimates from the generalized DiD model may be biased if there are different treatment effects across these groups. To investigate this possibility, we compare our main estimates to those from the doubly robust DiD model of Callaway and Sant'Anna (2021). We also verify that the treatment effects are symmetric when a PCP switches from a different EHR to the same EHR and

switches from the same EHR to a different EHR and that there is no effect of switching from one different EHR to another different EHR among physician pairs in the control group.

4. Results

4.1. Generalized difference-in-difference model estimates

Table 2 contains estimates from our generalized DiD model that show treatment effects of switching to a common EHR on out-of-network patient sharing between PCPs and specialists. In column 1, we report estimates from a simple DiD with no control variables, while in column 2 we add the controls for physician, hospital and market characteristics listed in Table 1. In the simple model, shared patients increase by 5.9% when the PCP's affiliated hospital switches to the same EHR as the out-of-network specialist (or when there is simultaneous switching), with the magnitude of the treatment effect estimate remaining nearly the same (5.8%) when we include control variables. This suggests that the treatment effect is not influenced by observable physician and hospital characteristics, supporting our assumption that EHR developer homophily independently influences referral behavior. The treatment effect in column 2 translates to an increase of 63 additional referred patients per PCP per year to out-of-network specialists using the common EHR among our sample of 16,988 PCPs.[18]

We also find that when a PCP switches from the same EHR as the specialist to a different developer, shared patients drop by 4.2%, translating to 46 fewer referrals per PCP per year to out-of-network specialists in our sample (column 5). By implication, referrals to same-developer specialists grow largely at the expense of referrals to different-developer specialists. In column 6 we report the effect of PCPs switching from a different developer than the specialist to another different developer, which is not statistically significant.

4.2. Common trend assumption and time-varying treatment effects

We use two methods to verify the common trend assumption of the DiD model. First, we show that the *Switch-to-same* treatment effect is similar when we add HRR-specific linear time trends

[18] We calculated this estimate by multiplying the treatment effect by the number of out-of-network specialist referrals per PCP per year in our treatment group (1,084).

to the model (Table 2, column 3). This specification permits differential pre-treatment trends across HRRs, such that identification is achieved through sharp deviations from HRR linear trends. Second, we estimate an event study with both treatment effect leads and lags. The plot of treatment effects in Figure 3 shows no significant effects in the pre-treatment period and 12.5% increase in patients shared with same-developer specialists one year after the PCP's affiliated hospital switches EHR developer.

We also consider the possibility of time-varying treatment effects that could lead to biased estimates when contrasting a timing group (physicians who switched to the same EHR developer as specialists each year) to an already-treated group (physicians who switched to the same developer in past years). Callaway and Sant'Anna (CS; 2021) and Goodman-Bacon (2021) demonstrate that estimates from the TWFE model are a variance-weighted average of several canonical DiD estimates. These underlying DiD models compare the treatment (timing) groups with different control groups, such as untreated groups and already treated groups. If the treatment effect is time-varying, the underlying DiD estimate may have the wrong sign, or be appreciably biased, when the already-treated timing group is used as a control and the timing vs already-treated DiD is assigned a high weight.

We use a Goodman-Bacon decomposition to examine whether the TWFE estimate is a function of heterogeneous time-varying treatment effects. As shown in Appendix A3, 98.5% of the TWFE treatment effect is estimated from comparisons between a timing group and the never-treated group, and only 0.6% of the treatment effect uses an already-treated timing group as the control group. Moreover, the treatment effect based on the never-treated control group (4.3%) is comparable in magnitude to the treatment effects in Table 2, columns 1 to 3. Finally, we estimate the CS DiD model on a balanced panel with time-invariant control variables and report the treatment effect estimate in Table 2, column 4. The treatment effect is statistically significant, but slightly smaller than those from the generalized DiD in columns 1 to 3. In Appendix Figure A2 we show the corresponding event study from the CS DiD model.

4.3. Variation in treatment effects across physician subgroups

In Table 3 we present estimates from triple-difference models where the *Switch-to-same* treatment effect is interacted with several physician-pair characteristics. We don't find any statistically significant differences relative to other physicians in additional shared patients from

switching to the same EHR developer when the PCP-specialist pair is in the same HSA or HRR or is composed of same-gender physicians. However, we find a negative coefficient on the triple-difference term when the PCP and specialist have a referral history of at least three consecutive years. When this differential is added to the baseline difference-in-differences (DD) estimate, the results suggest that switching to the same EHR developer does not significantly alter the volume of shared patients among physician pairs with an established long-term relationship.[19] In these cases, the strength of the professional relationship outweighs any incentives associated with commonality of the EHR, such that the total treatment effect is not statistically different from zero. The treatment effects are also higher when the PCP has more experience than the specialist (8.9%) and when the common EHR has greater than a 50% market share (14.1%).

4.5. Other patient-sharing channels

While referrals from PCPs to specialists are the most common type of patient sharing, there are other types of patient sharing that are well-studied in the literature (Brez et al., 2009). Barnett et al. (2012) found that 10% of referrals initiated by specialists were to PCPs and 32% - 56% were to other specialists. Indeed, the increasing complexity of medical therapies has resulted in more inter- and multi-disciplinary patient care, leading to more diverse referral patterns. Researchers have identified a shared model of patient care and IT systems that facilitate cooperation between physicians as the two most essential components of effective coordinated care delivery (Buljac-Samardzic et al. 2010; Deneckere et al. 2012; Graetz et al. 2015; Gross et al. 2016; Taplin et al. 2015). To examine whether switching EHR developers impacts other channels of patient sharing, we constructed estimation samples to analyze the following patient flows: (1) Specialist-to-PCP, (2) PCP-to-PCP, and (3) Specialist-to-specialist. Appendix Table A2 columns 1 to 6 report DiD estimates from models estimated using these additional samples. None of the patient-sharing channels are significantly affected by EHR developer switching. However, the signs of all estimates are positive, suggesting a tendency to increase in referrals when providers switch to the same EHR developer.

[19] Three years is the longest history we can trace back in the PSPP data.

As a complementary analysis, columns 7 and 8 of Appendix Table A2 examine PCP-to-specialist patient sharing where both physicians are part of the same health system but are affiliated with different hospitals. We find that switching to the same EHR developer leads to a marginally significant increase in shared patients within these cross-hospital system relationships. This result is consistent with our main findings and suggests that even within the same system, the absence of a shared EHR platform across hospitals may act as a barrier to patient sharing.

4.6. Robustness checks

We estimated additional specifications to investigate the robustness of our results to different sample definitions and modeling assumptions. First, we consider alternatives to our main sample. In Table 4, column 1 we report the baseline model from Table 2 and in column 2 we report results where we restrict the control group to physician pairs that never switched EHR developers, while in column 3 we exclude additional referrals to the same specialists for the same patients. In column 4 we exclude physician pairs from the treatment group that were treated more than once due to multiple instances of switching EHR developers and in columns 5 and 6 we create balanced panels. This is achieved in column 5 by removing physician pairs that shared less than 11 unique patients in any year (i.e. censored observations) and in column 6 by imputing five referred patients (the mid-point) to observations when the number of shared patients drops below 11. The treatment effect estimates are largely invariant across these different sample definitions, except for column 6 where the estimate decreases mechanically.

Next, we considered different empirical specifications. In column 7 of Table 4 we present estimates from a model where we include all possible EHR developer transitions (*Switch-to-same*, *Switch-to-different* and *Different-to-different*). The treatment effect estimate does not change with the inclusion of these two variables. Column 8 contains estimates from a linear probability model of the extensive margin measuring the probability that shared patients between the PCP-specialist pair exceed 10. The coefficient on *Switch-to-same* is not statistically significant, suggesting that the increase in shared patients from same-developer switching occurs among PCPs and specialists that already shared at least 11 patients. Finally, column 9 contains estimates from a model with the raw-scale outcome variable. The percentage treatment effect (5.9%) is very similar to the model estimated using the log-transformed outcome.

Finally, we test the sensitivity of our DiD estimates to the extrapolations we make during the data construction of the physician's hospital affiliation in 2011 and 2012. We re-estimated our main models after restricting the sample to 2013-2015, for which we have complete data on hospital affiliation. The treatment effect estimates, reported in Appendix B, are similar to those of our main models, albeit slightly larger in magnitude.

5. Distorted referral patterns and market agglomeration

The discrete choice model in Section 4 implies that PCPs gain utility from EHR developer homophily if $\beta > 0$ due to preferences for convenience. Our empirical estimates of this parameter indicate that PCPs prefer same-EHR developer specialist referrals, conditional on basic measures of specialist quality (years of experience and quality measures of the specialist's affiliated hospital). In this section, we discuss implications for quality-based referral patterns and market agglomeration.

5.1. Distortion of quality-based referral patterns

PCPs are the primary coordinators of patient care and often serve as the gatekeeper to specialist care. Even when PCP referrals are not required by insurance, they are often requested by specialist medical offices (Bodenheimer, Lo, and Casalino 1999; Franks, Clancy, and Nutting 1992; Grumbach et al. 1999). While numerous physician surveys indicate that PCPs place the greatest weight past patient experiences when making referral decisions (Forrest et al. 2006; Landon et al. 2012), recent studies document referral biases based on gender, race, and affiliation (Geissler, Lubin, and Ericson 2020; Ghomrawi et al. 2018; Zeltzer 2020). Our theoretical framework implies that switching EHR developers may distort quality-based referral patterns and reduce the probability that patients receive care from a high-quality specialist.

Consider a local physician referral market with only two EHR developers, where $(\mathcal{J}, \mathcal{K})$ is the set of PCPs and specialists, respectively, as defined in Section 4. Assume $k^* \in \mathcal{K}$ is the highest quality specialist and let h^* denote the specialist's EHR developer. For ease of notation, let P_{same,k^*} denote the probability of k^* receiving patients from a PCP using h^* and P_{diff,k^*} denote the probability of receiving patients from a PCP but using the other EHR developer (denoted by $\sim h^*$). In Appendix C, we derive:

(10) $$P_{same,k^*} = \frac{1}{n_{h^*}\delta_{h^*} + \exp(-\beta) n_{\sim h^*}\delta_{\sim h^*}} \; and$$

(11) $$P_{diff,k^*} = \frac{1}{n_{h^*}\delta_{h^*} + \exp(\beta) n_{\sim h^*}\delta_{\sim h^*}},$$

where $n_h : h \in \{h^*, \sim h^*\}$ is the number of specialists using the same or different EHR developer as k^*, and $\delta_h \equiv E_{k:h_k=h}[\exp(\boldsymbol{x}_{\boldsymbol{k}}'\boldsymbol{\gamma})]/\exp(\boldsymbol{x}_{\boldsymbol{k}^*}'\boldsymbol{\gamma})$ measures the expected quality of the specialist pool using either the same (h^*) or a different ($\sim h^*$) EHR developer, relative to the quality of k^*.

Proposition 1 (Distortion of quality-based referrals): In a referral market with a common specialist pool, referrals to the highest-quality specialist k^* are more likely to be made by PCPs who use k^*'s EHR developer if and only if switching to the same EHR developer provides a utility gain to the PCP. Namely, $P_{same,k^*} > P_{diff,k^*}$ iff $\beta > 0$.

With only two EHR developers, proposition 1 follows naturally from equations (10) and (11). When PCPs gain no utility from EHR developer homophily ($\beta = 0$), the highest quality specialist, k^*, has the same probability of receiving patients from PCPs who use a different EHR because $P_{same,k^*} = P_{diff,k^*}$. When $\beta > 0$, as we find in Section 4.1, PCPs who use h^* discount the utility received from the other specialists by $e^{-\beta}$ and therefore have a higher probability of referring patients to k^*. In Appendix C1, we present a proof and generalize this result to markets with more than two EHR developers.

Next, we consider how the choice of EHR developer h^* by a group of high-quality specialists may mitigate the distortion of quality-based referrals described in Proposition 1. This is a common scenario because specialists working in the same hospital (or hospital system) are exposed to similar professional standards and training programs, and they usually use the same EHR developer. Given fixed market shares for the two EHR developers ($n_{h^*}, n_{\sim h^*}$), similarity in the quality of specialists using h^* reduces referral distortions. We formalize this result below.

Proposition 2 (Clustering effect): In a referral market with common specialist pools and two EHR developers, the odds of referring to the highest-quality specialist k^* from same- versus different-developer PCPs —$P_{same,k^*}/P_{diff,k^*}$ — is a decreasing function of the relative quality of specialists using h^*, i.e $\delta_{h^*}/\delta_{\sim h^*}$.[20]

[20] The proof of Proposition 2 in Appendix C follows from the derivative of the odds ratio with respect the relative quality.

In Figure 4, we simulate the odds of same- versus different-developer referrals to the highest-quality specialist k^*. In the simulation, we set $\beta = 0.056$, per the estimate in Table 2, and assume $\delta_{\sim h^*} = 0.5$. Because $\beta > 0$, the odds ratio exceeds 1 (as shown in Proposition 1). The odds ratio depends on the market share and average quality of specialists that use h^*. If the market share of h^* is fixed, the odds of referring to the highest-quality specialist decrease when the average quality of specialists that use h^* increases. In extreme cases, when the market share of h^* approaches 100% and all specialists have the same quality, the odds ratio approaches 1.

Proposition 2 implies that the distortion in quality-based referrals is more severe in healthcare markets where the highest-quality specialists use a small-market-share EHR developer or when these specialists face less quality competition from the other specialists using the same EHR developer.

5.2. Market agglomeration

EHR developer homophily may also contribute to EHR market agglomeration: a phenomenon where large proportions of physicians in a given geographic area use one or a small number of EHR developers (Everson and Adler-Milstein 2016; Freedman, Lin, and Prince 2018). For example, the U.S.'s largest EHR developer, Epic increased its share of staffed hospital beds from 20 percent in 2012 to over 46 percent by 2021 (Holmgren and Apathy 2023). Similar patterns of concentration are observed in ambulatory care, where the top three developers (Epic, Oracle/Cerner, and Meditech) served over 80 percent of physician practices in 2024.[21] At the regional level, market agglomeration is reflected in the HRR- and state-level Herfindahl-Hirschman indexes for EHR developers, which frequently exceed the 1,500 threshold indicating moderately concentrated markets (Mandeville, Rahman, and Gardner 2020; Sorace et al., 2020).

To see how preferences for same-developer specialist referrals may contribute to EHR market agglomeration, again consider a market with two EHR developers $\mathcal{H} = \{A, B\}$ where the proportion of PCPs using A (denoted by $P(A)$) is greater than the proportion of PCPs using B (denoted by $P(B)$). A specialist k chooses between A and B to maximize his/her probability of

[21] Data source: https://www.definitivehc.com/blog/top-ambulatory-ehr-systems

receiving referrals, denoted by $\pi_h: h \in \{A, B\}$. When the number of specialists is sufficiently large to prevent n_h from affecting the choice of k, we have:

$$(12) \quad \pi_A = \frac{P(A)}{n_A\delta_A + e^{-\beta} n_B\delta_B} + \frac{P(B)}{n_A\delta_A + e^{\beta} n_B\delta_B} > \frac{P(A)}{n_A\delta_A + e^{\beta} n_B\delta_B} + \frac{P(B)}{n_A\delta_A + e^{-\beta} n_B\delta_B} = \pi_B$$

This statement results from the *rearrangement inequality* and is generalizable to markets with more than two EHR developers (see Appendix D for a proof). Intuitively, if switching to the same EHR developer causes more patient sharing due to greater convenience and stronger professional ties between a PCP and a specialist, profit maximizers are incentivized to switch to popular developers to maximize the number of shared patients. Such a herd effect makes the popular developers even more desirable and may reinforce EHR market agglomeration.

6. Discussion and conclusions

This paper extends the literature on outpatient physician referral decisions to determine the importance of EHR developer. We find that when a PCP's affiliated hospital switches to the same EHR developer as an out-of-network specialist, the proportion of the PCP's shared patients with that specialist increases by 5.8%, which is equivalent to 63 additional shared patients per year. This finding is robust to alternative specifications and passes standard specification tests. We also find an accompanying 4.2% reduction in the number of patients shared with out-of-network specialists who use the PCP's original developer. These results provide strong evidence for EHR developer homophily by PCPs.

Holding constant the quality of specialists, we believe the increase in same-developer specialist patient sharing reflects a preference for convenience. EHR developers often design their referral interface to increase the visibility of providers that use the same developer, and developer-based HIE makes subsequent communication with same-developer specialists relatively seamless (Adler-Milstein, Lin, and Jha 2016; Adler-Milstein and Pfeifer 2017; Barnett et al. 2012). Pylypchuk et al. (2022) suggests these factors lead to a concentration of out-of-network patient sharing from referrals and hospital transfers among inpatient physicians with the same EHR developer, paralleling our findings among outpatient physicians. Pylypchuk et al. (2022) also shows that the increase in same-developer patient sharing is increasing the EHR developer's market share. We likewise find that the increase in out-of-network patients shared with specialists

having the same EHR developer is 7.8% higher after the PCP switches to a developer that served more than 50% of hospital beds in the HRR.

These empirical findings are supported by theoretical results from our discrete choice framework indicating that EHR developer homophily among outpatient PCPs gives specialists an incentive to switch to the most popular EHR developers, leading to agglomeration, and ultimately, concentration in the EHR developer market. This suggests that preferences for convenience and the interactions between these preferences and EHR system design contribute to increases in the concentration of EHR developers documented by other studies (Chen, Peng, and Cao 2021; (Everson and Adler-Milstein 2016; Freedman, Lin, and Prince 2018; Pylypchuk et al. 2022).

We also find that there is variation in the strength of EHR developer homophily across PCP and specialist characteristics. When the PCP and specialist have a long-term professional relationship (share at least 11 patients for at least three years), changes in EHR developer have no statistically significant impact on patient sharing. We believe this reflects more complete information about the specialists that PCPs regularly interact with and the importance of long-standing professional networks to referral decisions. Barnett et al. (2012) likewise finds that PCPs concentrate 66% of referrals within their "professional network".

In contrast, there are instances when switching EHR developer causes a substantial change to shared patients. We find that the PCP's out-of-network specialist referrals are more responsive to a change in EHR developer when the PCP has more experience than the specialist. This result is, to some extent, the complement to PCP's reluctance to change referrals to long-time collaborators. When the specialist is relatively less experienced, the PCP may know less about specialist quality or have a weaker professional relationship with the specialist.

Because the concentration of specialist referrals caused by EHR developer adoption may distort optimal referral decisions and lead to greater market power among developers, our findings have implications for regulatory policies. Our discrete choice model suggests that PCP preferences for same-developer referrals reduce PCP referrals to the highest-quality specialist, and that this tendency increases when specialists face less quality competition from competitors that use the same EHR developer. One possible regulatory response is the auditing of referral patterns and information flows to prevent EHR developers from implementing technologies that disadvantage different-developer referral and communication. In a national survey of HIE effort leaders, Adler-Milstein and Pfeifer (2017) reported that 50% of EHR developers routinely engage in information

blocking, as do 25% of hospitals and health systems. In the current oligopolistic EHR market, deliberate information blocking (or the unintended adoption of unstandardized data formats) may create isolated data silos and negatively impact quality-based referrals and physician-patient matching. Moreover, when data isolation results in a concentration of same-developer patient sharing, it might lead to healthcare fragmentation. Our results suggest that information blocking can result from characteristics of EHR systems that increase the ease of referrals to out-of-network specialists using the same developer, thereby exploiting physician preferences for convenience. PCPs are only willing to overcome the additional costs of different-developer referrals when referring patients to specialists within their pre-existing professional networks.

Our study has limitations. Our data identify the number of patients shared between PCPs and specialists. Although previous studies suggest that most shared patients are referred from PCPs to specialists, some patients may be referred from specialists back to PCPs or independently visit PCPs and specialists in the same period. We show in a sensitivity analysis that the former are not very common and unlikely to be affected by changes in EHR developer adoption. We analyze out-of-network patient sharing because it is most likely to be affected by changes in EHR developers, but switching developers can also impact patient sharing within health care networks, particularly when EHR implementation occurs in stages (Meyerhoefer et al. 2016, 2018). We assume that hospital-level EHR adoption decisions made by health care network executives are beyond the control of individual PCPs. However, PCPs may select into networks that are less likely to switch EHR systems and executives' decisions may, at least in part, reflect the attitudes of network physicians. This type of selection could potentially exert a downward bias on our estimates. Therefore, a pragmatic interpretation of our estimates is as lower bounds of PCPs' same-developer referral preferences. Finally, referral patterns are influenced by complex social and professional dynamics, resulting in heterogeneous treatment effects across physicians of different genders and levels of experience. Without better explanation of how EHR technologies interact with these dynamics, it is difficult to make welfare statements for sub-groups of physicians. For example, while some less experienced female specialists may benefit from EHR homophily, others that use EHR developers with low market shares may be disadvantaged by the same market trends. A more detailed investigation of how EHR technologies affect referral patterns across sub-groups of physicians, and the associated welfare consequences, is important for future research.

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Tables and Figures

Table 1. Characteristics of physician-pair sample.

Variables	PCP switched to the same EHR as specialist $N \times T = 11{,}384$ Mean	S.D.	PCP never switched to same EHR as specialist $N \times T = 298{,}143$ Mean	S.D.	Normalized Difference[a]
Outcome variable					
Proportion of patients shared with specialist	0.21	0.26	0.19	0.25	0.06
PCP characteristics					
Experience	26.68	9.20	26.49	9.36	0.02
Male	0.80	0.40	0.84	0.36	-0.12
Affiliated with an emergency hospital	0.98	0.14	0.99	0.11	-0.05
Number of hospital beds	260.71	160.61	271.94	256.27	-0.05
Annual number of patients with heart failure	584.77	382.98	539.66	473.59	0.10
Annual number of patients with pneumonia	479.92	292.78	432.07	314.82	0.16
30-day readmission rate relative to national average (0/1)					
Heart failure, Higher	0.06	0.24	0.05	0.21	0.06
Heart failure, Similar	0.89	0.31	0.89	0.31	0.01
Heart failure, Lower	0.05	0.21	0.06	0.24	-0.07
Pneumonia, Higher	0.01	0.07	0.02	0.13	-0.11
Pneumonia, Similar	0.92	0.27	0.94	0.24	-0.06
Pneumonia, Lower	0.07	0.26	0.04	0.21	0.11
30-day mortality rate relative to national average (0/1)					
Heart failure, Higher	0.05	0.22	0.08	0.27	-0.11
Heart failure, Similar	0.92	0.27	0.87	0.33	0.15
Heart failure, Lower	0.03	0.18	0.05	0.22	-0.09
Pneumonia, Higher	0.05	0.22	0.09	0.29	-0.16
Pneumonia, Similar	0.87	0.33	0.83	0.37	0.11
Pneumonia, Lower	0.08	0.27	0.08	0.27	0.00
Market share of primary EHR developer (%)	35.43	30.08	22.13	27.84	0.46

Note: Summary statistics are based on the PCP-to-specialist patient-sharing sample. The left columns contain physician pairs where the PCP even switched to the same EHR developer as the specialist and the right columns report physician pairs where the PCP never switched to the same EHR as the specialist. [a] Values that exceed 0.25 indicate potentially problematic imbalance between the two groups (Imbens and Rubin, 2015; Baker et al., 2025).

Table 1. Characteristics of physician-pair sample, continued**.**

Variables	PCP switched to the same EHR as specialist $N \times T = 11{,}384$ Mean	S.D.	PCP never switched to same EHR as specialist $N \times T = 298{,}143$ Mean	S.D.	Normalized Difference[a]
Specialist characteristics					
Experience	26.01	8.96	26.16	8.67	-0.02
Male	0.89	0.31	0.91	0.29	-0.04
Affiliated with emergency hospital	1.00	0.04	0.99	0.11	0.12
Number of hospital beds	347.58	237.05	353.67	234.87	-0.03
Annual number of patients with heart failure	665.07	404.29	700.11	442.58	-0.08
Annual number of patients with pneumonia	517.91	281.19	531.05	308.26	-0.04
30-day readmission rate relative to national average (0/1)					
Heart failure, Higher	0.04	0.19	0.07	0.25	-0.13
Heart failure, Similar	0.91	0.29	0.87	0.33	0.11
Heart failure, Lower	0.05	0.23	0.06	0.24	-0.03
Pneumonia, Higher	0.01	0.09	0.02	0.16	-0.12
Pneumonia, Similar	0.95	0.22	0.92	0.27	0.11
Pneumonia, Lower	0.04	0.20	0.05	0.22	-0.06
30-day mortality rate relative to national average (0/1)					
Heart failure, Higher	0.06	0.24	0.09	0.29	-0.12
Heart failure, Similar	0.90	0.30	0.85	0.35	0.14
Heart failure, Lower	0.04	0.20	0.06	0.23	-0.07
Pneumonia, Higher	0.10	0.30	0.10	0.30	-0.01
Pneumonia, Similar	0.85	0.36	0.82	0.39	0.09
Pneumonia, Lower	0.05	0.22	0.08	0.27	-0.12
Physician-pair characteristics					
Same gender	0.74	0.44	0.78	0.41	-0.09
Same HSA	0.40	0.49	0.30	0.46	0.21
Same HRR	0.86	0.35	0.78	0.41	0.20
Long-term sharing relationship	0.63	0.48	0.65	0.48	-0.05

Note: Summary statistics are based on the PCP-to-specialist patient-sharing sample. The left columns contain physician pairs where the PCP even switched to the same EHR developer as the specialist and the right columns report physician pairs where the PCP never switched to the same EHR as the specialist. [a] Values that exceed 0.25 indicate potentially problematic imbalance between the two groups (Imbens and Rubin, 2015; Baker et al., 2025).

Table 2. Difference-in-differences estimates of switching the PCP's EHR developer on patients shared with out-of-network specialists.

	(1)	(2)	(3)	(4)	(5)	(6)
Switch-to-same	0.057**	0.056**	0.047*	0.037**		
	(0.026)	(0.025)	(0.024)	(0.015)		
	[0.059]	[0.058]	[0.048]	[0.041]		
Switch-to-different					-0.043*	
					(0.026)	
					[-0.042]	
Different-to-different						0.013
						(0.010)
						[0.013]
N	309,527	309,527	309,527	263,887†	309,527	309,527
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician and hospital controls		Yes	Yes	Time-invariant	Yes	Yes
HRR-specific time trend			Yes			
CS-DiD				Yes		

Note: The treatment variable in columns (1)-(3) measures PCP switching to the same EHR developer as the specialist (including simultaneous switching). Column (4) shows the PCP switching from the same to a different EHR developer as the specialist and column (5) shows the PCP switching from a different EHR than the specialist to another different EHR. Exact percentage changes calculate as $e^{\beta} - 1$ are in square brackets. All standard errors are clustered at the PCP's affiliated hospital level and are reported in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.
†Estimated using a balanced panel.

Table 3. Triple-differences estimates of switching the PCP's EHR developer on patients shared with same-developer specialist across subpopulations.

	(1)	(2)	(3)	(4)	(5)	(6)
Switch-to-same	0.150***	0.033	0.096	0.079*	0.027	0.054**
	(0.037)	(0.033)	(0.073)	(0.044)	(0.027)	(0.025)
Interactions (0/1)						
Long-term relationship	-0.117***					
	(0.039)					
Same HSA		0.059				
		(0.048)				
Same HRR			-0.045			
			(0.079)			
Same gender				-0.030		
				(0.039)		
PCP has more experience than specialist					0.058*	
					(0.030)	
EHR market share > 50%						0.078*
						(0.047)
Sub-group treatment	0.033	0.092	0.051	0.049	0.085	0.132
	[0.034]	[0.096]	[0.052]	[0.050]	[0.089]	[0.141]
N	309,527	309,527	309,527	309,527	309,527	309,527
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column in Table 3 represents a triple-difference model that includes the *Switch-to-same* treatment effect and its interaction with various physician-pair characteristics. we categorized "long-term referral relationships" as those where the PCP-specialist pair shared patients for at least three consecutive years. "Sub-group treatment" reports the summation of DiD and triple-difference coefficients with exact percentage changes calculate as $e^{\beta} - 1$ in square brackets. All standard errors are clustered at the PCP's affiliated hospital level and are reported in parentheses. * p < 0.10 ** p<0.05 *** p<0.01.

Table 4. Robustness checks.

	(1) Main model	(2) Control group never switched	(3) Remove multiple referrals of same patient	(4) Treated once	(5) Remove pairs w/ < 11 referrals	(6) Recode missing referrals to 5	(7) Model w/ all types of switching	(8) Pr(shared patients >10)	(9) Raw scale outcome
Switch-to-same	0.056**	0.055**	0.047**	0.053**	0.054*	0.038*	0.056**	0.001	1.136**
	(0.025)	(0.025)	(0.021)	(0.027)	(0.031)	(0.021)	(0.027)	(0.013)	(0.508)
	[0.058]	[0.057]	[0.048]	[0.054]	[0.055]	[0.039]	[0.058]	[0.002]	[0.059]
Switch-to-different							-0.032		
							(0.026)		
							[-0.031]		
Different-to-different							0.014		
							(0.010)		
							[0.014]		
N	309,527	272,116	309,527	308,541	107,520	591,396	309,527	591,396	309,527
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Column (1) contains estimates from the main model in Table 2, column (2). In column (2) we restrict the control group to physician pairs that never switched EHR developer, and in column (3) we removed PCP referrals of the same patient to the same specialist. Column (4) we restrict the treatment group to PCP-specialist pairs that changed EHR developer only once. Column (5) contains estimates from a balanced panel constructed by removing PCP-specialist pairs with less than 11 shared patients in any year, while in column (6) the panel is balanced by re-coding missing referrals among physician pairs to 5. In column (7) we simultaneously model all types of EHR developer switching. In column (8) we estimate the probability that referrals exceed 10 (the extensive margin) and in column (9) we estimate a model using the raw scale outcome. Standard errors are clustered at the PCP's affiliated hospital level. Exact percentage changes calculate as $e^{\beta} - 1$ are in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

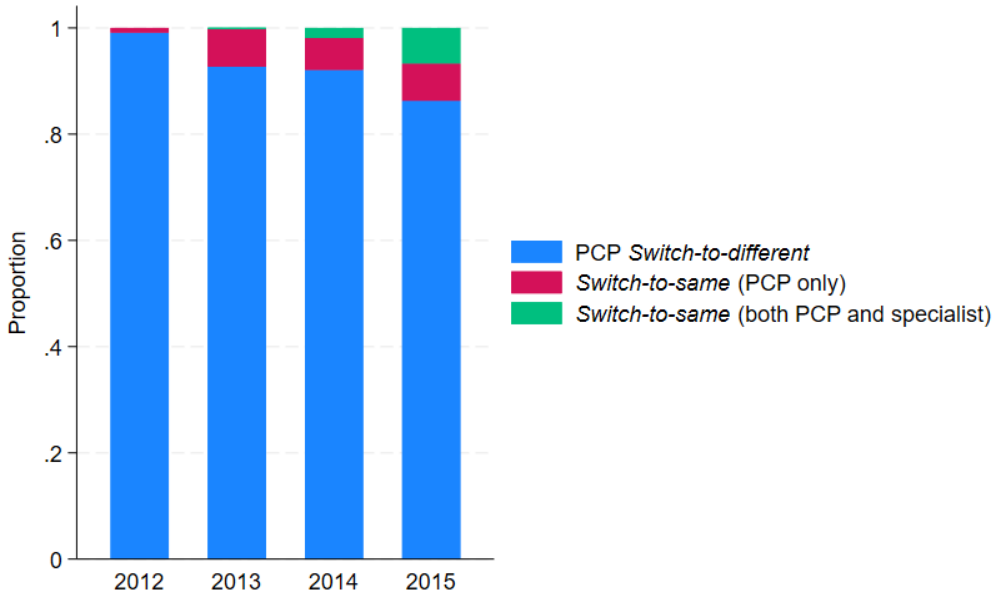
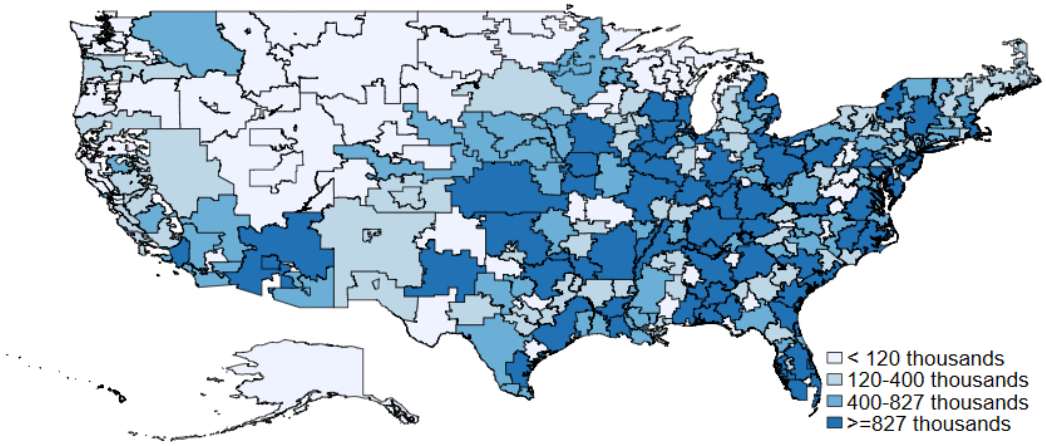
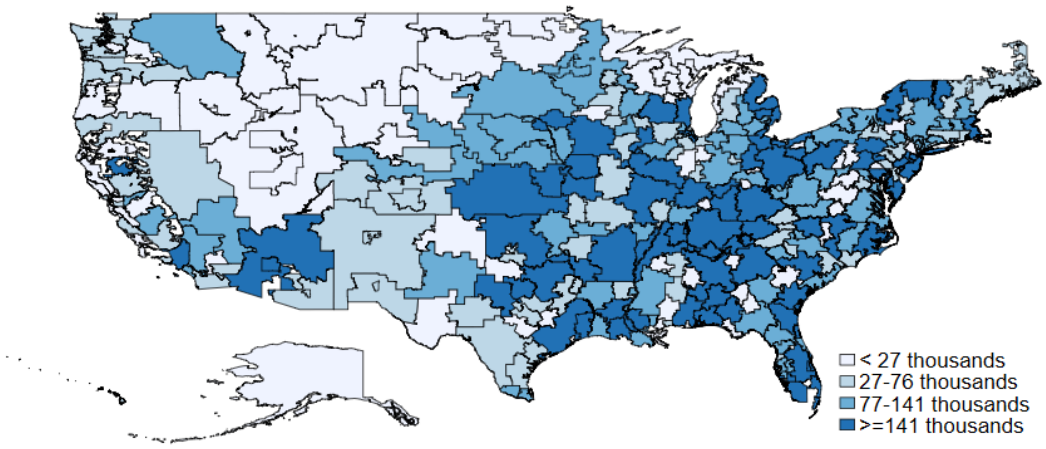


Figure 1. Trends in PCP patient sharing with specialists having the same EHR developer.

Note: Switching is defined as a change in the primary EHR developer used by PCPs' affiliated hospital, not including initial EHR adoption. *Switch-to-same* (PCP only) occurs when the PCP's affiliated hospital switches to the same primary EHR developer as the specialist, while *Switch-to-same* (both PCP and specialist) captures cases where both the PCP's and specialist's affiliated hospitals simultaneously switch to the same EHR. PCP S*witch-to-different* occurs when PCP's affiliated hospital switches to a different primary EHR developer than the specialist.



(A) Total number of shared Medicare patients



(B) Total number of shared patients between PCPs and specialists

Figure 2. Geographic variation in shared Medicare patients and patients shared between PCP and specialists across HRRs, 2011-2015 totals.

Note: Darker colors indicate higher levels of shared Medicare patients (in thousands) in panel A or of PCP-to-specialist referrals in panel B. The cutoff values used in the figure legends are quartiles of the corresponding measure.

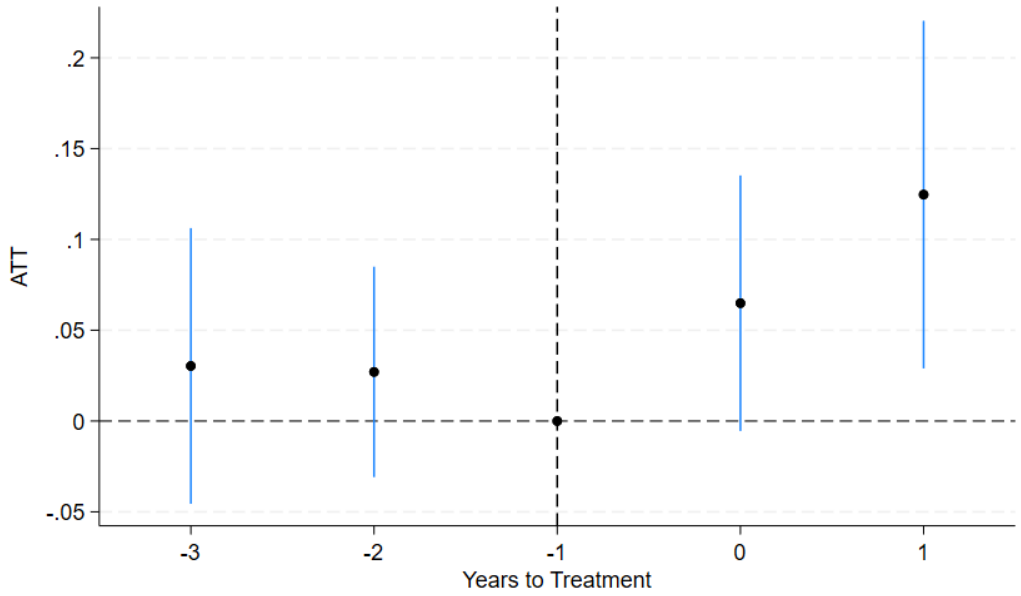


Figure 3. Event study for DiD model.

Note: The x-axis shows the relative time to the *Switch-to-same* event. Time = -1 is used as the baseline period. Y-axis is the coefficient on the leads and lags of *Switch-to-same*. 95% confidence intervals are displayed in the figure, with standard errors clustered at the PCPs' affiliated hospital level. The event study uses the same PCP-to-specialist sample as in the baseline DiD model.

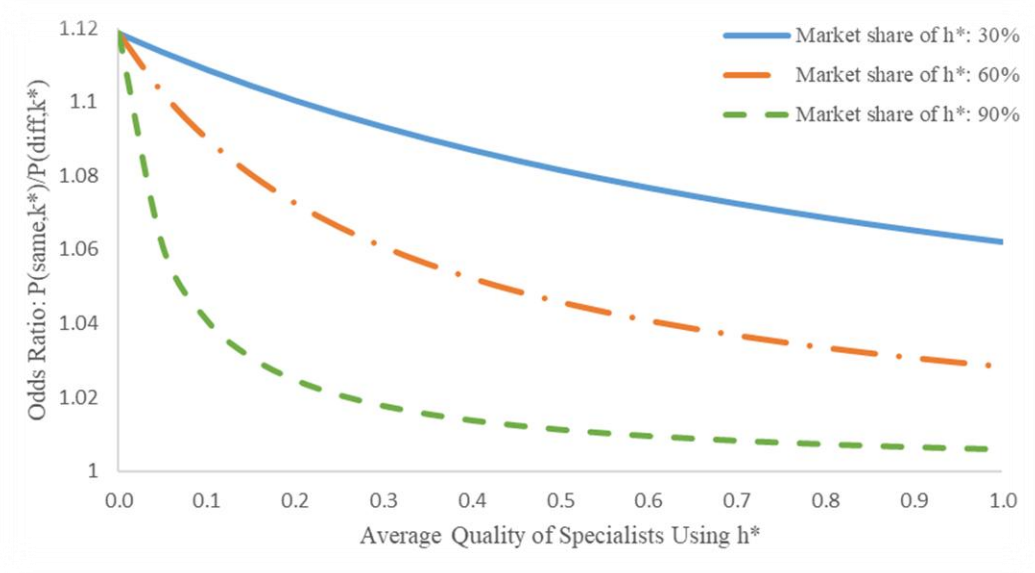


Figure 4. Distortion in quality-based referrals as a function of the same-developer specialist's average quality.

Note: The figure the simulation of the odds ratio — $(P_{same,k^*}/P_{diff,k^*})$ as a function as the average quality of specialists using the same EHR developer as specialist k^*, setting the average quality of specialists using the different EHR developer to 0.5. The topmost solid line shows the distortion when the market share of h^* is equal to 30%. The two dashed lines show the distortion effects when the market share of h^* is equal to 60% and 90%, respectively.

Appendix for "The Effects of Switching Electronic Health Record Developer on PCP-to-Specialist Patient Sharing"

A. Additional tables and figures.
B. Estimates using the 2013-2015 sample.
C. Proof of distorted referral patterns.
D. Proof of market agglomeration.

A. Additional tables and figures

Table A1. Two-way fixed effect estimation results with all control variables.

Variables	Coeff.	S.E.	t-statistic	p-value	95% Conf.	Interval
Switch-to-same	0.056	0.025	2.210	0.028	0.006	0.106
EHR market share of NPI1	0.000	0.000	-0.930	0.353	0.000	0.000
Same HSA	0.312	0.173	1.810	0.071	-0.027	0.650
Long-term sharing relationship	0.023	0.005	4.580	0.000	0.013	0.033
PCP characteristics						
Emergency hospital	0.021	0.025	0.840	0.400	-0.028	0.071
Number of hospital beds	0.000	0.000	1.050	0.296	0.000	0.000
umber of heart failure patients	0.000	0.000	-0.650	0.513	0.000	0.000
number of pneumonia patients	0.001	0.000	2.520	0.012	0.000	0.001
30-day readmission rate relative to national average (0/1)						
Heart failure, Similar	0.023	0.019	1.200	0.230	-0.014	0.060
Heart failure, Lower	0.014	0.015	0.990	0.324	-0.014	0.043
Pneumonia, Similar	0.016	0.028	0.580	0.560	-0.039	0.071
Pneumonia, Lower	0.006	0.026	0.220	0.826	-0.045	0.057
30-day mortality rate relative to national average (0/1)						
Heart failure, Similar	0.003	0.018	0.140	0.891	-0.033	0.038
Heart failure, Lower	0.013	0.012	1.150	0.250	-0.009	0.036
Pneumonia, Similar	0.010	0.015	0.670	0.501	-0.019	0.040
Pneumonia, Lower	0.023	0.010	2.270	0.024	0.003	0.043

Note: The table shows full estimates for Table 2, column (2) where the dependent variable is ln(proportion of shared patients from PCP *j* to specialists *k*). Standard errors are clustered at the PCP's affiliated hospital level.

Table A1, continued.

Variables	Coeff.	S.E.	t-statistic	p-value	95% Conf.	Interval
Specialist characteristics						
Emergency hospital	0.013	0.024	0.530	0.598	-0.034	0.060
Number of hospital beds	0.000	0.000	0.830	0.407	0.000	0.000
number of heart failure patients	0.000	0.000	-0.190	0.846	0.000	0.000
number of pneumonia patients	0.000	0.000	1.090	0.277	0.000	0.001
30-day readmission rate relative to national average (0/1)						
Heart failure, Similar	-0.011	0.016	-0.680	0.499	-0.043	0.021
Heart failure, Lower	-0.007	0.011	-0.620	0.534	-0.027	0.014
Pneumonia, Similar	0.019	0.018	1.030	0.303	-0.017	0.054
Pneumonia, Lower	0.018	0.015	1.230	0.218	-0.011	0.046
30-day mortality rate relative to national average (0/1)						
Heart failure, Similar	0.007	0.014	0.540	0.592	-0.020	0.034
Heart failure, Lower	0.002	0.009	0.170	0.862	-0.017	0.020
Pneumonia, Similar	0.021	0.014	1.510	0.132	-0.006	0.048
Pneumonia, Lower	0.002	0.010	0.210	0.832	-0.017	0.021
Year						
2012	0.039	0.005	8.660	0.000	0.030	0.048
2013	0.074	0.007	10.670	0.000	0.061	0.088
2014	0.096	0.008	12.190	0.000	0.080	0.111
2015	0.394	0.013	29.590	0.000	0.368	0.420
Constant	1.927	0.092	20.930	0.000	1.746	2.107

Note: The table shows full estimates for Table 2, column (2) where the dependent variable is ln(proportion of shared patients from PCP *j* to specialists *k*). Standard errors are clustered at the PCP's affiliated hospital level.

Table A2. Two-way fixed effect estimates for other patient-sharing channels.

	Specialist-to-PCP		PCP-to-PCP		Specialist-to-specialist		PCP-to-specialist within same hospital system	
	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
Switch-to-same	0.013	0.018	0.022	0.019	0.016	0.017	0.024	0.026*
	(0.020)	(0.020)	(0.047)	(0.047)	(0.013)	(0.012)	(0.016)	(0.015)
	[0.013]	[0.018]	[0.022]	[0.019]	[0.016]	[0.017]	[0.024]	[0.026]
N	316,876	316,876	40,338	40,338	1,189,635	1,189,635	92,138	92,138
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HRR-specific time trend		Yes		Yes		Yes		Yes

Note: Estimates in Table A2 are based on four different samples: Specialist-to-PCP, PCP-to-PCP, Specialist-to-specialist, and PCP-to-specialist (different hospitals of the same hospital system). For each subsample, we estimate a model with the same specification as Table 2, column (2) and a model with HRR-specific time trends. In all columns, we include physician-pair fixed effects, year-fixed effects, and physician and hospital characteristics. Standard errors are clustered at the affiliated hospital of NPI-1. Exact percentage changes calculate as $e^{\beta} - 1$ are in square brackets. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A3. Goodman-Bacon decomposition results.

	Beta	Total weight
Timing groups	0.012	0.006
	[0.012]	
Timing vs. never treated	0.043	0.985
	[0.044]	
Within	-0.111	0.010
	[-0.105]	

Note: Goodman-Bacon decomposition is performed using *bacondecomp* command in STATA using the baseline specification and including physician-pair fixed effects, year-fixed effects, and physician and hospital characteristics. The weights do not sum up to 1 due to rounding. The within row accounts for the inclusion of control variables in Goodman-Bacon decomposition. Exact percentage changes calculate as $e^{\beta} - 1$ are in square brackets. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

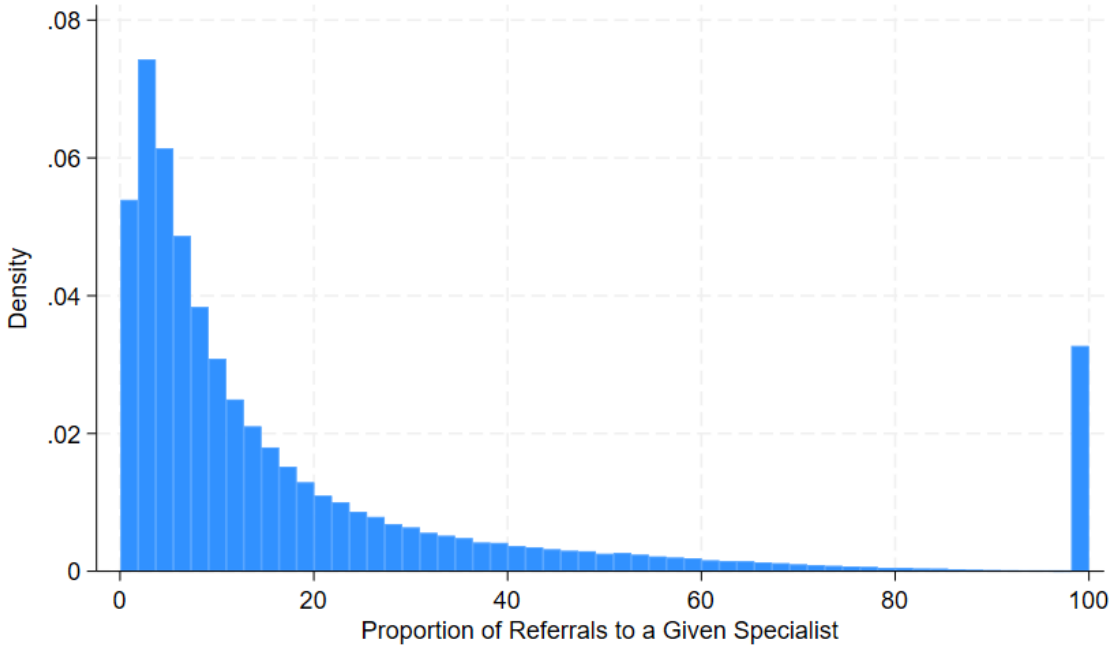


Figure A1. Empirical distribution of the proportion of patients shared with a given specialist.

Note: This figure presents the empirical density of the main outcome variable: the proportion of referrals from a primary care provider (PCP) to a given specialist, scaled from 0 to 100. The mass point at 100 indicates cases where the specialist was the sole recipient of referrals from a PCP—i.e., the only specialist to whom the PCP referred more than 10 patients in a given year.

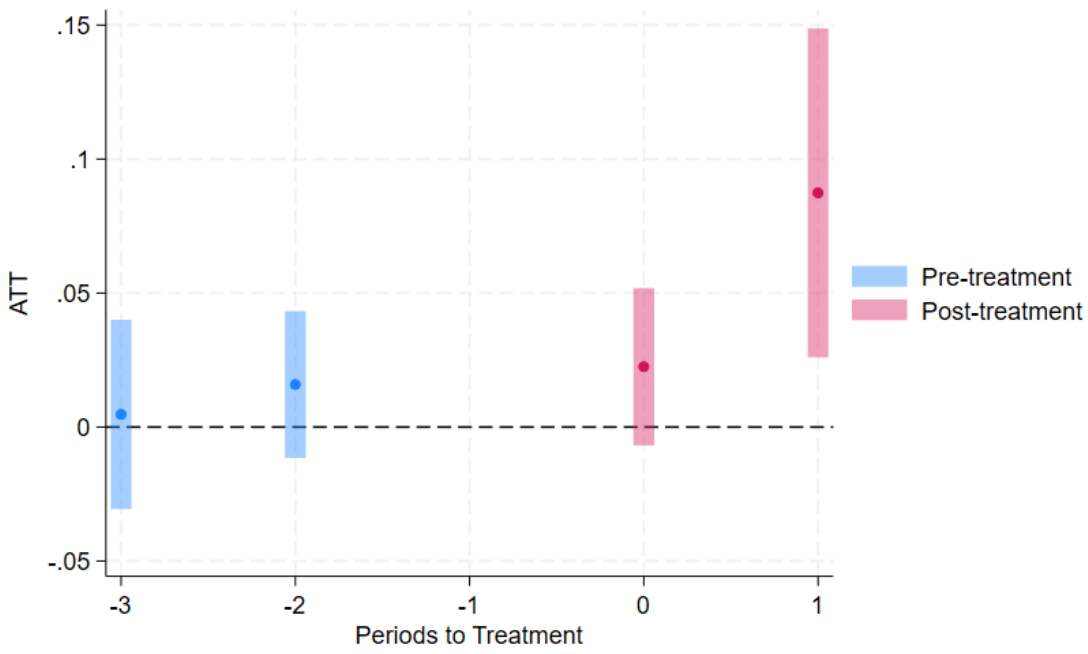


Figure A2. Event study for CS DiD model.

Note: This figure presents the event-study estimates using the doubly robust CS DiD estimator not-yet-treated observations as control group. The horizontal shows the relative time to the *Switch-to-same* treatment effect, with rime = -1 set as the base period. Coefficients on the leads and lags of the treatment effect are measured on the vertical axis with 95% confidence intervals constructed using standard errors clustered at the level of the PCPs' affiliated hospital.

B. Estimates using the 2013-2015 sample

When constructing the main sample, we assumed physicians did not change their hospital affiliation in 2011 and 2012 if they reported the same primary practice location during 2011-2015 and did not change their hospital affiliation from 2013 to 2015. To test whether our findings are sensitive to this assumption we re-estimated the models reported in Tables 2 and 3 using data from 2013-2015 for which we directly observe hospital affiliation.

Table B1 reports analogous results to those in Table 2, but for the shorter panel. The treatment effect coefficients all have the same sign for the main sample, but there are some small changes in the magnitudes. The coefficient on the *Switch-to-same* treatment effect in column 2 increases from 0.056 in Table 2 to 0.082 in Table B1 when the sample is restricted to 2013-2015. Coefficients on the *Switch-to-different* treatment effect are almost the same in the full and restricted sample, increasing in magnitude to only -0.047 from -0.043.

Table B2 contains estimates from the models with interacted treatment effects using the short panel that are analogous to Table 3. The results are qualitatively similar across the two samples. The coefficients on the interaction effect for long-term relationship is slightly smaller in magnitude in the 2013-2015 sample in Table B2, but the coefficient on the interaction term for EHR market share > 50% is larger in the short panel. The coefficient on the interaction term for PCP with more experience becomes statistically insignificant when the model is estimated using the short panel.

Table B1. Difference-in-differences estimates of switching the PCP's EHR developer on patients shared with out-of-network specialists (2013-2015).

	(1)	(2)	(3)	(4)	(5)	(6)
Switch-to-same	0.071***	0.082***	0.063***	0.052***		
	(0.023)	(0.024)	(0.024)	(0.017)		
	[0.074]	[0.085]	[0.065]	[0.053]		
Switch-to-different					-0.047*	
					(0.025)	
					[-0.046]	
Different-to-different						0.001
						(0.010)
						[0.001]
N	158,824	158,824	158,824	123,787	158,824	158,824
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Time invariant	Yes	Yes
HRR-specific time trend			Yes			
CS-DiD				Yes		

Note: The treatment variable in columns (1)-(3) measures PCP switching to the same EHR developer as the specialist (including simultaneous switching). Column (4) shows the PCP switching from the same to a different EHR developer as the specialist and column (5) shows the PCP switching from a different EHR than the specialist to another different EHR. Exact percentage changes calculate as $e^{\beta} - 1$ are in square brackets. All standard errors are clustered at the PCP's affiliated hospital level and are reported in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. †Estimated using a balanced panel.

Table B2. Difference-in-differences estimates of switching the PCP's EHR developer on patients shares with same-developer specialists, by subgroups (2013-2015).

	(1)	(2)	(3)	(4)	(5)	(6)
Switch-to-same	0.149***	0.060*	0.104**	0.117***	0.086***	0.024
	(0.044)	(0.032)	(0.049)	(0.039)	(0.025)	(0.031)
Interactions (0/1)						
Long-term relationship	-0.080*					
	(0.041)					
Same HSA		0.055				
		(0.043)				
Same HRR			-0.025			
			(0.056)			
Same gender				-0.047		
				(0.033)		
PCP has more experience					-0.009	
					(0.031)	
EHR share > 50%						0.093**
						(0.040)
Sub-group treatment	0.069	0.110	0.079	0.070	0.077	0.117
	[0.071]	[0.116]	[0.082]	[0.073]	[0.080]	[0.124]
N						
Clusters	158,824	158,824	158,824	158,824	158,824	158,824
Outcome Mean	2,572	2,572	2,572	2,572	2,572	2,572
Indicator Mean	20.591	20.591	20.591	20.591	20.591	20.591
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column in Table B2 represents a triple-difference model that includes the *Switch-to-same* treatment effect and its interaction with various physician-pair characteristics. Exact percentage changes calculate as $e^{\beta} - 1$ are in square brackets. All standard errors are clustered at the PCP's affiliated hospital level and are reported in parentheses. * p < 0.10 ** p<0.05 *** p<0.01.

C. Distorted referral patterns

C1. Proof of Proposition 1.

Consider a local physician referral market $(\mathcal{J},\mathcal{K})$ with only two EHR developers. Let $k^* \in \mathcal{K}$ be the specialist of the highest quality and let h^* denote the EHR developer used by k^*. Suppose n_{h^*} is the number of specialists using h^*, and $n_{\sim h^*}$ the number using the other developer.

Let P_{h,k^*} denote the conditional probability of k^* receiving referrals from a PCP using EHR developer $h \in \{h^*, \sim h^*\}$. Let $\delta_h \equiv E_{\kappa:h_\kappa=h}[\exp(\boldsymbol{x}'_{\boldsymbol{\kappa}}\boldsymbol{\gamma})]/\exp(\boldsymbol{x}'_{\boldsymbol{k}^*}\boldsymbol{\gamma})$, with $h \in \{h^*, \sim h^*\}$ denote the expected quality of the specialist pool using h^* (same) or the other EHR developer, relative to the quality of k^*.

Then, the probability of receiving referrals from a same-developer PCP is:

$$P_{h^*,k^*} = \frac{\exp(\beta+\boldsymbol{x}'_{\boldsymbol{k}^*}\boldsymbol{\gamma})}{\sum_{\kappa\in\mathcal{K}}\exp(V_{j\kappa})} \tag{C1}$$

$$= \frac{\exp(\beta+\boldsymbol{x}'_{\boldsymbol{k}^*}\boldsymbol{\gamma})}{\sum_{\kappa:h_\kappa=h^*}\exp(\beta+\boldsymbol{x}'_{\boldsymbol{\kappa}}\boldsymbol{\gamma})+\sum_{\kappa:h_\kappa\neq h^*}\exp(\boldsymbol{x}'_{\boldsymbol{\kappa}}\boldsymbol{\gamma})}. \tag{C2}$$

Normalize by the numerator and apply law of large number, we have:

$$\xrightarrow{p} \frac{1}{n_{h^*}\delta_{h^*}+\exp(-\beta)n_{\sim h^*}\delta_{\sim h^*}}. \tag{C3}$$

Similarly, the probability of receiving referrals from a different-developer PCP is:

$$P_{\sim h^*,k^*} \xrightarrow{p} \frac{1}{n_{h^*}\delta_{h^*}+\exp(\beta)n_{\sim h^*}\delta_{\sim h^*}}. \tag{C4}$$

More generally, when the market has more than two EHR developers, i.e. $|\mathcal{H}| > 2$, the referral probability from a same-developer PCP becomes:

$$P_{h^*,k^*} \xrightarrow{p} \frac{1}{n_{h^*}\delta_{h^*}+\exp(-\beta)\sum_{h\in\mathcal{H}\backslash\{h^*\}} n_h\delta_h}\ , \tag{C5}$$

and the probability of k^* receiving referrals from a PCP using a different EHR developer $h' \in \mathcal{H}\backslash\{h^*\}$ is:

$$P_{h',k^*} \xrightarrow{p} \frac{1}{n_{h^*}\delta_{h^*}+(e^{\beta}-1)n_{h'}\delta_{h'}+\sum_{h\in\mathcal{H}\backslash\{h^*\}} n_h\delta_h}\ . \tag{C6}$$

When $\beta = 0$, referral probabilities are symmetric across EHR developers: $P_{h^*,k^*} = P_{h',k^*}$ for all$h' \in \mathcal{H}\backslash\{h^*\}$. When $\beta > 0$, referrals to the highest-quality specialist k^* are more likely to

be made by PCPs who use k^*'s EHR developer: $P_{h^*,k^*} > P_{h',k^*}$, because $\sum_{h\in\mathcal{H}\setminus h^*}(n_h\delta_h) > e^{-\beta}\sum_{h\in\mathcal{H}\setminus h^*}(n_h\delta_h)$ and $\left(e^{\beta}-1\right)n_{h'}\delta_{h'} > 0$.

C2. Proof of Proposition 2.

The odds ratio of referrals to k^* from a PCP using the same versus a different EHR developer is given by:

(C7) $$\frac{P_{h^*,k^*}}{P_{\sim h^*,k^*}} = \frac{n_{h^*}\delta_{h^*}+e^{\beta}n_{\sim h^*}\delta_{\sim h^*}}{n_{h^*}\delta_{h^*}+e^{-\beta}n_{\sim h^*}\delta_{\sim h^*}}$$

(C8) $$= \frac{e^{\beta}+\frac{n_{h^*}\delta_{h^*}}{n_{\sim h^*}\delta_{\sim h^*}}}{e^{-\beta}+\frac{n_{h^*}\delta_{h^*}}{n_{\sim h^*}\delta_{\sim h^*}}}.$$

Let $R \equiv \delta_{h^*}/\delta_{\sim h^*}$ denote the relative quality of specialists using same and different EHR developers. Define $\alpha = n_{h^*}/n_{\sim h^*}$. Then the odds ratio simplifies to

(C9) $$= \frac{e^{\beta}+\alpha R}{e^{-\beta}+\alpha R}.$$

Differentiating the odds ratio with respect to R, we obtain:

(C10) $$\frac{\partial}{\partial R}\left(\frac{P_{h^*,k^*}}{P_{\sim h^*,k^*}}\right) = \frac{\alpha\left(e^{-\beta}+\alpha R\right)-\alpha\left(e^{\beta}+\alpha R\right)}{\left(e^{-\beta}+\alpha R\right)^2}$$

(C11) $$= \frac{\alpha\left(e^{-\beta}-e^{\beta}\right)}{\left(e^{-\beta}+\alpha R\right)^2}.$$

Since $\alpha > 0$ and $\beta > 0$, we have $\frac{\partial}{\partial R}\left(\frac{P_{h^*,k^*}}{P_{\sim h^*,k^*}}\right) < 0$. That is, the odds of referring to the highest-quality specialist k^* from same- versus different-developer PCPs is a decreasing function of the relative quality of specialists using h^*.

D. Proof of market agglomeration

Consider a market of two EHR developers $\{A, B\}$ with the proportion of PCPs using *A* greater than the proportion of PCPs using *B*. A specialist *k* is choosing between *A* and *B* to maximize his/her probability of receiving referrals, denoted by $\pi_h : h \in \{A, B\}$. When the number of specialists is sufficiently large to prevent n_h from affecting the choice of *k*, we have:

(D1) $\pi_A = P(A)P_{A,k} + P(B)P_{B,k}$

(D2) $= \frac{P(A)}{n_A\delta_A + e^{-\beta}n_B\delta_B} + \frac{P(B)}{n_A\delta_A + e^{\beta}n_B\delta_B}$,

and

(D3) $\pi_B = P(A)P_{A,k} + P(B)P_{B,k}$

(D4) $= \frac{P(A)}{n_A\delta_A + e^{\beta}n_B\delta_B} + \frac{P(B)}{n_A\delta_A + e^{-\beta}n_B\delta_B}$.

When $\beta = 0, \pi_A = \pi_B$. When $\beta > 0$, we have $(n_A\delta_A + e^{\beta}n_B\delta_B) > (n_A\delta_A + e^{-\beta}n_B\delta_B)$. Because $P(A) > P(B)$, pairing $P(A)$ with $1/(n_A\delta_A + e^{-\beta}n_B\delta_B)$ will yield the greatest summation of products (rearrangement inequality).

Next, consider a market with more than two EHR developers. Without loss and generality, let $\mathcal{H} = \{h_i\}_{i=1}^{|\mathcal{H}|}$ with $P(h_1) > P(h_2) > \ldots > P(h_{|\mathcal{H}|})$.

(D5) $\pi_i = \sum_\iota P(h_\iota)P_{\iota,k}$,

where

(D6) $$P_{\iota,k} = \begin{cases} \frac{1}{n_i\delta_i + e^{-\beta}\sum_{h\neq h_i} n_h\delta_h}, & if\ i = \iota \\ \frac{1}{n_i\delta_i + \sum_{h\neq h_i} n_h\delta_h + (e^{\beta}-1)n_i\delta_i}, & if\ i \neq \iota \end{cases}$$

When comparing π_1 with any other choice $\pi_{i:i\neq 1}$, most terms in Equation (D5) remains same across i and therefore cancel out. As a result, comparing π_1 with $\pi_{i:i\neq 1}$ is equivalent to comparing

$$\frac{P(h_1)}{n_1\delta_1 + e^{-\beta}\sum_{h\neq h_i} n_h\delta_h} + \frac{P(h_i)}{n_1\delta_1 + \sum_{h\neq h_1} n_h\delta_h + (e^{\beta}-1)n_i\delta_i}$$

with

$$\frac{P(h_1)}{n_i\delta_i + \sum_{h\neq h_i} n_h\delta_h + (e^{\beta}-1)n_1\delta_1} + \frac{P(h_i)}{n_i\delta_i + e^{-\beta}\sum_{h\neq h_i} n_h\delta_h}.$$

Assuming all EHR developers have similar aggregated quality, $n\delta$, the multiple-developer scenario degenerates to the two-developer case.