The Effects of Switching Electronic Health Record Developer on Specialty Referrals

By Bingjin Xue*

Draft: November 14, 2022

Latest Draft

I use national physician-pair panel data to assess the effect of switching electronic health record (EHR) developers on patient sharing patterns among outpatient primary care physicians and specialists. To address the potential endogeneity of individual physicians' preferences for specific EHR developers, I exploit EHR switching decisions made by the physicians' affiliated hospitals and implement an instrumental variables analysis. I estimate that primary care physicians (PCP) increase their referrals to same-developer specialists by 5.3% after switching to a new EHR developer. Based on a discrete choice framework, I also find evidence of market agglomeration and misallocation of referrals across specialists of different quality. My results have implications for health care market structure as well as regulatory policies that seek to limit information blocking by EHR developers.

JEL: C25; D90; I11; I18

Keywords: Electronic Health Record; Physician Referral; Physician Homophily; Information Blocking

* Xue: Department of Economics, Lehigh University, bix216@lehigh.edu. I thank Chad Meyerhoefer for his guidance and advice; I am also grateful to Jee-Hun Choi, Ernest Lai, Thomas McAndrew, Jing Li, Kevin Smith, Nathaniel Breg, and participants at the 2022 American Society of Health Economists Annual Meeting for many helpful comments.All errors are my own.

Introduction

The past decade has witnessed the increasingly important role of electronic health records (EHR) in the expansion of health information exchange (Adler-Milstein, Lin and Jha, 2016; Holmgren and Adler-Milstein, 2017; Lin, Jha and Adler-Milstein, 2018). As the EHR market has grown, so has competition among EHR developers. 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 supply certified health IT to 4,520 non-federal acute care hospitals (CB Insights, 2021; HealthIT.gov, 2017). At the same time, top EHR developers kept gaining larger market shares, which drove a lot of EHR developer switches for system functionality, lower cost, or the attainment of Meaningful Use milestones (Freedman, Lin and Prince, 2018; Coustasse et al., 2018; Seth Joseph et al., 2014). Despite advances in our understanding of the motivation and user experiences associated with such transitions, less is known about the impact of switching EHR developers on physician patient-sharing patterns, especially in the outpatient setting.

This paper provides causal evidence that switching EHR developer significantly impacts primary care physicians (PCPs) specialty referral decisions. Specifically, I show that when a PCP switches to the same developer as a specialist, a larger number of patients is shared between the two physicians. Although homophily in physician referrals has been widely studied, this paper is among the first to investigate homophily associated with Health IT. This is an import margin to study not only because 96% of U.S. non-federal acute care hospitals employ EHR systems (Office of the National Coordinator for Health Information Technology, 2022), but also because physician referrals through EHRs can significantly influence patient outcomes (Han et al., 2019; Kossman and Scheidenhelm, 2008; Blease et al., 2021).

Combining various data sources, I construct and examine a nationwide physician-pair-level panel with information on the number of Medicare patients shared between each pair of physicians between 2011 and 2015.[1,2] Because the EHR developer switches simultaneously for physicians affiliated with the same hospital and, with a high probability, for those in the same healthcare system, I consider only patient-sharing outside the referral-initiating physician's healthcare system. This exclusion also rules out the effect that vertical integration in healthcare has on physician referrals (Brot-Goldberg and de Vaan, 2018; Carlin, Dowd and Feldman, 2015). Further, to avoid the influence of physician migration (Arah, Ogbu and Okeke, 2008), my sample only includes physicians who did not change hospital affiliation and primary practice location during the sample period.

A key challenge to identifying the effect of EHR switching is the potential endogeneity of physician preferences. In this context, the referral-initiating physician may intentionally switch to the same EHR developer as a referred-to physician in seek of better cooperation. Or alternatively, a referral-initiating physician may be reluctant to switch the current EHR developer due to formed habits. To address this problem, I only consider EHR switching decisions made by the physician's affiliated hospital. Since EHR decisions at the hospital level are less affected by individual preferences, this strategy allows me to rule out the effect of physician preferences.[3]

I also analyze a period of time (2011 to 2015) when EHR switching decisions were significantly affected by policies. In 2011, the Centers for Medicare and Medicaid Services (CMS) established an incentive payment program - the Promoting Interoperability (PI) program - to promote the adoption and meaningful use of EHRs at both the physician and hospital levels. The program created "Meaningful Use" criteria to evaluate the amount of incentive payment sent to health care providers.[4] In a 2014 survey, Adler and Edsall (2015)

[1] The main data source is the Physician Shared Patient Patterns (PSPP) 30-day data file. PSPP is produced from the Integrated Data Repository (IDR) database, which houses Medicare claims from the National Claims History (NCH) database

[2] Sharing is identified from Medicare claims where two physicians participate in the delivery of health services to the same patient within a 30 days period.

[3] Implementation of a EHR system at the hospital level requires significant financial investment, comprehensive planning, and ongoing assessment. When selecting an EHR, hospitals will create a selection committee encompassing doctors and administrative staff from different departments. (Bartley and Daiker, 2022)

[4] Meaningful Use (MU) sets specific objectives that eligible professionals and hospitals must achieve to participate in the CMS PI program. These objectives aim at the utilization of certified EHR systems to (1) improve quality, safety, efficiency, and reduce health disparities; (2) engage patients and family; (3) improve care coordination, and population and public health; and (4) maintain privacy and security of patient health information (HealthIT.gov, 2015).

reported that the top two reasons for EHR transitions were to get added functionality and to achieve Meaningful Use. Such policy-driven transitions can be viewed as a pseudo-experiment that is relatively exogenous to individual physicians' patient-sharing decisions. In an alternative identification strategy, I employ an instrumental variable approach to address the endogeneity of hospital EHR switching decisions by constructing the following instruments: (1) whether the hospital enters a new CMS PI program stage and (2) whether the hospital is merged into or acquired by a healthcare system. I show that physicians with EHR developers affected by PI program stage or system mergers and acquisitions have a greater tendency in referring patients to same-developer physicians.

My results indicate that switching primary EHR developer results in more patient-sharing between PCPs and specialists using the same developer. On average, when a hospital adopts a new EHR developer, the proportion of out-of-healthcare-system patient sharing from a PCP to a same-developer specialist increases by 5.3%, which translates to 12 more patients per year. This change is at the expense of a 4.3% decrease in patient sharing with specialists who had the same EHR developer as the PCP before the switch. In addition, there is no change in patient-sharing patterns with specialists who used a different developer prior to the switch. I also examine other types of referrals and find no significant change in sharing patterns in PCP-to-PCP, specialist-to-specialist, or specialist-to-PCP patient sharing.

I show how my findings are consistent with the prediction from a discrete choice model. In particular, PCPs who use a different EHR developer are less likely to refer patients to the highest-quality specialist compared with PCPs who use the same developer as the specialist. This gap in probability becomes larger as the highest-quality developer faces less competition in service quality from the other specialists who use the same developer. The model also indicates that specialists can maximize their probability of receiving referrals by choosing the EHR developer used by most PCPs, which predicts EHR market agglomeration.

This study contributes to the physician referral literature as the first to examine the impact EHR developers on outpatient sharing between physicians. Previous studies have primarily considered patient, physician, and health care system structural characteristics associated with physicians' referral behavior (Barnett et al., 2012; Dunlea and Lenert, 2015; Forrest et al., 2006; Kinchen et al., 2004; Linde, 2019). Although these studies provide important insights into the determinants of physician referrals, they do not consider the increasingly important role of EHRs on physicians' referral patterns. I contribute to this strand of literature by modelling EHR developer choices in PCPs' specialty-referral utility and empirically identifying the effect of switching EHR developers on physician patient-sharing patterns.

This paper also adds to the literature on EHR developer market agglomeration. Despite extensive research on agglomeration and innovation in other setting (Carlino and Kerr, 2015; Behrens and Robert-Nicoud, 2015), we know little about whether and how EHR developer competition leads to a more concentrated market (Freedman, Lin and Prince, 2018). This paper is among the first to study EHR developer market transitions and agglomeration and, to the best of my knowledge, the first to examine its association with physician referrals.

Finally, this paper informs studies and policies related to information blocking. The term *information blocking* refers to intentional and unreasonable interference with the exchange or use of electronic health information (HealthIT.gov, 2022). For EHR developers, emphasizing within-developer exchange of information and impeding the connectivity to other developers can be financially beneficial but detrimental to patient outcomes (Everson and Adler-Milstein, 2016; Eastaugh, 2013). Despite the ongoing policy efforts such as the 21st Century Cures Act to curtail information blocking, Everson, Patel and Adler-Milstein (2021) found in a recent national survey that EHR developers regularly engage in information blocking. This paper demonstrates that physicians prefer to share patients through the same EHR developers, which suggests the cost associated with between-developer patient sharing significantly influences physician referral decisions. If EHR interfaces deliberately increase these costs, they are in violation of rules against information blocking.

The rest of the paper proceeds as follows. Section I provides background on EHR and the CMS PI program. Section II describes the data and summary statistics, and section III establishes the empirical framework. Section IV presents the results and checks robustness. Section V discusses implications and counterfactual analyses, followed by conclusions in VI.

I. Background

EHRs are digital forms of patient records that include information on the patient's residential address, medical history, allergies, test results, and treatment plan (Häyrinen, Saranto and Nykänen, 2008). Such digitization relies on the services and products offered by various EHR developers and aims to reduce administrative waste and duplication, facilitate better health information exchange and patient referrals among health care providers, and ultimately improve public health outcomes (de la Vega et al., 2019; Bowles et al., 2017).

In 2009, the Congress passed the Health Information Technology for Economic and Clinical Health (HITECH) Act to promote meaningful EHR adoption. Two years following the Act, the Centers for Medicare & Medicaid Services (CMS) established an incentive payment program now known as the EHR Promoting Interoperability Program (PI). Eligible Medicare professionals who adopt, implement, upgrade, and demonstrate meaningful use of certified EHR technology could receive up to $44,000 over five years from CMS (Kibbe, 2010). For eligible hospitals, the maximum Medicare incentive payment in the first year of attestation was $6.3 million.[5] The program was effective in that the portion of US hospitals with at least a basic EHR system increased from 9% in 2008 to 84% in 2015 (CMS, 2017; Henry et al., 2016).[6]

To qualify for the incentive payment from the PI program, eligible health care providers had to meet certain criteria set by CMS and the Office of the National Coordinator for Health IT. This set of criteria, formally known as the Meaningful Use measures, evolved in a three-stage manner, each of which required meeting increasingly comprehensive EHR standards. In 2011, Meaningful Use Stage 1 established preliminary requirements for the

[5] https://www.cms.gov/regulations-and-guidance/legislation/ehrincentiveprograms/downloads/mln_tipsheet_medicarehospitals.pdf

[6] Basic EHR adoption requires supports for electronic clinical information, computerized provider order entry, and results management.

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, importantly, the exchange of information among providers. For example, Meaningful Use Core Measure 12-1 requires eligible hospitals and Critical Access Hospitals (CAH) who transit or refer their patients to another setting of care to provide a summary of care records for more than 50 percent of the referrals. In addition, Core Measures 12-2 and 12-3 further require the electronic transmission of these care records using certified EHR technology to a recipient. In October 2015, CMS released a final rule that established Stage 3 with a focus on health outcome measures.

Because of the HITECH Act's requirement, CMS publicly posted information on eligible hospitals that successfully attested meaningfully using a certified EHR during this period.[7] These public data include two hospital identifiers – the CMS Certification Number (CCN) combined with the National Provider Identifier (NPI) - and a hospital-year specific EHR Certification Number (CMS ID). The latter can be linked to a detailed list of EHR products and developers used in the attestation.

II. Data

A. *Referral Data*

My analysis combines data from several sources. The main sample is primarily based on the CMS Physician Shared Patient Patterns 30 days data file (PSPP): a panel dataset that contains the annual number of shared Medicare patients among all health care providers in the United States. *Sharing* in the PSPP is defined as when two organizations or practitioners participate in the delivery of health services to the same Medicare patient within 30 days, as identified in the National Claims History (NCH) database. To protect patients' privacy, CMS only reports physician pairs with at least 11 distinct shared patients over the course of a given year. These data inform the direction of sharing through the Medicare claim date of each provider (with the earlier date indicating the referring physician).

[7]See EH Recipients of Medicare EHR Incentive Payments, and Eligible Hospitals Public Use File (PUF). Note that these releases contain EHR Incentive Program data on eligible hospitals in the Medicare EHR Incentive Program. Attestation to the Medicaid Incentive program is not publicly available.

Henceforth, I use the terms "referral" and "patient-sharing" synonymously to indicate the existence of patient-sharing direction. Because this study focuses on physicians, I exclude any sharing from (or to) organizational health providers - providers with a Type 2 National Provider Identifier (NPI) in the CMS National Plan and Provider Enumeration System (NPPES). [8]

Using 2011 - 2015 archived data from NPPES, I also merge in variables that indicate the physician's primary practice address and the associated zip code. I further exclude physicians who changed primary practice address (relocated) during the sample period. This exclusion precludes simultaneous changes in referral patterns and EHR systems as a result of relocation.

Long-term versus short-term sharing history

To investigate the role of patient-sharing history, I compute a measure of PCP's familiarity with specialist based on their patient-sharing records. Specifically, I define *Long-term Sharing* relationship as an indicator for whether a PCP-specialist pair is observed in PSPP for at least three consecutive years up until a given year. [9]

B. Physician Affiliations

I obtain each physician's primary hospital affiliation, primary specialty, experience, and demographic information from the Physician Compare National Downloadable File (PC).[10,11] Because PC starts in 2013, I extrapolate physicians' hospital affiliation in 2013 to 2011 and 2012. This assumes that physicians who remained in the same primary practice addresses from 2011 to 2015 did not change their primary hospital affiliation during

[8] The National Plan and Provider Enumeration System (NPPES) assigns National Provider Identifiers (NPI) – a 10-digit unique identification number – to covered health care 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. NPPES assigns a Type 1 NPI to individual health care providers, including physicians, dentists, and all sole proprietors, and a Type 2 NPI to all organizations. I subset the data to providers with a Type 1 NPI.

[9] The choice of the window width - 3 year - is due to data availability. To identify Long-term Sharing relationships in the earliest sample period, 2011, I use PSPP 2009 and 2010 data.

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

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

2011-2013. I carry out a sensitivity analysis regarding this assumption in Appendix B. Restricting the sample to 2013-2015 shows consistent findings.

I define physicians as PCP if their primary specialty is one of the followings: family practice, internal medicine, pediatric medicine, geriatric medicine, and general practice. Correspondingly, the other physicians are defined as specialists. In the main analysis, I restrict the sample to PCP-to-specialist sharing pairs so that the interpretation of referral is consistent with the common healthcare delivery models where the PCP acts as the gatekeeper in authorizing patients' access to specialty care, hospital care, and diagnostic tests (Garrido, Zentner and Busse, 2011). I also examine the other directions of referrals in Section IV.C.

To control for hospital level confounders, I merge hospital characteristics from two data sources. First, I obtain the number of hospital beds, health care system designation, Hospital Service Area (HSA) code, and Hospital Referral Region (HRR) code from The Dartmouth Atlas of Health Care Hospital Research data. Second, from the CMS Hospital Compare data archives, I obtain the type of hospital, whether the hospital has 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 relative to the national means.

Finally, I exclude physicians whose primary hospital affiliation change during 2011 to 2015 to preclude the effect of relocation. In addition, I exclude physician pairs that are affiliated with that same hospital or hospital system, because they always (or with a high probability in the case of sharing the same hospital system) use the same EHR developer.

C. Primary EHR Developer of The Affiliated Hospital

I use two additional data sources to identify the primary EHR developer of each hospital.[12] First, I link each hospital-year observation to a CMS ID, a unique identifier assigned by the CMS PI program to hospital-years that successfully attest for the EHR incentive payment, using the CMS Eligible Hospitals Public Use File (PUF). With these CMS ID, I

[12]Hospitals eligible for the incentive payment from the PI program are one of the following types of hospitals: (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

obtain a complete list of Certified-EHR products and developers associated with each attestation from the Certified Health IT Product List (CHPL) API. I then define the primary EHR developer as one that provides the largest number of Certified EHR products to a hospital in a given year. In addition, I calculate the market share of the referral-initiating physician's EHR developer within the HRR to account for the variations in health information exchange due to EHR developer's marketplace dominance (Sorace et al., 2020).

D. Panel Construction and EHR Developer Switch

Before creating a variable to indicate an EHR developer switch, I balance the panel sample such that all physician pairs have five years of observations. This means that if sharing is not present in PSPP data due to left truncation, the number of patients shared is designated as zero. This enables me to analyze the extensive margin and identify the exact timing of an EHR switch. Note that despite the missing values in PSPP, the other variables, such as hospital affiliation and primary EHR developer, may not be missing and are constructed in the same manner as described in the previous sections.

I create several indicators to measure EHR developer switching. I define a *Switch-to-Same* event as: the referral-initiating physician switches from their current EHR developer to a different one and ends up using the same EHR developer as the referred-to physician. This excludes physicians' initial adoption of an EHR system or when there is a gap in the physicians' attestation to the CMS PI program. Figure 1.(A) displays the relative frequencies of switching EHR developers (regardless of the direction) and the *Switch-to-Same* events in each year of the sample period.

Figure 1.(A) displays the relative frequencies of switching EHR developers (regardless of the direction) and the *Switch-to-Same* events in each year of the sample period. As shown in 1.(A), EHR developer switches have become increasingly common since the commencement of the CMS PI program in 2011. In 2014 alone, more than one-fifth of the primary care physicians underwent a primary EHR developer switching. Although a large proportion of these transitions did not result in physicians' using the same EHR developer, there is a steady upward trend in the relative frequency of *Switch-to-Same*. The percentage of PCPs

that switches EHR and end up using the same developer as the referred-to specialists went up from less than 0.1% in 2012 to around 2% in 2015, accounting for 12.81% of all switches in that year. A similar trend can be observed in Figure 1.(B). The percentage of physician pairs that have the same EHR developer shows an 18.43% compounded annual growth rate over the sample period.

E. Summary Statistics

The main sample contains 130,649 unique PCP-to-specialist pairs and 653,245 pair-year level observations. The sample covers all HRRs except UT-PROVO. In Figure 2, I demonstrate the spatial variation of the relative frequency of *Switch-to-Same* and the total number of shared patients among HRRs. Interestingly, Switch-to-Same and patient sharing intensity show similar geographical distribution: with high relative frequency and intensity in Middle and South Atlantic, West and East North Central, and West South Central regions. The observed spatial pattern also coincides with the distribution of Medicare beneficiaries who have multiple chronic conditions (Lochner and Shoff, 2015).

Table 1 contains the summary statistics of the key variables in the PCP-to-specialist sample. On average, physician pairs that have ever switched to same EHR developer are similar to those who have not in terms of PCP and Specialist experience, whether the affiliated hospital have an emergency department, and hospital patient volume and quality. However, physician pairs in the ever-switch-to-same subsample have a smaller proportion of male PCPs, less referrals per PCP per year, and are generally affiliated with hospitals with less beds. On the contrary, the primary EHR developer of the PCPs in the the ever-switch-to-same subsample have a larger market share. In my empirical model, I account for these differences by controlling for sharing-pair fixed effects and HRR-specific time trends, and I test for the common-trend assumption in the robustness test.

In addition, patient sharing happens predominantly within geographical areas. Although only 25-28% of patient sharing occurs in the same city, same-state sharing accounts for 90-95% of patient sharing in both ever-switch-to-same and never-switch-to-same subsample. On average, a PCP refer patients to 8-10 specialists per year. Approximately 44% of these sharing relationships last longer than two years.

III. Empirical Framework

To quantify the effect of EHR developer on physician referral decisions, I analyze a discrete choice model in which PCPs choose specialists based on whether they are using the same EHR developer and other pair-specific characteristics. I use this framework to discuss how the effect of switching is related to a two-way fixed effect model where the *Switch-to-Same* variable is used to predict the natural logarithm of the proportion of shared patients from a PCP to a specialist.

Consider a static bipartite physician referral network where patients are only referred from PCPs to specialists. Let J and K denote the set of PCPs and specialists in a given HRR, respectively. The primary EHR developer used by PCP j and specialist k are denoted by h_j and h_k, and let $H = \{h_j\}_{j \in J} \cup \{h_k\}_{k \in K}$ be the set of all EHR developers in an HRR. Given the choice set K, a PCP maximize the following utility function by choosing a specialist k,

$$arg \max_{k \in K} U_j(k) = \beta \mathbf{1}\{h_j = h_k\} + \mathbf{X_{jk}} \gamma + \epsilon_{jk}, \tag{1}$$

where $\mathbf{1}\{h_j = h_k\}$ indicates PCP j and the specialist k use the same primary EHR developer. If $\beta > 0$, referral preference of the PCP is biased towards same-developer specialists. Equation (1) specifies a conditional-logit model, in which $\mathbf{X}_{jk}$ is a vector of characteristics of either the specialist (e.g. specialty, experience) or the pair (e.g. PCP and the specialist being in the same HSA; having the same gender). Assuming ϵ_{jk} is an independently and identically distributed Gumbel extreme value, we can derive the following conditional probability:

$$p_{jk} \equiv Pr(K = k | J = j) = \frac{e^{v_{jk}}}{\sum_{\kappa} e^{v_{j\kappa}}}, \tag{2}$$

where $v_{jk} \equiv E[U_j(k)] = \beta \mathbf{1}\{h_j = h_k\} + \mathbf{X_{jk}}\gamma$ is the expected utility of PCP j referring patient to k.

A direct estimation of Equation 2 requires observations on individual referrals, but my sample only contains referrals at an aggregated level - the number of referred patients between each pair of physicians. To identify the parameters in Equation (2), I take natural logarithm of both sides of Equation (2):

$$ln(p_{jk}) = \beta \mathbf{1}\{h_j = h_k\} + \mathbf{X_{jk}}\gamma - ln(\sum_{\kappa} e^{v_{j\kappa}}). \tag{3}$$

Note that the last term in Equation (3) is a measure of the total utility that PCP j obtains from referring patients, regardless of which specialist he/she refers to. In other words, $-ln(\sum_{\kappa} e^{v_{j\kappa}})$ is PCP-specific and we can rewrite Equation (3) as:

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

Finally, we introduce uncertainty by replacing p_{jk} with its sample estimate:

$$\hat{p}_{jk} \equiv \frac{\text{Number of patient shared from PCP } j \text{ to specialist } k}{\text{Number of patient shared from PCP } j}. \tag{5}$$

$\hat{p}_{jk}$ is the fraction of PCP j's patients that are referred to specialist k, and it converges to p_{jk} by the law of large number. Combining Equation (3) and (5), we have

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

$$\approx ln(E[\hat{p_{jk}}]) - \frac{V(\hat{p_{jk}})}{2E[\hat{p_{jk}}]} + u_{jk} \tag{7}$$

$$= \beta \mathbf{1}\{h_j = h_k\} + \mathbf{X_{jk}}\gamma + \alpha_j - \frac{V(\hat{p_{jk}})}{2E[\hat{p_{jk}}]} + u_{jk}. \tag{8}$$

Assuming α, β and γ do not vary in time, and the time variation of $\alpha_j - \frac{V(\hat{p_{jk}})}{2E[\hat{p_{jk}}]} + u_{jk}$ is additive, we arrive at the following two-way fixed effect specification that I estimate:

$$(9) \qquad ln(\hat{p}_{jkt}) = \beta \times \text{Switch-to-Same}_{jkt} + \mathbf{X}_{jkt}\gamma + \alpha_{jk} + \tau_t + v_{jkt},$$

where *Switch-to-Same*$_{jkt}$ indicates PCP i switches to the same developer as specialist k at time t or earlier and is still using the same EHR developer as specialist k. $\mathbf{X}_{jkt}$ is a vector of time-varying control variables, including the market share of the EHR developer employed by the PCP, a variable to indicate whether the two physicians belong to the same Hospital Service Area (HSA) and whether the pair has a long-term sharing relationship.[13] In addition, I control, at the hospital-year level, for the number of hospital beds, whether the hospital has an emergency unit, and eight readmission and mortality measures for heart failure and pneumonia for both physicians' affiliated hospitals. α_{jk} and τ_t capture the pair- and year-fixed effects, which accounts for the total utility of PCP from referring patients, the difference between $E[ln(\hat{p_{jk}})]$ and $ln(E[\hat{p_{jk}}])$, and any pair- of year-specific confounders not included in $\mathbf{X}_{jkt}$. Finally, v_{jkt} is a residual term with zero mean.

Specification (9) modifies Equation (8) in two important ways. First, since my analysis focuses on the effect of EHR switching instead of initial adoption, I only consider the influence of physicians' using the same EHR developer as a result of PCP switching from one EHR developer to a new EHR developer. Specifically, when a physician does not use any EHR, I define $h_{i;i \in J \cup K} = Null$. Let $\tilde{H}$ denote the set of all available EHR developers for PCPs and specialists, such that $\tilde{H} \equiv H \backslash \{Null\}$. I replace $\mathbf{1}\{h_j = h_k\}$ with *Switch-to-Same*$_{jkt}$, where the latter is defined as

(10)

$$\text{Switch-to-Same}_{jkt} = \mathbf{1}\{h_{jt} = h_{kt}\} \times \mathbf{1}\{\exists t_0 < t : h_{jt_0} \neq h_{kt_0}, h_{j\tau} = h_{k\tau} \forall \tau \in (t_0, t), h_{t_0} \in \tilde{H}\}.$$

[13] Hospital service areas (HSAs) are local health care markets for hospital care defined by the Dartmouth Atlas Project. This geographic delineation is updated on a yearly basis by assigning ZIP codes to the hospital area where the greatest proportion of their Medicare fee-for-service residents were hospitalized.

Second, I assume $\alpha_{jt} - \frac{V(\hat{p_{jkt}})}{2E[\hat{p_{jkt}}]} + u_{jkt}$ is additively separable with respect to jk and t. This assumption could be violated if PCP j intentionally switches to the same EHR developer as specialist k in search of more referrals. In this case, the total utility gain of PCP j in year t is affected by this structural change in physician preferences.

To identify β in the presence of such confounders, I use EHR developer transition decisions made by the PCPs' primary affiliated hospital, so that $\textit{Switch-to-Same}_{jkt}$ is exogenous to the PCPs' referral decisions, conditional on the control variables in Equation (9).

The treatment group implied by the model includes physician pairs where the affiliated hospital of the referral-initiating PCP switches from one EHR developer to the same EHR developer used by the referred-to specialist's affiliated hospital. In the control group, there are physician pairs where the PCP switched to a different EHR developer than that used by the specialist or did not change the EHR developer at all during the studied period.

I also study changes in the composition of referrals associated with the *Switch-to-Same* events. As a PCP switches to a new EHR developer, there is a composition change in the group of specialists who use the same developer as the PCP. Hence, the *Switch-to-Same* event that occurs in some physician pairs automatically triggers Switch-to-Different events in other pairs associated with the same PCP. I study these changes in referral patterns by replacing the *Switch-to-Same* variable with two complimentary event dummies that characterize *Switch-to-Same* events: (a) switch from a different EHR developer to another different EHR developer, and (b) switch from the same EHR developer to a different EHR developer.

Finally, I estimate a set of models where the treatment dummy is interacted with: (a) whether the pair of physicians have the same gender; (b) whether the pair reside in the same HRR; and (c) whether the pair has formed a long-term sharing relationship (i.e. share more than 11 Medicare patients for at least two-consecutive years). In all models, the standard errors are cluster-corrected at the level of the PCP's affiliated hospital level.

IV. Results

A. Two-Way Fixed Effect Model Estimates

Table 2 contains estimates of the impact of EHR developer switching on the proportion of patients referred by the PCP. Estimates from the fixed effect model without any additional controls show a strong positive correlation between EHR developer switching and the number of patients shared with a specialist who uses the same developer (Column 1). The effect decreases in magnitude but is still significant when I control for time-varying factors, such as the number of hospital beds, hospital quality measures, physician homophily measures, and HRR and HSA assignments (Column 2). I find that switching to the same EHR developer adopted by the referred-to specialists leads to a 5.3% increase in the proportion of patients shared from the EHR-switching PCP to the same-EHR specialist. Given that the mean percentage of patients shared through each sharing pair is 19.99 percent, and, on average, a PCP refers 1116 patients to out-of-system specialists per year, the estimates indicate that a PCP reallocates approximately 12 patients to the specialists who share the same EHR developer after the switching.

Table 2 columns (4) and (5) present the estimates for two other treatments: a) when the two physicians switch from the same EHR to a different EHR; and b) when they switch from a different EHR to another different EHR. These results illustrate the source of the additional patients reallocated to the same EHR sharing pairs when the focal PCP adopts a new EHR. Specialists who initially have the same EHR developer lose about 4.3% in shared patients from the focal PCP. Specialists whose EHR developers differ from the PCPs before and after the PCP switches EHR do not gain or lose referrals from the focal PCP.

B. Effect Heterogeneity

In Table 3, I present estimates of Equation 9 with interactions of the *Switch-to-Same* treatment variable and several physician-pair features. I find that the increase in referrals to specialists with the same EHR developer is larger if the two physicians have not formed a long-term sharing relationship. In the case of a PCP-specialist pair with a long history of sharing patients, the total effect of switching EHR is 2.9% and is insignificantly different from zero (p-value = 0.24). When the PCP has more experience than the referred-to specialist, switching to the same EHR developer results in a seven percentage point increase in referrals relative to the other sharing pairs.

Although gender homophily does not affect referral patterns after switching EHRs, there is a shift in referral across providers of differing genders. In particular, when a male PCP refers to a female same-developer specialist, referrals increase approximately four times more than for other gender combinations.

Following Pylypchuk et al. (2022), I also test whether the shift in referrals varies by the switched-to EHR developer's market share. Specifically, I interact the treatment variable with a dummy variable indicating whether the EHR developer serves more than 50 percent of the hospital beds in the HRR. I find a positive but insignificant effect of the interaction.

C. Other Patient Sharing Channels

Specialty referrals are commonly perceived as a patient-sharing relationship from primary care physicians to specialty physicians. However, other directions of patient sharing exist and are well-documented in the literature (Brez et al., 2009). Barnett et al. (2012) found there was substantial proportion of referrals initiated by specialists. Among these specialists-initiated referrals, 10% were with PCPs, while 32%-56% were with 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. Such unconventional patient sharing is of interest because it offers a new venue of coordinated care which is essential for resolving health care fragmentation and improving patient outcomes. Researchers have identified (a) having a shared model of care and (b) an IT system that facilitates the 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, I reconstruct estimation samples using different specialty pairs: (1) Specialist to PCP, (2) PCP to PCP, and (3) Specialist to Specialist. Appendix A2 reports the estimates from these additional samples. None of these additional patient sharing channels are significantly affected by EHR developer switching. However, the signs of all estimates are positive, ranging from 1.2% to 6.3%, and the largest effect magnitude is obtained from the PCP to PCP sample.

V. Robustness Checks

A. Pre-existing Trend

Because the two-way fixed effect model is equivalent to a difference-in-differences with variable treatment timing, interpreting the estimates as causal effects requires that the model meats the common-trend and treatment effect homogeneity assumptions. I begin by testing the robustness of my results to potential pre-existing trends using two approaches.

First, I add a full set of HRR-specific linear time trends to the baseline model delineated in Equation (9). In this specification, identification is achieved through sharp deviation from HRR patient sharing trends. The new estimates are consistent with those from the baseline model. The effect of switching-to-same EHR developer is significant at the 5% significance level and has a slightly smaller magnitude (4.67%) than the baseline findings (see Table 2 Column 3).

Next, I implement an event-study design, where I include the leads and lags of the *Switch-to-Same* variable to the model in place of the *Switch-to-Same* dummy, to check whether there are any effects in the pre-treatment period. As shown in Figure 3, the event-study estimates show no significant treatment effects in the pre-period. In addition, the increase in patient sharing among same-developer physicians does not occur immediately after EHR developer switching. Instead, there is a 10.7% increase in the proportion of patients shared with a specialist one year after Switch-to-Same.

B. Time-Varying Treatment Effect

Another concern is that a time-varying treatment effect may lead to biased estimates when contrasting a timing group (treatment group with a specific treatment timing) to an already-treated group. This issue is discussed in detail by Callaway and Sant'Anna (2021) and Goodman-Bacon (2021). Estimates from the two-way fixed model (TWFE) are a variance-weighted average of several canonical difference-in-differences (DD) estimates. These underlying DD models compare the treatment (timing) groups with different control groups. When there are multiple treatment groups due to event timing and, at the same time. If the treatment effect is time-varying, the underlying DD estimate may have the wrong sign when the already-treated timing group is used as a control. If this timing-vs-already-treated DD is assigned a high weight, it can bias the TWFE estimate. I 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, 98.45% of the TWFE treatment effect comes from comparisons between a timing group and the never-treated group, and only 0.55% of the effect is due to DD models that use an already-treated timing group as the control group. Moreover, even in the latter scenario, I find a positive but smaller effect (1.45%) of EHR switching on same-developer sharing.

VI. Distorted Referral Patterns, Market Agglomeration, and Reluctance to Switch

Based on the discrete choice model in Section III and the estimates from Section IV.A, the PCP perceives EHR developer homophily as an utility gain, i.e. $\beta > 0$. Hence, we can conclude from Equation (4) that specialist k would receive a higher fraction of PCP j's referrals if j switches to the same EHR developer as k. In this section, I discuss the implication of this effect on quality-based referral patterns and market agglomeration. I also provide evidence of PCP's reluctance to switch their current EHR developer.

A. Distorted Quality-Based Referral Patterns

The role of PCPs is to coordinate care and control access to specialists. On the one hand, PCPs serve as the "gatekeeper" that limit the cost of care and ensure appropriate use of medical services (Franks, Clancy and Nutting, 1992), on the other hand, they make judicious decisions about where patients may receive the best treatment and act as a "health advisor" (Grumbach et al., 1999; Bodenheimer, Lo and Casalino, 1999). In its core, PCPs should make specialty referrals based on the quality of care, instead of non-medical considerations.

While numerous physician surveys indicate that PCPs view past patient experiences with the referred-to specialist as the most important reason for referring to a specialist (Barnett et al., 2012; Forrest et al., 2002), recent studies have documented referral biases based on the gender, race, and affiliation of the specialities (Zeltzer, 2020; Ghomrawi et al., 2018; Geissler, Lubin and Ericson, 2020). In what follows, I show that the influence of switching EHR developer distorts quality-based referral patterns and reduces the probability of patients' receiving care from a high-quality specialist.

Consider a local physician referral market (J, K) with only two EHR developers, where J, K are the set of PCPs and specialists, respectively, as defined in Section III. Assume $q \in K$ is the specialist of the highest quality and let h_q denote the EHR developer he/she uses. For ease of notation, I denote the probability of q receiving patients from a PCP using h_q by $P_{same,q}$, and I denote the probability of q receiving patients from a similar PCP but using the other EHR developer by $P_{diff,q}$. From Equation (2), In Appendix C, I derive:

$$P_{same,q} = \frac{1}{e^{-\beta} n_{diff} \delta_{diff} + n_{same} \delta_{same}}, \tag{11}$$

and

$$P_{diff,q} = \frac{1}{e^{\beta} n_{diff} \delta_{diff} + n_{same} \delta_{same}}. \tag{12}$$

where $n_h : h \in \{same, diff\}$ is the number of specialists using the same or different EHR developer as q, and $\delta_h \equiv \frac{E[e^{x_h \gamma}]}{e^{x_q \gamma}}$ measures the expected quality of specialists using h_q or the other EHR developer, relative to the quality of q.

PROPOSITION 1 (Distorted Quality-Based Referral Patterns): *In a referral market with a common specialists pool, the probability of referring patients to the highest-quality specialist q is biased towards PCPs who use the same EHR developer as q if and only if switching to same EHR developer provides a utility gain to the PCP. Namely, $P_{same,q} > P_{diff,q}$ if and only if $\beta > 0$.*

When there are only two EHR developers, proposition 1 follows naturally from Equation (11) and (12). If PCPs are insensitive to EHR developer homophily, i.e. $\beta = 0$, the best-quality specialist q has the same probability of receiving patients from *cetris paribus* PCPs who use a different EHR developer, i.e. $P_{same,q} = P_{diff,q}$. When $\beta > 0$, as I find in Section IV.A, PCPs who use h_q discount the utility received from other specialist by a factor of $e^{-\beta}$ and therefore have a higher probability of referring patients to q. In Appendix C, I show that this result is generalizable to markets with more than two EHR developers.

Next, I consider the effect of a group of high-quality specialists choosing a specific EHR developer h_q. This is a common scenario, because specialists working in the same hospital (or hospital system) are exposed to similar high (or low)-quality training programs, and also usually use the same EHR developer. Given fixed market shares of EHR developers (n_{diff}, n_{same}), when specialists using h_q perform better on average, the similarity among specialists using h_q will alleviate the referral distortion created by EHR developer homophily. I formalize this clustering effect in Proposition 2.

PROPOSITION 2 (The Clustering Effect): *In a referral market with common specialists pool and two EHR developers, the odds ratio of referring to the highest-quality specialist q from same- versus different-developer PCPs — $\frac{P_{same,q}}{P_{diff,q}}$ — is a decreasing function of the relative quality of specialists using h_q, i.e. $\frac{\delta_{same}}{\delta_{diff}}$.*[14]

In Figure 4, I simulate the odds ratio of same- versus different-developer referral to the best-specialist q. In the simulation specification, I set $\beta = 0.053$ as estimated in Section

[14]The proof of Proposition 2 (see Appendix C) follows from the derivative of the odds ratio with respect the relative quality.

IV.A, and assume $\delta_{diff} = 0.5$. Because $\beta > 0$, the odds ratio is always greater than 1. I show that the odds ratio depends on the average quality of specialists that use h_q and the market share of h_q. Given a fixed market share of h_q, when the average quality of specialists using h_q increases, the odds ratio decreases. In an extreme case, when the market share of h_q approaches 100% and when 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 health care 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.

B. Market Agglomeration

The effect of EHR developer homophily may also serve as a mechanism for EHR market agglomeration - a phenomenon where large proportions of physicians are clustered in several major EHR developers (Everson and Adler-Milstein, 2016; Freedman, Lin and Prince, 2018). In Figure 5, I show the distribution — using a histogram and a empirical cumulative distribution function (ECDF) — of changes in Herfindahl–Hirschman Index (HHI) from 2012 to 2015 across all HRRs. Overall, 65.74% of the HRRs have a lower HHI in 2015 than in 2012, and 9.96% of the HRRs have no change in HHI. The distribution provides evidence of less competitive EHR developer markets over time.

To see how $\beta > 0$ may partly account for the EHR market agglomeration, consider a market of two EHR developers $\{A, B\}$ with the proportion of PCPs using A (denoted by $P(A)$), 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 receiving referrals, denoted by $\pi_h : h \in \{A, B\}$. When there is a sufficient number of specialists, such that the choice of k does not affect n_h, we have

(13)
$$\pi_A = \frac{P(A)}{n_A\delta_A + e^{-\beta}n_B\delta_B} + \frac{P(B)}{n_A\delta_A + e^{\beta}n_B\delta_B} > \frac{P(A)}{n_A\delta_A + e^{\beta}n_B\delta_B} + \frac{P(B)}{n_A\delta_A + e^{-\beta}n_B\delta_B} = \pi_B.$$

The conclusion is a direct result of the *rearrangement inequality* and is generalizable to markets with more than two EHR developers (see Appendix D for proof). Intuitively, if switching to the same EHR developer causes a stronger tie (more patient sharing) 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, in turn, may trigger more PCPs to switch developer and accelerate EHR market agglomeration.

C. Reluctance to Switch EHR

A related issue is that physicians may be reluctant to switch from their current EHR system due to the potential cost of learning and worry over negative patient outcomes during the EHR switching (Meyerhoefer et al., 2018). Such reluctance increases with the physicians' familiarity of the current EHR developer (Noor, Mahmood and Khan, 2012) and could impede a hospital's new EHR implementation. In the presence of reluctance, the two-way fixed effect estimates in Section IV.A is biased and provides a lower bound to the effect of *Switch-to-Same*.

To investigate whether reluctance exists, I contrast my main results from the two-way fixed effect model to estimates from an alternative instrumental variable (IV) model, where I instrument *Switch-to-Same* with hospital-level factors that are relevant to EHR developer switching but independent of physician reluctance. Specifically, I use variables measuring (1) whether the PCP's affiliated hospital enters a new CMS PI program stage and (2) whether the PCP's affiliated hospital is acquired or merged with a new hospital system, as instruments.

The instruments are relevant because both events increase the probability that hospitals switch to a new EHR system (Adler and Edsall, 2015; Ballaro and Washington, 2016; Coustasse et al., 2018). In addition, the two events are not correlated with physician's reluctance to switch EHR developer. In the case of the first IV, the roll-out of CMS PI stages does not depend on physician referral characteristics, and in the case of the second IV, the primary driver of hospital mergers and acquisitions is financial incentives associated with economies of scale (Krishnan and Krishnan, 2003).

Equation (14) shows the first stage of the IV two stage least squares (2SLS) model:

$$\text{Switch-to-Same}_{jkt} = \eta_1 \mathbf{1}\{\text{New PI Stage}\} + \eta_2 \mathbf{1}\{\text{New Hospital System}\} + \mathbf{X}_{jkt} + \alpha_{jk} + \tau_t + \epsilon_{jkt}. \tag{14}$$

Because the error term ϵ_{jkt} in Equation 14 is non-homoskedastic, I follow the suggestion of Andrews, Stock and Sun (2019) and test for weak instruments using the Montiel-Pflueger effective F-statistic (Olea and Pflueger, 2013). As shown in Table 4, the effective F-statistic on the excluded instruments is equal to 11.95, which is greater than the 5% critical value of the worst-case bias - 6.004 (Olea and Pflueger, 2013), and greater than the rule of thumb value of 10 (Andrews, Stock and Sun, 2019). [15] Hence, the two instruments are not weak.

Focusing on compilers of CMS PI program stage advancement and hospital system changes, the IV-2SLS estimates show that *Switch-to-Same* EHR is associated with a much higher increase in the proportion of patient sharing than I find using the two-way fixed effect model. However, the qualitative conclusions of the new model are the same. Since IV-2SLS measures the local average treatment effect of switching on the compliers, while the two-way fixed effect model measures an intent-to-treat effect, I expect that estimates of the former to exceed the latter. Nevertheless, the IV-2SLS estimates suggest that my main finding is robust and provides a lower bound of the EHR switching effect.[16]

VII. Conclusion

This paper extends the literature on physician referral determinants to the effect of switching EHR developers. I find that when a PCP's affiliated hospital switches to the same EHR developer as a referred-to specialist, the PCP increases the proportion of patients shared with that specialist by an average of 5.3%, which is equivalent to 12 additional shared patients per year. This finding is robust to alternative specifications and passes

[15] The critical value of the Montiel & Pflueger Effective F-statistics are calculated using a level of significance $\alpha = 5\%$, and a desired threshold $\tau = 5\%$.

[16] This is true if reluctance increases as the more patients are shared between physicians through the current EHR developer. And reluctance is negatively correlated with *Switch-to-Same*

standard specification tests. I also find an accompanying reduction in the number of patients shared with specialists who use the PCP's original EHR developer (-4.3%). The increase in referrals from switching EHR is larger when the PCP refers to a specialist with fewer shared patients prior to the EHR switch. The effect is also larger when the PCP is more experienced than the referred-to specialists, when the switched-to EHR developer has more market power, and when a male PCP refers to a female specialist.

My findings reveal that EHR developer homophily factors into the PCPs' referral decisions. Based on a discrete choice model, I show that this homophily makes PCPs who use a different EHR developer less likely to share patients with the highest-quality specialists; a bias that increases when the highest-quality specialists face less quality competition from other same-developer specialists. Although there has been a steady stream of research that assesses physician homophily in gender (Zeltzer, 2020; Levinson, McCollum and Kutner, 1984), race (Miller et al., 2022), and professional affiliations (Mascia et al., 2015; Linde, 2019), this paper is among the first that concentrates on EHR developer homophily. Against the background of the worldwide expansion of EHR, the rising telemedicine market, and the unremitting efforts to advance health care coordination (Baker and Stanley, 2018; Kannampallil and Ma, 2020), evaluations on patient allocation due to EHR developer homophily deserve more attention.

My paper also contributes to the literature on EHR developer market agglomeration. There has been a consistent evidence of top EHR developers dominating the market (Pylypchuk et al., 2022; Freedman, Lin and Prince, 2018; Chen, Peng and Cao, 2021). My findings complement this line of research by providing a potential mechanism: I show that EHR developer homophily gives specialists an incentive to switch to the most popular EHR developer, and therefore leads to EHR developer market agglomeration.

In addition to having implications for market structure, my results indicate that there are barriers to the efficient health information exchange (HIE). This is because any changes to referrals by PCP should uniformly affect all sharing relationships under well functioning HIE. When same-developer sharing is made more advantageous to the PCP after switching EHR, it suggests that the EHR developers may engage in Information Blocking (Adler-milstein and Pfeifer, 2017; Everson and Adler-Milstein, 2016; Rosenbloom et al., 2019). In a national survey of HIE effort leaders, Adler-milstein and Pfeifer (2017) reported that 50% of EHR developers routinely engage in information blocking, and 25% of hospitals and health systems routinely do so. 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 health care fragmentation.

This paper provides consistent evidence that specialists receive more patients from PCPs who switch to the same EHR developer. My finding suggests EHR developers have significant influence on physician referrals, in a way that motivates within-developer patient sharing and reinforces EHR market agglomeration. Scrutinization of these referral pattern changes may contribute to the meaningful use of EHRs and promote efficient health care coordination. Although I focus on EHR developer switching, with careful considerations, the underlying takeaway from this study can be applied to future studies on technological changes and information exchange.

REFERENCES

Adler, Kenneth G, and Robert L Edsall. 2015. "EHR switch survey: responses from 305 family physicians." *Family Practice Management*, 22(1): 13–18.

Adler-milstein, Julia, and Eric Pfeifer. 2017. "Information blocking: is it occurring and what policy strategies can address it?" *The Milbank Quarterly*, 95(1): 117–135.

Adler-Milstein, Julia, Sunny C Lin, and Ashish K Jha. 2016. "The number of health information exchange efforts is declining, leaving the viability of broad clinical data exchange uncertain." *Health Affairs*, 35(7): 1278–1285.

Andrews, Isaiah, James H Stock, and Liyang Sun. 2019. "Weak instruments in instrumental variables regression: Theory and practice." *Annual Review of Economics*, 11(1).

Arah, Onyebuchi A, Uzor C Ogbu, and Chukwudi E Okeke. 2008. “Too poor to leave, too rich to stay: developmental and global health correlates of physician migration to the United States, Canada, Australia, and the United Kingdom.” *American journal of public health*, 98(1): 148–154.

Baker, John, and Anthony Stanley. 2018. “Telemedicine technology: a review of services, equipment, and other aspects.” *Current allergy and asthma reports*, 18(11): 1–8.

Ballaro, Julie M, and Elaine R Washington. 2016. “The Impact of Organizational Culture and Perceived Organizational Support on Successful Use of Electronic Healthcare Record (EHR).” *Organization Development Journal*, 34(2).

Barnett, Michael L, Nancy L Keating, Nicholas A Christakis, A James O’malley, and Bruce E Landon. 2012. “Reasons for choice of referral physician among primary care and specialist physicians.” *Journal of general internal medicine*, 27(5): 506–512.

Bartley, Joanne, and Mara L Daiker. 2022. “Selection, Implementation, Support and Maintenance.” In *The CAHIMS Review Guide.* 91–106. Productivity Press.

Behrens, Kristian, and Frédéric Robert-Nicoud. 2015. “Agglomeration theory with heterogeneous agents.” *Handbook of regional and urban economics*, 5: 171–245.

Blease, Charlotte, Liz Salmi, Hanife Rexhepi, Maria Hägglund, and Catherine M DesRoches. 2021. “Patients, clinicians and open notes: information blocking as a case of epistemic injustice.” *Journal of Medical Ethics.*

Bodenheimer, Thomas, Bernard Lo, and Lawrence Casalino. 1999. “Primary care physicians should be coordinators, not gatekeepers.” *Jama*, 281(21): 2045–2049.

Bowles, Kathryn H, Sarah J Ratcliffe, Mary D Naylor, John H Holmes, Susan K Keim, and Emilia J Flores. 2017. “Nurse generated EHR data supports post-acute care referral decision making: development and validation of a two-step algorithm.” Vol. 2017, 465, American Medical Informatics Association.

Brez, Sharon, Margo Rowan, Janine Malcolm, Sheryl Izzi, Julie Maranger, Clare Liddy, Erin Keely, and Teik Chye Ooi. 2009. “Transition from specialist to primary diabetes care: a qualitative study of perspectives of primary care physicians.” *BMC family practice*, 10(1): 1–8.

Brot-Goldberg, Zarek C, and Mathijs de Vaan. 2018. “Intermediation and vertical integration in the market for surgeons.” *Chicago (IL): University of Chicago.*

Buljac-Samardzic, Martina, Connie M Dekker-van Doorn, Jeroen DH van Wijngaarden, and Kees P van Wijk. 2010. “Interventions to improve team effectiveness: a systematic review.” *Health policy*, 94(3): 183–195.

Callaway, Brantly, and Pedro HC Sant’Anna. 2021. “Difference-in-differences with multiple time periods.” *Journal of Econometrics*, 225(2): 200–230.

Carlin, Caroline S, Bryan Dowd, and Roger Feldman. 2015. “Changes in quality of health care delivery after vertical integration.” *Health services research*, 50(4): 1043–1068.

Carlino, Gerald, and William R Kerr. 2015. “Agglomeration and innovation.” *Handbook of regional and urban economics*, 5: 349–404.

CB Insights. 2021. “Top Investors Fueling The Electronic Health Record Ecosystem.”

Chen, Yiping, Lihong Peng, and Wenzhi Cao. 2021. “Health evaluation and coordinated development characteristics of urban agglomeration: Case study of Fujian Delta in China.” *Ecological Indicators*, 121: 107149.

CMS. 2017. “Stages of promoting interoperability programs: first year demonstrating meaningful use.”

Coustasse, Alberto, Pete Andresen, Michelle Schussler, Kyle Sowards, and Craig Kimble. 2018. “Why Physicians Switch Electronic Health Record Vendors.” *Perspectives in Health Information Management.*

de la Vega, Pablo Buitron, Stephanie Losi, Linda Sprague Martinez, Allison Bovell-Ammon, Arvin Garg, Thea James, Alana M Ewen, Marna Stack, Heloisa DeCarvalho, Megan Sandel, et al. 2019. "Implementing an EHR-based screening and referral system to address social determinants of health in primary care." *Medical care*, 57: S133–S139.

Deneckere, Svin, Martin Euwema, Pieter Van Herck, Cathy Lodewijckx, Massimiliano Panella, Walter Sermeus, and Kris Vanhaecht. 2012. "Care pathways lead to better teamwork: results of a systematic review." *Social science & medicine*, 75(2): 264–268.

Dunlea, Robert, and Leslie Lenert. 2015. "Understanding patients' preferences for referrals to specialists for an asymptomatic condition." *Medical Decision Making*, 35(6): 691–702.

Eastaugh, Steven R. 2013. "The total cost of EHR ownership: healthcare organizations should consider support costs, upgrade fees, and other long-term costs of EHR systems in determining the total cost of ownership." *Healthcare financial management*, 67(2): 66–71.

Everson, Jordan, and Julia Adler-Milstein. 2016. "Engagement in hospital health information exchange is associated with vendor marketplace dominance." *Health Affairs*, 35(7): 1286–1293.

Everson, Jordan, Vaishali Patel, and Julia Adler-Milstein. 2021. "Information blocking remains prevalent at the start of 21st Century Cures Act: results from a survey of health information exchange organizations." *Journal of the American Medical Informatics Association*, 28(4): 727–732.

Forrest, Christopher B, Paul A Nutting, Barbara Starfield, and Sarah Von Schrader. 2002. "Family physicians' referral decisions." *J Fam Pract*, 51(3): 215–222.

Forrest, Christopher B, Paul A Nutting, Sarah Von Schrader, Charles Rohde, and Barbara Starfield. 2006. "Primary care physician specialty referral decision making: patient, physician, and health care system determinants." *Medical decision making*, 26(1): 76–85.

Franks, Peter, Carolyn M Clancy, and Paul A Nutting. 1992. "Gatekeeping revisited—protecting patients from overtreatment."

Freedman, Seth, Haizhen Lin, and Jeffrey Prince. 2018. "Does competition lead to agglomeration or dispersion in EMR vendor decisions?" *Review of Industrial Organization*, 53(1): 57–79.

Garrido, Marcial Velasco, Annette Zentner, and Reinhard Busse. 2011. "The effects of gatekeeping: a systematic review of the literature." *Scandinavian journal of primary health care*, 29(1): 28–38.

Geissler, Kimberley H, Benjamin Lubin, and Keith M Marzilli Ericson. 2020. "The role of organizational affiliations in physician patient-sharing relationships." *Medical Care Research and Review*, 77(2): 165–175.

Ghomrawi, Hassan MK, Russell J Funk, Michael L Parks, Jason Owen-Smith, and John M Hollingsworth. 2018. "Physician referral patterns and racial disparities in total hip replacement: a network analysis approach." *PloS one*, 13(2): e0193014.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Graetz, Ilana, Jie Huang, Richard Brand, Stephen M Shortell, Thomas G Rundall, Jim Bellows, John Hsu, Marc Jaffe, and Mary E Reed. 2015. "The impact of electronic health records and teamwork on diabetes care quality." *The American journal of managed care*, 21(12): 878.

Gross, Anne H, Ryan K Leib, Anne Tonachel, Richard Tonachel, Danielle M Bowers, Rachel A Burnard, Catherine A Rhinehart, Rahila Valentim, and Craig A Bunnell. 2016. "Teamwork and electronic health record implementation: a case study of preserving effective communication and mutual trust in a changing environment." *Journal of Oncology Practice*, 12(11): 1075–1083.

Grumbach, Kevin, Joe V Selby, Cheryl Damberg, Andrew B Bindman, Charles Quesenberry Jr, Alison Truman, and Connie Uratsu. 1999. "Resolving the gatekeeper conundrum: what patients value in primary care and referrals to specialists." *Jama*, 282(3): 261–266.

Han, Hae-Ra, Kelly T Gleason, Chun-An Sun, Hailey N Miller, Soo Jin Kang, Sotera Chow, Rachel Anderson, Paul Nagy, Tom Bauer, et al. 2019. "Using patient portals to improve patient outcomes: systematic review." *JMIR human factors*, 6(4): e15038.

Häyrinen, Kristiina, Kaija Saranto, and Pirkko Nykänen. 2008. "Definition, structure, content, use and impacts of electronic health records: a review of the research literature." *International journal of medical informatics*, 77(5): 291–304.

HealthIT.gov. 2015. "MIPS Builds on Meaningful Use."

HealthIT.gov. 2017. "Hospital Health IT Developers."

HealthIT.gov. 2022. "Help Us Stop Information Blocking."

Henry, J, Yuriy Pylypchuk, Talisha Searcy, and Vaishali Patel. 2016. "Adoption of electronic health record systems among US non-federal acute care hospitals: 2008–2015." *ONC data brief*, 35(35): 2008–2015.

Holmgren, A Jay, and Julia Adler-Milstein. 2017. "Health information exchange in US hospitals: the current landscape and a path to improved information sharing." *Journal of hospital medicine*, 12(3): 193–198.

Kannampallil, Thomas, and Jun Ma. 2020. "Digital translucence: adapting telemedicine delivery post-COVID-19." *Telemedicine and e-Health*, 26(9): 1120–1122.

Kibbe, David C. 2010. "A physician's guide to the medicare and medicaid EHR incentive programs: The basics." *Family practice management*, 17(5): 17.

Kinchen, Kraig S, Lisa A Cooper, David Levine, Nae Yuh Wang, and Neil R Powe. 2004. "Referral of patients to specialists: factors affecting choice of specialist by primary care physicians." *The Annals of Family Medicine*, 2(3): 245–252.

Kossman, Susan P, and Sandra L Scheidenhelm. 2008. "Nurses' perceptions of the impact of electronic health records on work and patient outcomes." *CIN: Computers, Informatics, Nursing*, 26(2): 69–77.

Krishnan, Ranjani A, and Hema Krishnan. 2003. "Effects of hospital mergers and acquisitions on prices." *Journal of Business Research*, 56(8): 647–656.

Levinson, Richard M, Kelly T McCollum, and Nancy G Kutner. 1984. "Gender homophily in preferences for physicians." *Sex roles*, 10(5): 315–325.

Linde, Sebastian. 2019. "The formation of physician patient sharing networks in medicare: Exploring the effect of hospital affiliation." *Health economics*, 28(12): 1435–1448.

Lin, Sunny C, Ashish K Jha, and Julia Adler-Milstein. 2018. "Electronic health records associated with lower hospital mortality after systems have time to mature." *Health affairs*, 37(7): 1128–1135.

Lochner, Kimberly A, and Carla M Shoff. 2015. "Peer reviewed: County-level Variation in prevalence of multiple chronic conditions among Medicare beneficiaries, 2012." *Preventing Chronic Disease*, 12.

Mascia, Daniele, Fausto Di Vincenzo, Valentina Iacopino, Maria Pia Fantini, and Americo Cicchetti. 2015. "Unfolding similarity in interphysician networks: the impact of institutional and professional homophily." *BMC health services research*, 15(1): 1–8.

Meyerhoefer, Chad D, Susan A Sherer, Mary E Deily, Shin-Yi Chou, Xiaohui Guo, Jie Chen, Michael Sheinberg, and Donald Levick. 2018. "Provider and patient satisfaction with the integration of ambulatory and hospital EHR systems." *Journal of the American Medical Informatics Association*, 25(8): 1054–1063.

Miller, Ann Neville, Andrew Todd, Robert Toledo, and Venkata Naga Sreelalitapriya Duvuuri. 2022. "The Relationship of Ethnic, Racial, and Cultural Concordance to Physician–Patient Communication: A Mixed-Methods Systematic Review Protocol." *Health Communication*, 1–7.

Noor, Ms Sarooj, S Mahmood, and Ms Khadijah Khan. 2012. "Reluctance of US Doctors in Adopting EHR Technology." *Global Journal of Management and Business Research*, 12(23): 1–20.

Office of the National Coordinator for Health Information Technology. 2022. "National Trends in Hospital and Physician Adoption of Electronic Health Records."

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A robust test for weak instruments." *Journal of Business & Economic Statistics*, 31(3): 358–369.

Pylypchuk, Yuriy, Chad D Meyerhoefer, William Encinosa, and Talisha Searcy. 2022. "The role of electronic health record developers in hospital patient sharing." *Journal of the American Medical Informatics Association*, 29(3): 435–442.

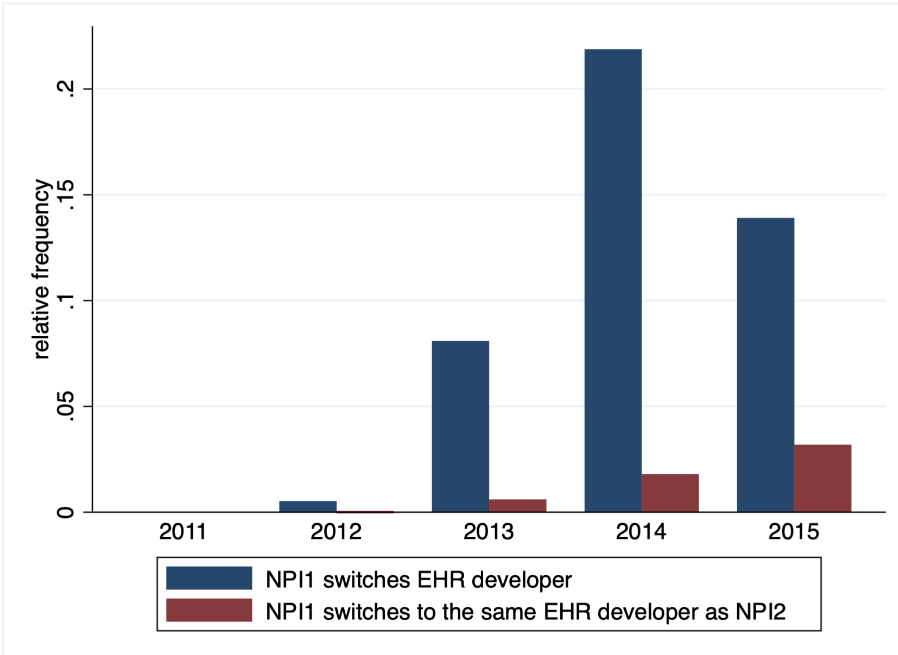
Rosenbloom, S Trent, Jeffery RL Smith, Rita Bowen, Janelle Burns, Lauren Riplinger, and Thomas H Payne. 2019. "Updating HIPAA for the electronic medical record era." *Journal of the American Medical Informatics Association*, 26(10): 1115–1119.

Seth Joseph, MBA, MBA Max Sow, F Furukawa Michael, MS Steven Posnack, and MS Chaffee. 2014. "HITECH spurs EHR vendor competition and innovation, resulting in increased adoption." *Am J Manag Care*, 20(9): 734–740.

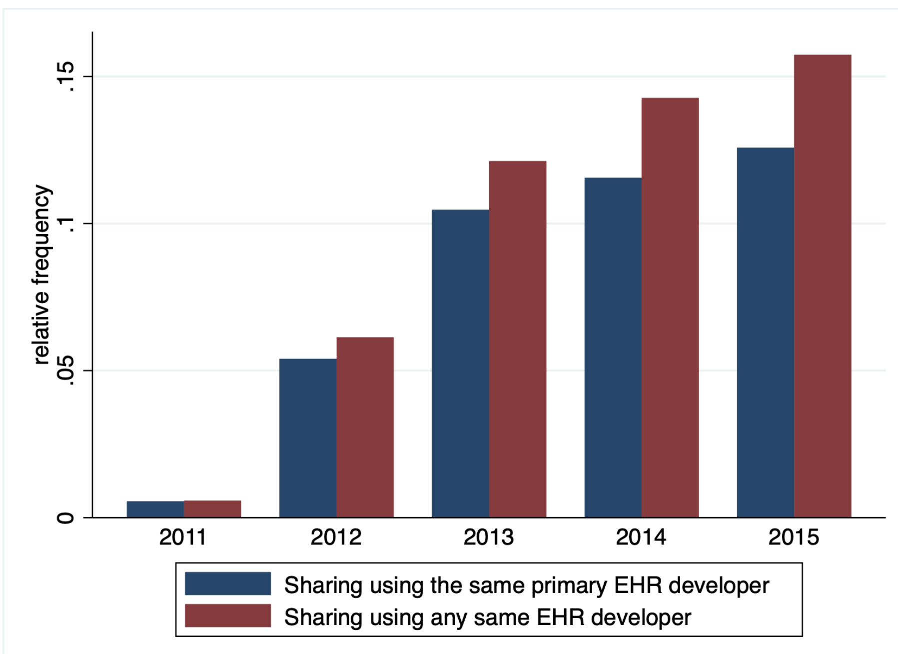
Sorace, James, Hui-Hsing Wong, Thomas DeLeire, Dashi Xu, Sheila Handler, Bruno Garcia, and Thomas MaCurdy. 2020. "Quantifying the competitiveness of the electronic health record market and its implications for interoperability." *International Journal of Medical Informatics*, 136: 104037.

Taplin, Stephen H, Sallie Weaver, Eduardo Salas, Veronica Chollette, Heather M Edwards, Suanna S Bruinooge, and Michael P Kosty. 2015. "Reviewing cancer care team effectiveness." *Journal of Oncology Practice*, 11(3): 239–246.

Zeltzer, Dan. 2020. "Gender homophily in referral networks: Consequences for the medicare physician earnings gap." *American Economic Journal: Applied Economics*, 12(2): 169–97.



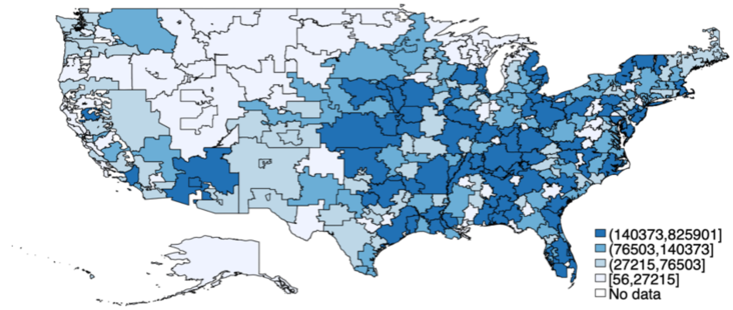
(A) Relative Frequency of EHR Developer Switches and Switch-to-Same Events.



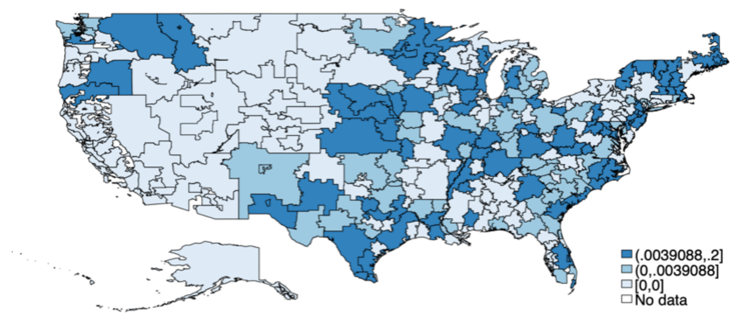
(B) Relative Frequency of Patient Sharing through the Same Primary EHR Developer.

Figure 1. Trends in EHR Developer Switches and Same-developer Patient Sharing.

Note: Relative frequencies reported in the figures describe the fraction of physician pairs with a labelled feature (switch, switch to same, sharing using the same primary EHR developer, or sharing using any same EHR developer) in a given year. In panel (A), Switches are defined as a change in the primary EHR developer used by PCPs' affiliated hospital. It does not include the initial adoption of an EHR system. *Switch-to-Same* describes the event where a PCP' affiliated hospital switches the primary EHR developer, and it results in a PCP-to-specialist pair having the same EHR developer. In panel (B), because hospitals may use more than one EHR developers, I present the fraction of patient sharing between hospitals that (1) use the same primary EHR developer, and (2) have any common EHR developer in the set of all used EHR products.



(A) Total Number of Shared Medicare Patients



(B) Relative Frequency of Switch-to-Same

Figure 2. Geographic Variation in Patient Sharing Intensity and Switch-to-Same across HRRs during 2011-2015.

Note: Data from the PCP-to-specialists sample, and statistics reported in the figures are computed at the Hospital Referral Region (HRR) level. Except for UT-PROVO, 305 out of 306 HRRs have nonzero patient sharing and are reported in the figure. Darker colors indicate higher values. Note the scales of measurement are different in panel (A) and (B). Specifically, panel (A) reports the numbers of patients, while panel (B) reports relative frequencies.

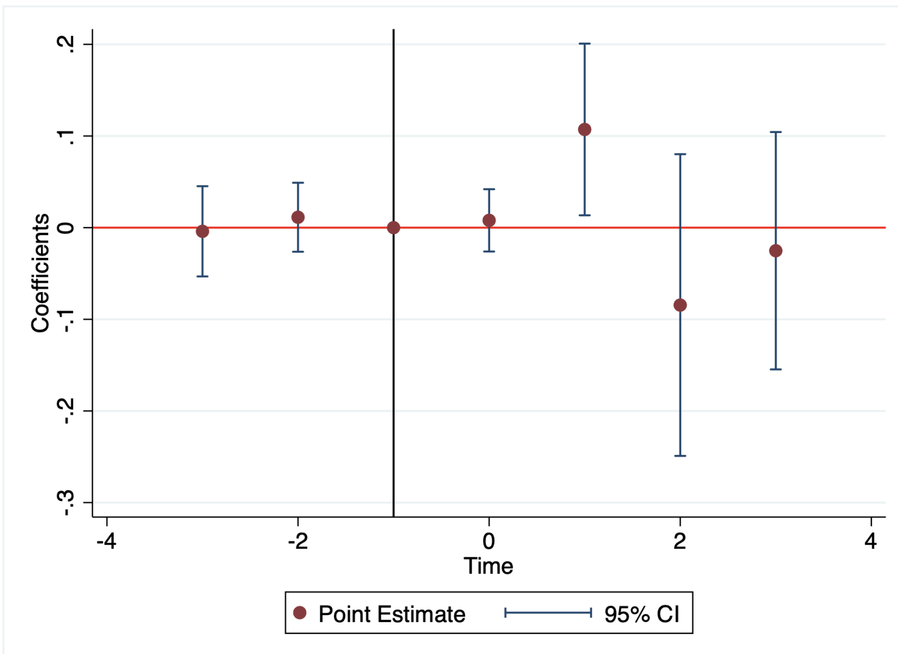


Figure 3. Estimates from the Event Study.

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 two-way fixed effect estimation.

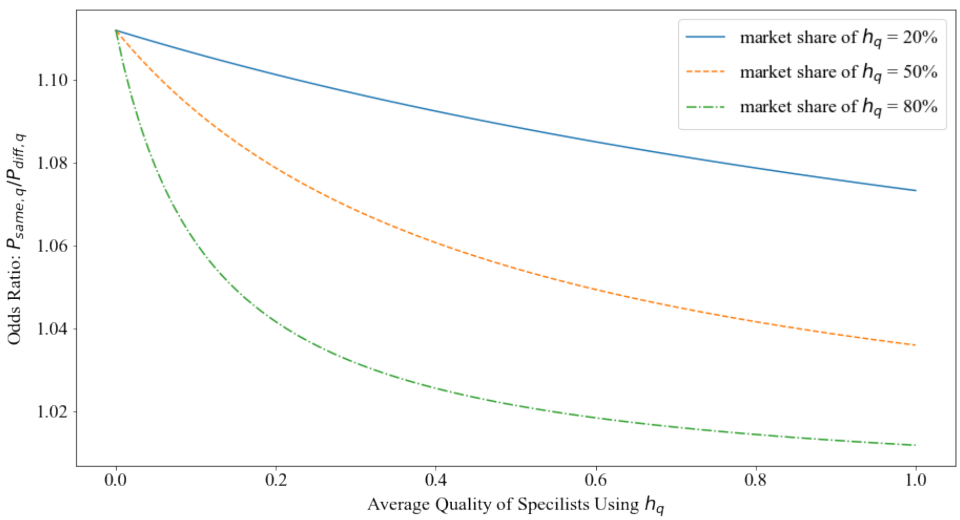


Figure 4. Distortion in Quality-Based Referrals as Functions of Same-Developer Specialists' Average Quality.

Note: The figure shows simulation of the odds ratio — $(P_{same,q}/P_{diff,q})$ as functions as the average quality of specialists using the same EHR developer as the best-quality specialist q. The calculation is based on setting the average quality of specialists using the different EHR developer to 0.5. The topmost solid line shows the distortion effects when the market share of h_q is equal to 20%. The two dashed lines show the distortion effects when the market share of h_q is equal to 50% and 80%, respectively.

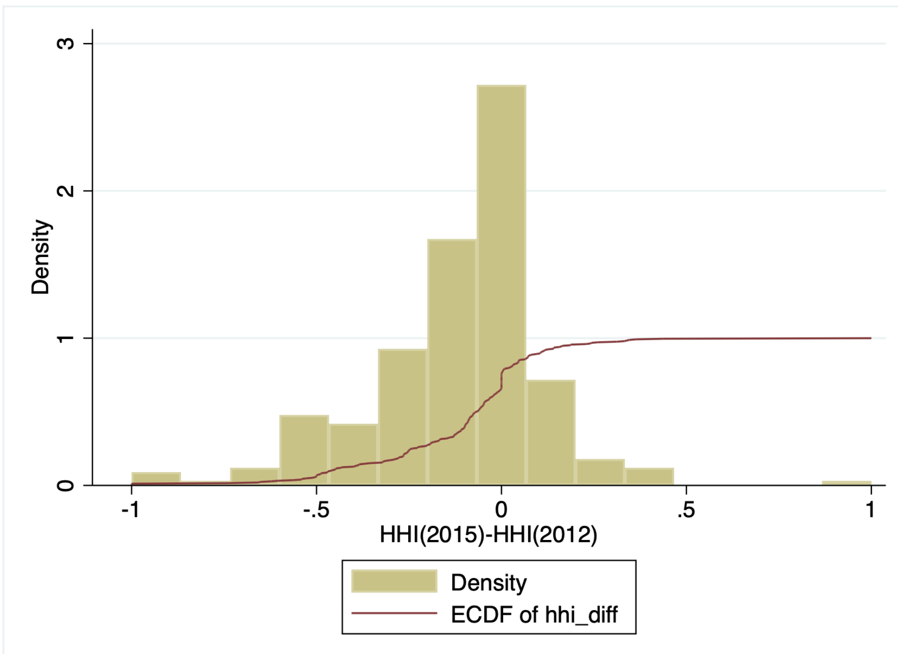


Figure 5. Histogram of HHI Changes from 2012 to 2015

Note: The Herfindahl–Hirschman Index (HHI) is computed at HRR level. Within each HRR, $HHI = \sum_{h \in H} \frac{n_h}{\sum n_h}^2$. I weight the number of physicians using a certain EHR developer by the average number of patients shared by each physician using h. The red curve shows the empirical cumulative distribution function of the change in HHI from 2012 to 2015. Because changes can not be identified in the first year of my sample, 2011 is not included in the figure.

Table 1—: Summary Statistics of the PCP-to-Specialists Patient Sharing Sample.

Variables	Ever Switch to Same N=22,806 mean	Ever Switch to Same N=22,806 std	Never Switch to Same N=567,633 mean	Never Switch to Same N=567,633 std
PCP Characteristics				
Experience	26.261	9.577	26.197	9.538
Male	0.771	0.420	0.814	0.389
Affiliated with emergency hospital	0.971	0.167	0.987	0.112
Number of hospital beds	250.786	177.982	270.185	261.751
Annual number of patients with heart failure	588.698	403.501	550.707	478.414
Annual number of patients with pneumonia	495.606	332.896	455.945	346.077
30-day readmission rate indicators (0/1)				
(Heart failure) Indifferent to national mean	0.045	0.207	0.062	0.242
(Heart failure) Better than national mean	0.830	0.376	0.843	0.364
(Pneumonia) Indifferent to national mean	0.064	0.246	0.046	0.210
(Pneumonia) Better than national mean	0.865	0.341	0.898	0.303
30-day mortality rate indicators (0/1)				
(Heart failure) Indifferent to national mean	0.030	0.171	0.045	0.207
(Heart failure) Better than national mean	0.834	0.372	0.830	0.376
(Pneumonia) Indifferent to national mean	0.069	0.254	0.074	0.262
(Pneumonia) Better than national mean	0.816	0.387	0.802	0.399
Market share of primary EHR developer	37.208	30.254	22.994	27.330
Number of referred-to specialists	8.471	8.442	10.264	11.650

Note: Summary statistics are based on the PCP-to-specialist patient-sharing sample. Two subsamples are created - (1) Ever Switch-to-Same EHR developer and (2) Never Switch-to-Same EHR developer - based on the Switch-to-Same indicator designated to each physician pair. Both PCP and specialists characteristics are reported in the table and included in all regression models. The mean of the indicator variables indicates fractions of physician pairs with a certain feature.

Table 1 Continued	Ever Switch to Same N=22,806		Never Switch to Same N=567,633	
Variables	**mean**	**std**	**mean**	**std**
Specialists Characteristics				
Experience	26.353	8.996	26.614	8.802
Male	0.896	0.305	0.903	0.296
Affiliated with emergency hospital	0.996	0.063	0.979	0.144
Number of hospital beds	347.521	240.849	355.271	250.937
Annual number of patients with heart failure	652.740	409.094	695.583	449.787
Annual number of patients with pneumonia	534.188	304.254	554.245	340.608
30-day readmission rate indicators (0/1)				
(Heart failure) Indifferent to national mean	0.047	0.212	0.062	0.241
(Heart failure) Better than national mean	0.884	0.320	0.841	0.365
(Pneumonia) Indifferent to national mean	0.048	0.213	0.058	0.234
(Pneumonia) Better than national mean	0.923	0.267	0.889	0.314
30-day mortality rate indicators (0/1)				
(Heart failure) Indifferent to national mean	0.044	0.206	0.052	0.223
(Heart failure) Better than national mean	0.879	0.326	0.829	0.376
(Pneumonia) Indifferent to national mean	0.048	0.215	0.081	0.272
(Pneumonia) Better than national mean	0.834	0.372	0.792	0.406
Pair Characteristics (0/1)				
Same gender	0.724	0.447	0.755	0.430
Same city	0.281	0.449	0.247	0.432
Same state	0.942	0.233	0.908	0.289
Same HRR	0.842	0.365	0.753	0.432
Same HSA	0.359	0.480	0.285	0.451
Long-term sharing relationship	0.433	0.495	0.448	0.497

Note: Summary statistics are based on the PCP-to-specialist patient-sharing sample. Two subsamples are created - (1) Ever Switch-to-Same EHR developer and (2) Never Switch-to-Same EHR developer - based on the Switch-to-Same indicator designated to each physician pair. Both PCP and specialists characteristics are reported in the table and included in all regression models. The mean of the indicator variables indicates fractions of physician pairs with a certain feature.

Table 2—: Estimates of the EHR Developer Switching Effects on Proportion of Patients Sharing.

	(1)	(2)	(3)	(4)	(5)
Switch-to-Same	0.212***	0.053**	0.047**		
	(0.035)	(0.025)	(0.024)		
Same-to-Different				-0.043*	
				(0.025)	
Different-to-Different					0.014
					(0.010)
Physician pair fixed effects	x	x	x	x	x
Year fixed effects	x	x	x	x	x
Control variables		x	x	x	x
HRR specific time trends			x		

Note: All estimations are based on the PCP-to-specialist sample. Column (1)-(3) display two-way fixed effect estimates of the effect Switch-to-Same has on the proportion of patient sharing from a PCP to a certain specialist, with different level of additional controls. Column (1) controls only for physician-pair fixed effects and year fixed effects. Column (2) additionally controls for physician and hospital characteristics. I also control for HRR specific time trends in Column (3). Column (4) and (5) reports the effect of switching from same to different EHR developer and from different to different developer, respectively. All standard errors are clustered at the PCP's affiliated hospital level and are reported in the parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 3—: Estimates of Effect Heterogeneity

	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Switch-to-Same	0.147***	0.028	0.096	0.063	0.042*	0.019	0.018
	(0.038)	(0.036)	(0.074)	(0.046)	(0.024)	(0.028)	(0.035)
Switch-to-Same x 1(Long-term relationship)	-0.118**						
	(0.036)						
Switch-to-Same x 1(Same HSA)		0.063					
		(0.046)					
Switch-to-Same x 1(Same HRR)			-0.048				
			(0.079)				
Switch-to-Same x 1(Same gender)				-0.013			
				(0.0431)			
Switch-to-Same x 1(Male to female)					0.179**		
					(0.086)		
Switch-to-Same x 1(PCP has more exp)						0.070**	
						(0.029)	
Switch-to-Same x 1(market share >50)							0.067
							(0.044)

Note: In Column (6)-(12), I regress log(proportion of shared patients) on Switch-to-Same and its intersection with various physician-pair characteristics. The intersection terms are reported as row titles in the table. 1(.) is a characteristic function. All standard errors are clustered at the PCP's affiliated hospital level and are reported in the parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 4—: Estimates from the IV-2SLS Model

	Coeff	S.E.	Effective F-statistics
First Stage			11.95
New CMS PI Stage	-.013***	0.003	
Hospital System Change	.009	0.006	
			p-value for Hansen's J-test
Second Stage			0.675
Switch-to-Same	0.617***	0.232	

Note: The IV-2SLS model controls for both time and physician pair fixed effects and all physician and hospital characteristics; The critical value of the Montiel & Pflueger Effective F-statistics - 6.004 - is calculated using a level of significance $\alpha = 5\%$, and a desired threshold $\tau = 5\%$. Standard errors are clustered at the PCP's affiliated hospital level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix A

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

Variables	Coef.	S.E.	t-statistic	p-value	95% Conf. Interval	
Switch-to-Same	0.053	0.025	2.130	0.033	0.004	0.102
EHR market share of NPI1	0.000	0.000	-1.070	0.287	0.000	0.000
same HAS	0.314	0.174	1.800	0.071	-0.027	0.655
Long-term sharing relationship	0.022	0.005	4.470	0.000	0.012	0.032
PCP						
Emergency hospital	0.020	0.025	0.810	0.420	-0.029	0.069
Number of hospital beds	0.000	0.000	1.230	0.219	0.000	0.000
number of heart failure patients	0.000	0.000	-0.420	0.671	0.000	0.000
number of pneumonia patients	0.001	0.000	2.280	0.022	0.000	0.001
30-day readmission rate						
Heart failure indifferent to national mean	0.005	0.018	0.290	0.773	-0.030	0.040
Heart failure better than national mean	-0.022	0.019	-1.160	0.246	-0.059	0.015
Pneumonia indifferent to national mean	-0.013	0.012	-1.030	0.305	-0.037	0.011
Pneumonia better than national mean	-0.021	0.027	-0.780	0.435	-0.075	0.032
30-day mortality rate						
Heart failure indifferent to national mean	0.014	0.011	1.220	0.223	-0.008	0.036
Heart failure better than national mean	0.005	0.018	0.290	0.773	-0.030	0.040
Pneumonia indifferent to national mean	0.013	0.011	1.200	0.231	-0.008	0.034
Pneumonia better than national mean	-0.011	0.015	-0.730	0.467	-0.041	0.019

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	Coef.	S.E.	t-statistic	p-value	95% Conf. Interval	
Specialist						
Emergency hospital	0.024	0.023	1.050	0.292	-0.020	0.068
Number of hospital beds	0.000	0.000	1.250	0.211	0.000	0.000
number of heart failure patients	0.000	0.000	-0.050	0.957	0.000	0.000
number of pneumonia patients	0.000	0.000	0.940	0.347	0.000	0.001
30-day readmission rate						
Heart failure indifferent to national mean	0.002	0.009	0.220	0.823	-0.016	0.020
Heart failure better than national mean	0.005	0.018	0.290	0.773	-0.030	0.040
Pneumonia indifferent to national mean	0.007	0.010	0.710	0.478	-0.012	0.026
Pneumonia better than national mean	0.005	0.013	0.370	0.710	-0.021	0.031
30-day mortality rate						
Heart failure indifferent to national mean	0.004	0.013	0.330	0.740	-0.020	0.029
Heart failure better than national mean	0.003	0.009	0.390	0.698	-0.014	0.020
Pneumonia indifferent to national mean	0.026	0.013	2.040	0.042	0.001	0.051
Pneumonia better than national mean	0.009	0.009	0.960	0.340	-0.009	0.026
Year						
2012	0.040	0.004	8.820	0.000	0.031	0.048
2013	0.075	0.007	10.730	0.000	0.061	0.088
2014	0.097	0.008	12.450	0.000	0.082	0.112
2015	0.393	0.013	29.920	0.000	0.367	0.419
constant	1.968	0.091	21.680	0.000	1.790	2.146

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

	Specialists to PCP		PCP to PCP		Specialists to Specialists	
	N=319,515		N=42,975		N=1,175,022	
Switch-to-Same	0.012	0.018	0.036	0.063	0.016	0.017
	(0.018)	(0.019)	(0.045)	(0.045)	(0.013)	(0.012)
HRR specific time trend		x		x		x

Note: Estimates in Table A2 are based on three different samples: specialist-to-PCP, PCP-to-PCP, and Specialist-to-specialist. For each subsample, I estimate a model with the same specification as Table 2 Column (2) and a model with HRR specific time trends. In all columns, I control for physician-pair fixed effects, year fixed effects, and physician and hospital characteristics. Standard errors are clustered at the affiliated hospital of NPI-1; * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A3—: Goodman-Bacon Decomposition Results

	Beta	Total Weight
Timing groups	0.014	0.006
Timing vs. Never	0.041**	0.985
Within	0.004	0.010

Note: Goodman-Bacon decomposition are performed using *bacondecomp* command in STATA. Decomposition is performed on the baseline specification where I control for physician-pair fixed effects, year fixed effects, and physician and hospital characteristics. Total weight does not sum up to 1 due to rounding. The within row accounts for the inclusion of control variables in Goodman-Bacon decomposition. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Appendix B. Sensitivity Analysis

In the main sample, I assumed that 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 my findings are sensitive to this assumption. I re-estimate Table 2 and 3 using only data from 2013 to 2015.

Table B1 shows the same set of results as those in Table 2. All findings remain the same sign and magnitude, the effect of switch-to-same EHR developer (Column 2) increases from 5.3% to 8% when only considering the last three years in the panel. Physician pairs switching from same to different EHR developer (Column 4) is associated with approximately 4.1% decrease in the percentage of shared patients with a p-value of 0.11 (compared with 0.09 in Table 2).

In Table B2, I present comparable results of effect heterogeneity analysis with those in Table 3. Similar to the baseline findings, short-term sharing relationship and male-to-female sharing predicts larger increase in the number of shared patients when the PCP switches to the same EHR used by the specialist. The only difference between Table B2 and Table 3 is that seniority of PCP (Column 11) no longer significantly boost patient reallocation in the sensitivity analysis.

Table B1—: Estimates of the EHR Developer Switching Effect on Proportion of Patients Sharing (2013-2015)

	(1)	(2)	(3)	(4)	(5)
Switch-to-Same	0.175***	0.080***	0.063***		
	(0.041)	(0.023)	(0.024)		
Same-to-Different				-0.041	
				(0.026)	
Different-to-Different					-0.000
					(0.009)
Pair fixed effects	x	x	x	x	x
Control variables		x	x	x	x
HRR specific time trends			x		

Note: All estimations are based on the PCP-to-specialist 2013-2015 subsample. Column (1)-(3) display two-way fixed effect estimates of the effect Switch-to-Same has on the proportion of patient sharing from a PCP to a certain specialist, with different level of additional controls. Column (1) controls only for physican-pair fixed effects and year fixed effects. Column (2) additionally controls for physician and hospital characteristics. I also control for HRR specific time trends in Column (3). Column (4) and (5) reports the effect of switching from same to different EHR developer and from different to different developer, respectively. All standard errors are clustered at the PCP's affiliated hospital level and are reported in the parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B2—: Estimates of Effect Heterogeneity (2013-2015)

	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Switch-to-Same	0.145***	0.059*	0.098**	0.111***	0.072***	0.080***	0.054
	(0.043)	(0.032)	(0.049)	(0.039)	(0.022)	(0.025)	(0.034)
Switch-to-Same x 1(Long-term relationship)	-0.078*						
	(0.041)						
Switch-to-Same x 1(Same HSA)		0.055					
		(0.042)					
Switch-to-Same x 1(Same HRR)			-0.021				
			(0.056)				
Switch-to-Same x 1(Same gender)				-0.041			
				(0.035)			
Switch-to-Same x 1(Male to female)					0.128**		
					(0.062)		
Switch-to-Same x 1(PCP has more exp)						0.001	
						(0.031)	
Switch-to-Same x 1(market share >50)							0.050
							(0.043)

Note: Estimates are from the PCP-to-specialist 2013-2015 subsample. In Column (6)-(12), I regress log(proportion of shared patients) on Switch-to-Same and its intersection with various physician-pair characteristics. The intersection terms are reported as row titles in the table. 1(.) is a characteristic function. All standard errors are clustered at the PCP's affiliated hospital level and are reported in the parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Appendix C. Proves of Distorted Referral Patterns

C1. Proof of Proposition 1

Consider a local physician referral market (J, K) with only two EHR developers. Assume $q \in K$ is the specialist of the highest quality and let h_q denote the EHR developer he/she uses. The number of specialists using h_q is denoted by n_{same}, and the number of specialists using the other developer is denoted by n_{diff}. $P_{same,q}$ and $P_{diff,q}$ denotes the probability of q receiving patients from PCPs using either h_q or the other EHR developer, respectively. $\delta_h \equiv \frac{E[e^{x_h \gamma}]}{e^{x_q \gamma}}$ with $h \in \{same, diff\}$ measures the expected quality of specialists using h_q or the other EHR developer,relative to the quality of q. We have

$$P_{same,q} = \frac{e^{\beta + x_q \gamma}}{\sum_{\kappa} e^{v_{j\kappa}}} \tag{C1}$$

$$= \frac{e^{\beta + x_q \gamma}}{\sum_{\kappa:h_\kappa \neq h_q} e^{x_\kappa \gamma} + \sum_{\kappa:h_\kappa = h_q} e^{\beta + x_\kappa \gamma}} \tag{C2}$$

$$\xrightarrow{p} \frac{1}{e^{-\beta} n_{diff} \delta_{diff} + n_{same} \delta_{same}}, \tag{C3}$$

The derivation of $P_{diff,q}$ is similar. When the market has more than two EHR developers, i.e. $|H| > 2$, we have

$$P_{same,q} \xrightarrow{p} \frac{1}{n_{same} \delta_{same} + e^{-\beta} \sum_{h \in H:h_k \neq h_q} (n_h \delta_h)}, \tag{C4}$$

and the probability of q receiving patient from PCPs using a different EHR developer $h' \in H \backslash h_q$ is

$$P_{h',q} \xrightarrow{p} \frac{1}{n_{same} \delta_{same} + \sum_{h \in H:h_k \neq h_q} (n_h \delta_h) + (e^{\beta} - 1) n_{h'} \delta_{h'}}. \tag{C5}$$

When $\beta = 0$, $P_{same,q} = P_{h',q}$ for $\forall h' \in H \backslash h_q$. When $\beta > 0$, $P_{same,q} > P_{h',q}$ because

$e^{-\beta}\sum_{h\in H:h_k\neq h_q}(n_h\delta_h) < \sum_{h\in H:h_k\neq h_q}(n_h\delta_h)$ and $(e^{\beta}-1)n_{h'}\delta_{h'} > 0$

C2. Proof of Proposition 2 - Cluster Effect

The odds ratio of same versus different EHR developer referring to q is given by

$$\frac{P_{same,q}}{P_{diff,q}} = \frac{e^{\beta}n_{diff}\delta_{diff} + n_{same}\delta_{same}}{e^{-\beta}n_{diff}\delta_{diff} + n_{same}\delta_{same}} \tag{C6}$$

$$= \frac{e^{\beta} + \frac{n_{same}}{n_{diff}}\frac{\delta_{same}}{\delta_{diff}}}{e^{-\beta} + \frac{n_{same}}{n_{diff}}\frac{\delta_{same}}{\delta_{diff}}} \tag{C7}$$

Take derivative of the odds ratio with respect to the relative quality of $\frac{\delta_{same}}{\delta_{diff}}$

$$\frac{\partial \frac{P_{same,q}}{P_{diff,q}}}{\partial \frac{\delta_{same}}{\delta_{diff}}} = \frac{\frac{n_{same}}{n_{diff}}(e^{-\beta} + \frac{n_{same}}{n_{diff}}\frac{\delta_{same}}{\delta_{diff}}) - \frac{n_{same}}{n_{diff}}(e^{\beta} + \frac{n_{same}}{n_{diff}}\frac{\delta_{same}}{\delta_{diff}})}{(e^{-\beta} + \frac{n_{same}}{n_{diff}}\frac{\delta_{same}}{\delta_{diff}})^2} \tag{C8}$$

$$= \frac{(e^{-\beta} - e^{\beta})\frac{n_{same}}{n_{diff}}}{(e^{-\beta} + \frac{n_{same}}{n_{diff}}\frac{\delta_{same}}{\delta_{diff}})^2} < 0 \tag{C9}$$

Appendix D. Proves 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 there is a sufficient number of specialists such that k's choice does not affect n_h, we have

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

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

and

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

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

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

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

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

where

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

When comparing π_1 with any other choice $\pi_{i:i\neq 1}$, most terms in Equation (D5) will cancel off. As a result, we arrive at a situation where comparing π_1 with $\pi_{i:i\neq 1}$ is equivalent to comparing $\frac{P(h_1)}{n_1\delta_1+e^{-\beta}\sum_{h\neq h_1} n_h\delta_h} + \frac{P(h_i)}{n_1\delta_1+\sum_{h\neq h_1} n_h\delta_h+(e^{\beta}-1)n_i\delta_i}$ 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.