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# Peer Effects in Physician Adoption of Electronic Medical Records: Evidence from California

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**Abstract**

I study peer effects in adoption of Electronic Health Records (EHR) by medical professionals in California during the period 2011–2014, following the Medicare and Medicaid "Meaningful Use" EHR Incentive Programs. Peer effects are identified by combining annual adoption reports from the program with public records on physician shared patients networks. Results suggests large peer effects exists in EHR adoption: adoption by all peers increases the odds of adopting EHR within a year by 76%, even after accounting for the fact that practice group members are likely to adopt EHR at the same time. Results imply that using available data on provider networks may allow policymakers to expedite overall adoption rates. These methods can be used to study a wide range of technology adoption processes.

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# 1 Introduction

The decision by physicians to adopt new technologies is hardly a lonely one. Professional networks give them ample opportunities for learning from peers. Despite mounting evidence of peer effects in other contexts, and although in medicine technology adoption processes affect both patients' health and expenditure growth, the role of peer effects in these processes are largely unknown. Understanding such network interactions among physicians can help policymakers expedite the diffusion of technologies, such as when, due to positive externalities, adoption is too slow.

This study shows peer effects exist among U.S. medical providers in the adoption of Electronic Health Records, which is an umbrella term for multiple functionalities such as e-prescribing and the ability to obtain results of lab tests electronically. Despite their clear benefits to patient management and prospects of improving care coordination and reducing medical mistakes, EHR adoption in the U.S. has been staggered, particularly in office settings.[1] A major policy response, the HITECH Act of 2009, provided substantial and time-sensitive financial incentives to EHR adopters with the goal of making adoption universal.[2] This study shows that even faced with strong individual incentives to adopt EHR, individual decisions to adopt were significantly influenced by others: The odds of providers adopting EHR increase almost twofold once colleagues with whom they share patients adopt. Results imply that early adopters induce further adoption indirectly, and thus that augmenting wholesale incentive programs with the targeting of well-connected individuals could, therefore, expedite adoption at a lower cost.

Peer effects are identified using two sources of variation in the data: spatial (in the network sense), and temporal. Detailed data on professional networks combined with longitudinal data on adoption times help address two known difficulties with identifying peer effects. First, peers might behave similarly not because they influence each other, but because they face common external shocks. To separately identify peer effects, earlier

[1] Generally, electronic billing is typically adopted early, patient and case management functions later, and interactions across settings last. (Hsiao et al., 2012)

[2] The Health Information Technology for Economic and Clinical Health (HITECH) Act was part of the Recovery and Reinvestment Act of 2009.

works relied on exogenous shocks to peers (Tucker, 2008), on random or semi-random assignments (Sacerdote, 2001; Bayer et al., 2009; Ammermueller and Pischke, 2009; Kuhn et al., 2011), or on experimental designs (Duflo and Saez, 2003; Banerjee et al., 2013). This work uses longitudinal data that reveal whether individuals adopt *after* their peers have done so. Because actions occur at different points in time, they are not due to common shocks, at least not to shocks that are simultaneous. Second, observing a network structure solves the reflection problem that arises with the identification of peer effects using data on groups (Manski, 1993). The problem is that when all members of a group are each others' reference, group outcomes, and its mean characteristics are perfectly collinear. In contrast, social networks are intransitive, so reference groups vary even among connected individuals, and peer effects are identified. This use of network intransitivity for identification, proposed by (Bramoullé et al., 2009), is also similar to the use of overlapping group affiliation suggested by De Giorgi et al. (2010). Similar data on networks and action logs have been recently used to study peer effects in user behaviors in online settings, where such data is abundantly available from social network platforms (see Goyal et al., 2010; Aral et al., 2009, for examples using Flikr and Yahoo! data).

This study also contributes to the literature by demonstrating and correcting for the potential survival bias that arises when adoption times are not observed precisely, but rather at some coarse frequency. Such data limitations are typical for many administrative data sets, as they are often collected through a costly reporting process. (The HITECH, for example, requires annual reports.) This is much unlike the complete action logs that are continuously available, for example, through online social networking platforms. The problem is that infrequent sampling may generate survival bias: many sequential decisions appear simultaneous in the data. This study demonstrates how this issue can be alleviated using indirect inference, a simulation-based estimation method (Gourieroux et al., 1993; Smith, 2008). Indirect inference uses simulations to overcome intractable likelihood functions. Estimates are calculated by comparing actual data against data that are simulated from a model of the adoption processes. Estimations from another, auxiliary model are used as criteria for comparison. Indirect inference chooses the parameters of the underlying economic model so that estimates of the parameters of the auxiliary model obtained from actual and simulated data are as close as possible. In the current context, simulations allow for matching actual data with "snapshots" of the adoption state obtained from a peer-influence process simulated at a different frequency than the one observed.

Data used are a combination of EHR adoption reports following the HITECH Act and data on physician professional networks. The focus is on physicians in ambulatory settings, whose payments were time sensitive (reporting late resulted in lower payments) making truthful reporting compatible with incentives. Since providers could claim benefits through either Medicare or Medicaid (Medicaid payments were also higher: $63,000 per provider, compared with $44,000 in Medicare), the focus is on California, where data from both programs are available.

In such context of strong external incentives to adopt EHR, one may wonder whether peer effects would have any significance at all. To address this question, adoption data are combined with data on professional networks of two types. A link in the first network encodes providers who share group-practice affiliations. A link in the second network encodes providers with 11 or more common patients within a year. Observing both types of links helps separate peer effects from adoption by practice groups—who likely share costs and thus have every reason to coordinate, although reporting and attestation for meaningful use must still be made individually. On average, more than 80% of their colleagues with whom providers share patients are outside their practice groups.

EHR adoption exhibits substantial peer effects. All else being equal, individuals are significantly more likely to adopt EHR when a greater fraction of their colleagues with whom they share patients adopt EHR, even after accounting for gender, experience, medical specialty, and for the (unsurprisingly high) correlation with adoption by practice group affiliates. Logit and Cox proportional hazard specifications estimated from annual data show the odds ratio of adopting EHR the following year increase substantially when colleagues adopt (the odds ratio increases by 76%, CI [61%, 92%]).[3] Overall, peer effects

[3]Put differently, each ten percentage point increase in the cumulative EHR adoption rate of their peers increase the odds of individuals adopting EHR in the subsequent year by 7.6%.

account for more of the variation in adoption times than heterogeneity in individual gender, experience, and medical specialty combined. Indirect inference estimates are in accord with reduced form estimates, showing robust peer effects even when the underlying process is specified at semi-annual or quarterly frequencies.

This study is the first to use data on networks to study physician technology adoption and to show its peer influence. Peer effects have been documented in various other contexts, including: schooling performance (Sacerdote, 2001; Ammermueller and Pischke, 2009), criminal behavior (Bayer et al., 2009), participation in retirement funds (Duflo and Saez, 2003), adoption of online services (Aral et al., 2009), and microfinance (Banerjee et al., 2013). A continuing line of research tracks the progression of EHR adoption in the U.S., prior to and during the incentive program (Hsiao et al., 2012; Decker et al., 2012; Patel et al., 2013; Hsiao et al., 2013; Wright et al., 2013; Xierali et al., 2013; Furukawa et al., 2014; DesRoches, 2015; Mennemeyer et al., 2015). However, that research did not consider peer effects.

Considering the interactions between providers could allow policymakers both better predict and expedite further adoption. Specifically, it could provide new insight into why EHR adoption in the United States has been slow, and show current policies aimed at expediting adoption could expedite further adoption by making sure information reaches influential individuals (as Banerjee et al., 2013, have demonstrated for microfinance). Encouraging EHR adoption is still a pressing concern, as most providers have still only adopted basic EHR functionality (such as drug interaction alerts), and lack advanced functions (such as inter-operability across providers).[4]

More generally, peer effects like the ones studied here can have the potential to inform our understanding of technology adoption processes in medicine in general. Technology in medicine has so far been studied more at the aggregate or individual levels (but not using explicit networks data). Existing work focuses on technology's impact on expenditure growth (Cutler and McClellan, 2001; Chandra and Skinner, 2012), costs and benefits of specific treatments Skinner et al. (2006), the impact of insurance type on aggregate

[4]Furukawa et al. (2014) for example show that by the end of 2013, only 48% of office-based physicians reported having a system that met the criteria for a basic system.

diffusion rates (Baker, 2001), and the impact of economic incentives on innovation (Kremer and Snyder, 2006; Berndt et al., 2007; Sampat and Williams, 2015). Such work has not considered the network structure between providers, which this study shows can be consequential. More broadly, this study is also related to earlier work on variation in practice styles between providers. Such variation has been previously explained, among other explanations, in terms of differences in productivity spillovers (Chandra and Staiger, 2007), information spillovers, (Agha and Molitor, 2015), or diagnostic skills (Currie and MacLeod, 2013; Currie et al., 2015). Networks analysis has the potential to reveal more directly the relationships between physician interactions, their financial incentives, and the ways they learn from each other and affect each others' clinical choice of treatment technology.

## 2 Background

This section discusses the institutional details of the Health Information Technology for Economic and Clinical Health (HITECH) Act. Part of the American Recovery and Reinvestment Act of 2009, the act came after a decade when EHR adoption in the United States by physicians lagged that of many other developed countries and was designed to improve the United States health care delivery system through the adoption and use of health information technology.

**The HITECH Act** The Act offered incentives to eligible professionals and hospitals that adopted and demonstrated the meaningful use of EHR. In 2011, the Medicare Electronic Health Records (EHR) Incentive Program of the Centers for Medicare and Medicaid Services began providing incentive payments to eligible professionals who adopt and "meaningfully" use specific EHR capabilities. Under the programs, by taking specific predetermined EHR capabilities, eligible professionals could receive as much as $44,000 over a five-year period through Medicare or $63,750 through Medicaid. Both programs were federally designed and financed, but the states administered the Medicaid program.

Between 2011 and 2015, more than $21.1 billion in Medicare EHR Incentive Program payments and \$10.3 billion in Medicaid EHR Incentive Program payments have been made. Incentives were time sensitive: providers that started participating in the program in 2014 or later received lower payments; to receive full benefits for the Medicaid incentive program, providers have to start participating by 2016. However, despite the increase in EHR adoption rates following the incentive program, EHR adoption still exhibits persistent gaps. According to a recent survey, by the end of 2013, only 48% of office-based physicians reported having a system that met the criteria for a basic system.[5] Studying the EHR incentive program, Furukawa et al. (2014) show physicians in solo practices and non–primary care specialties are lagging behind others.

**Eligible Professionals** Incentive payments were made to individual professionals and eligibility was based on individual reporting of adoption and attestation for meeting a set of criteria discussed below. Eligible professionals under the Medicare EHR incentive program included physicians, dentists, podiatrists, optometrists and chiropractors. Under the Medicaid program, eligible professionals included physicians, nurse practitioners, certified nurse-midwives, dentists, and physician assistants who lead rural clinics are eligible. Providers were eligible to participate in the Medicaid program only if 30% or more of their services are furnished to Medicaid patients (20% for pediatricians). Professionals eligible for both the Medicare and the parallel Medicaid EHR incentive programs had to choose which program they wish to participate in when they registered.[6] Hospital-based eligible professionals were not eligible for incentive payments. An eligible professional is considered hospital-based if 90% or more of his or her services are performed in a hospital inpatient or emergency room setting.

**Group Practices** In a group practice, each eligible professional had to qualify separately for an incentive payment by successfully demonstrating meaningful use of certified

[5] A "basic system", according to the survey, has all of the following functionalities: patient history and demographics, patient problem lists, physician clinical notes, comprehensive list of patients' medications and allergies, computerized orders for prescriptions, and ability to view laboratory and imaging results electronically. Source NCHS Data Brief, Use and Characteristics of Electronic Health Record Systems Among Office-based Physician Practices: United States, 2001–2013, January 2014.

[6] Data source: EHR Incentive Program - CMS, `https://www.cms.gov/regulations-and-guidance/legislation/ehrincentiveprograms/eligibility.html`, Accessed March 2017

EHR technology. Eligible professionals were only eligible for one incentive payment per year, regardless of the number of practices or locations at which they provided services. An eligible professional who worked at multiple locations, but did not have certified EHR technology available at all of them had to have 50% of their total patient encounters at locations where certified EHR technology is available and would base all meaningful use measures only on encounters that occurred at locations where certified EHR technology is available.

**Reported Measures** To receive payments, eligible professionals must have completed 15 core objectives, five objectives out of 10 from menu set, six total Clinical Quality Measures, three core or alternate core, and three out of 38 from the additional set.[7] Measures are calculated based on all patients seen or admitted during the EHR reporting period. The 15 core measures include: computerized provider order entry (CPOE); e-prescribing (eRx); reporting ambulatory clinical quality measures to CMS; implementing one clinical decision support rule; providing patients with an electronic copy of their health information, upon request; providing clinical summaries for patients for each office visit; drug-drug and drug-allergy interaction checks; recording patient demographics; maintaining an up-to-date problem list of current and active diagnoses; maintaining active medication list; maintaining active medication allergy list; recording and charting changes in vital signs; recording smoking status for patients 13 years or older; capability to exchange key clinical information among providers of care and patient-authorized entities electronically; protecting electronic health information. The menu objectives are: drug-formulary checks; incorporating clinical lab test results as structured data; generating lists of patients by specific conditions; sending reminders to patients per patient preference for preventive/follow up care; providing patients with timely electronic access to their health information; using certified EHR technology to identify patient-specific education resources and providing them to patient, if appropriate; medication reconciliation; generating summary of care record for each transition of care/referrals; capability

[7] Data source: Medicare & Medicaid EHR Incentive Program Meaningful Use Stage 1 Requirements Overview, `https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/downloads/MU_Stage1_ReqOverview.pdf`, Accessed March 2017

to submit electronic data to immunization registries/systems; capability to provide electronic syndromic surveillance data to public health agencies. The core clinical quality measures are hypertension and blood pressure measurement, tobacco use assessment, and adult weight screening and follow-up.

**Incentive Timing** Payments were higher for early adopters, which made reporting of adoption times incentive compatible. In order to receive the maximum incentive payments of $44,000 (paid over five years), Medicare providers had to start participation early, in 2011 or 2012. Those joining in 2013 received only $39,000, and those joining in 2014 received only $24,000. From 2015, those not joining are subject to a one percent penalty on their Medicare reimbursement. The penalty increases to two percent in 2016 and three percent in 2017. Providers have to start participating by 2016 to receive the maximum payments of $63,750 through the Medicaid program (paid over six years).

# 3 Data

This study combines data on reported EHR adoption times, physician characteristics, and physician affiliations and common patients, for California medical professionals. Data on both Medicare EHR incentive payments and providers' affiliations are maintained by the Centers for Medicare and Medicaid Services (CMS). Data on Medicaid EHR incentive payments in California are maintained by California's Medicaid program, Medi-Cal. All datasets are publicly available online.

Data on EHR adoption are obtained from CMS and Medic-Cal public records of adoption times reported by eligible professionals, as part of the EHR Meaningful Use incentive program progress monitoring and public reporting (the programs are described in Section 2).[8] To qualify for incentive payments, professional have to attest to implementing and meaningfully using EHR in their practice. Since payments depended on the starting year of EHR use, there are strong incentives to report EHR adoption not later

[8] Data and Program Reports CMS, https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/DataAndReports.html, Accessed March 2016

Table 1: Descriptive Statistics: EHR Adoption by California Providers

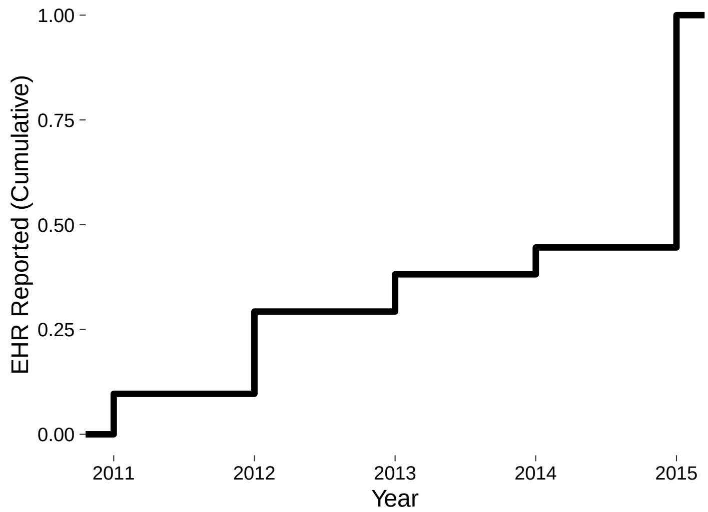
| Year | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|
| Adopted EHR During Year[†] | 0.097 | 0.217 | 0.126 | 0.104 |
| Male | 0.670 | 0.668 | 0.663 | 0.663 |
| Experience (years) | 23.5 | 23.2 | 22.6 | 22.4 |
| | | | | |
| Previous Cumulative Adoption Among: | | | | |
| % Practice Peers | | 0.055 | 0.158 | 0.202 |
| % Common-Patients Peers | | 0.043 | 0.121 | 0.150 |
| At Risk Individual Providers | $57,575$ | $52,018$ | $40,714$ | $35,599$ |

*Notes:* † As reported through either Medicare or Medicaid incentive programs. Data sources: Provider Characteristics and Medicare EHR adoption, CMS; California Medicaid EHR adoption Medi-Cal. The sample excludes providers in specialties with fewer than 30 professionals or where less than 20% of all practicing professionals adopted EHR by 2014. The sample may still contain professionals who work mostly in hospital settings and are therefore ineligible to participate. See Section 2 for eligibility details and appendix for detailed data on adoption by specialty.

than the year it occurred. However, there are no incentives to record precisely the starting date *within* the year, and data are effectively reported at annual frequency (reporting dates exhibit considerable bunching around year ends).

The sample used consists of all Medicare and Medicaid providers in California practicing in one of 51 medical specialties. The sample is restricted to California as it is the only state in which Medicaid EHR adoption reports are publicly available. Since providers could adopt through either Medicare or Medicaid (in case 30% or more of their patient covered by Medicaid), data from Medicare only does not distinguish between Medicaid adopters and non-adopters. Table A3 shows that indeed a non-negligible fraction reported adoption through Medicaid. (Since the Medicaid program payments were higher, it is likely that those eligible for both programs would choose to report through Medicaid.) Since medical professionals working mostly in hospital settings are not eligible to participate, and since some specialties were not included in the program, only medical specialties with an overall adoption rate of 20% or more (at the end 2015) were included in the sample, under the assumption that most providers in those specialties were unlikely to be eligible. Table A2 shows 2015 adoption rates by specialty. Excluded specialties include several specialties that were not eligible to participate in the program, such as clinical psychology and physical therapy, as well as specialties like pathology and emergency medicine that are typically practiced in a hospital setting. Specialties with fewer than 30 practicing individuals were also excluded.

Figure 1: Cumulative Aggregate Adoption Rates, by Year




*Notes:* Cumulative fractions for 2011–2014 denote adoption by California providers of EHR through either Medicaid or Medicare during that year. The remaining 2015 fraction denotes censored observations *not* adopting by 2014. Data source: CMS, Medi-Cal.

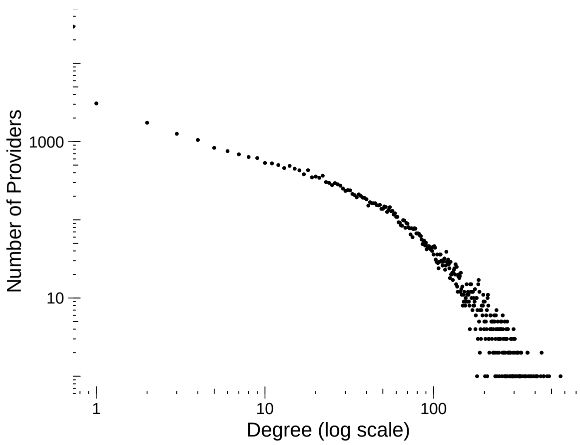
Physician characteristics are obtained from Physician Compare, a public CMS database.[9] The included characteristics are: sex, specialty, group affiliation, year of graduation (used to calculate experience), and state (used to restrict the sample to California providers).

Two networks of interactions between physicians are elicited from the data: sharing a group practice affiliation and having common patients. Data on common patients were made available by CMS in response to a FOIA request.[10] The data record each pair of physicians who had 11 or more patients in common during 2010, as recorded on Fee-For-Service Medicare claims. (A patient is considered common to a pair of physicians if both physicians encountered the patient within a 30-day period.) Additional layer of connections is elicited from Physician Compare group-affiliation data, by recording a link between each pair of providers who are affiliated with at least one common practice group.

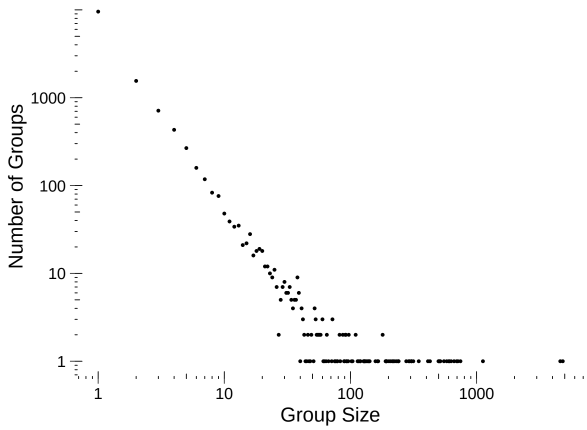
[9]Physician Compare Database, `https://data.medicare.gov/data/physician-compare` Accessed February 2016.

[10]The request was made by a software developer and open-data proponent, Fred Trotter, in 2012. Data are available through CMS FAQ7977, `https://questions.cms.gov/faq.php?faqId=7977` Accessed February 2016.

Figure 2: Degree Distributions




(a) Common-Patients Degree




(b) Practice Group Size

*Notes:* (a) Common-Patients network degree distribution and (b) group size distribution. A link in the shared-patient network exists providers with more than 11 common patients in 2010. Log-log scales: liner relationships reflect power-law distributions. 14.4% of their colleagues with whom providers had (11 or more) common patients also practice in their same practice groups.

Table A1 shows the distribution of the distinct number of groups physicians are affiliated with. About 90% of physicians are affiliated with at least one practice group, and 80% are affiliated exactly one. The degrees distribution in both networks is approximately power-law. Simply put, there are many nodes with few neighbors and few nodes with many neighbors. Figure 2 shows the distribution of degrees (i.e., the number of neighbors) in the shared-patient network and of group size (which is identical to degree in the affiliation networks for physicians with one group affiliation).

The years 2011–2014, when the incentive programs was in effect, where a period of transition, with a significant fraction of the ambulatory providers adopting during that time. Figure 1 shows the cumulative overall adoption rates for the 57,575 providers in the sample. The peak of adoption occurred in 2012, consistent with the incentives (joining the Medicare program after 2012 involved lower benefits). Table 1 shows individual characteristics and adoption rates by peers per year, for the sub-sample of individuals still "at risk" (i.e., who have not yet adopted by each year). Later sub-samples have lower fractions of males and a lower average experience, suggesting some effect of these characteristics on early adoption (later confirmed by the analysis). Reflecting the progression of adoption in the overall population, the mean fraction of neighbors of each type who have already adopted the technology increases over time. Since program payments started in 2011, with strong incentives for previous adopters to report during that year, 2011 adoption reflects a mix of incentive-driven and baseline adoption. The overall low base adoption rate of 9.7% reflects in part the fact that some ineligible professionals are still included in the sample. Results should be interpreted with this fact in mind. The inclusion of ineligible professional could bias estimates of the impact of various factors on adoption downwards.

# 4 Empirical Strategy

A model of network diffusion is used to study the spread of technology over provider networks. Identification of peer effects in the adoption of EHR is based on two sources of variation: the variation over time in adoption by peers, and the variation between individuals in the composition of their peer groups. Combined, data on networks and adoption reveal whether adoption is related to the fraction of peers who have already adopted the technology. Annual reporting frequency could make consecutive adopters appear as if they adopted simultaneously. To overcome the ensuing survival bias, I use indirect inference. I simulate data from an underlying model of adoption specified at higher-than-observed frequencies, and match simulated and observed data. The rest of this section described the empirical strategy.

## 4.1 Setup

Consider a graph (network) $\langle V, X, (G^1, G^2)\rangle$, where $V$ is the set of nodes (providers), $X$ is their individual time invariant characteristics (the sets $X_i$ for all nodes $i \in V$); and $G^1$, and $G^2$ are row-normalized adjacency matrices that summarize two types of links between providers: group practice affiliation and having common patients. That is, for each $i, j \in V$, the matrix cell $G_{ij}$ is zero if $i$ and $j$ are not linked and $\frac{1}{n_i}$ if $i$ and $j$ are linked, where $n_i$ is the total number of nodes with whom $i$ is linked. Hence rows of $G$ sum to one for providers who have any links and to zero for isolated providers. Specifically, a link is recorded in $G^1$ for each pair of providers affiliated with at least one common group practice; a link is recorded in $G^2$ for each pair of providers who have seen at least 11 common patients in 2010. (a patient is considered common to $i$ and $j$ if $i$ and $j$ both encountered the patients within a 30-day period). I assume the graph is fully observed and fixed over time and treat links as undirected and unweighted. (data on link weights, direction, and evolution over time allow relaxing any of these assumptions without much change to the framework).

Over time, providers can decide to adopt irreversibly EHR technology. The (right-censored) *adoption time* of provider $i$, denoted $\tau_i \in \mathcal{T} = \{t_1, t_2, \ldots, T\}$, is the time $i$ adopted the technology. Let $Y_{it} = 1$ if $i$ adopted by period $t$, namely, if $\tau_i \leq t$, and $Y_{it} = 0$ otherwise. A *snapshot* $Y_t = (Y_{it})_{i \in V}$ is the overall state of adoption by time $t$. To study the diffusion of EHR adoption, I adapt to the current context a commonly used theoretical model, the linear threshold model (Granovetter, 1978; Schelling, 1978). The linear threshold model describes a contagion process, where every infected neighbor for a node contributes certain weights, and if their sum is greater than a threshold, the node is infected. In the model used here, individuals who have not done so already adopt in $t$ iff net benefits of adoption are positive. These benefits depend on both individual characteristics and adoption by peers. Namely, conditional on $\tau_i \geq t, Y_{t-1}, X_i$, and $G$:

$$Y_{it} = \mathbb{1}\{b_{it} > \varepsilon_{it}\} \tag{1a}$$

Where

$$b_{it} = \alpha + \beta_1 G_i^1 Y_{t-1} + \beta_2 G_i^2 Y_{t-1} + \gamma X_i + \eta_t \tag{1b}$$

Net benefits may depend on individual characteristics in $X_i$, on the period ($\eta_t$ denotes a set of period dummies), and on the fraction of neighbors having already adopted by $t-1$, which is given by the product $G_i Y_{t-1}$. ($G_i$ is the row corresponding to $i$ in the adjacency matrix $G$.) The term $\varepsilon_{it}$ is the stochastic and unobserved individual threshold for adoption that may capture individual costs of using or adopting EHR.

This latent variable model that can be interpreted as reflecting a decision to adopt that follows an individual weighing of costs and benefits, where net benefits of using EHR are heterogeneous (e.g., they may be greater for certain medical specialties, for more experienced providers, and in years where incentive payments are higher) and increase in the number of neighbors adopting the technology. This model accommodates peer effects working through either cost reduction or increase in benefits, though it does not distinguish between the two. Both costs and benefits considered could be either real or perceived, and could be either monetary (such as government incentive payments or system setup costs) or non-monetary (such as the psychic cost of adapting to new technology). This model neglects strategic considerations. The model, by considering overall cumulative adoption rates implicitly assumes that adoption by others has persistent influence.[11] A variant of this model is studied where instead of cumulative adoption by peers only recent adoption by peers is considered influential.

## 4.2 Identification

The goal is to identify separately whether individual providers' decision to adopt EHR is influenced by their peer adoption decisions or by their own characteristics.[12] The challenge is to identify separately peer influence from shocks that are correlated across connected individuals. Such unobserved shocks could occur, for example, if certain areas were exposed to more intense marketing of EHR systems in certain years. Using longitudinal data and detailed network structure limits mitigate such concerns compared with cross sectional or group data, in two ways. First, longitudinal data reveal the extent to which individuals adopt the technology *after* their friends do so. Such intertemporal correlation does not arise from correlated shocks that are simultaneous, even if such shocks

[11] The linear threshold model is one of two models of diffusion commonly used in many applications such as viral marketing (Domingos, 2005), and contagion models (Dodds and Watts, 2004). The other model is the independent cascade model (e.g., Goldenberg et al., 2001), where each infected node is allowed one chance to infect a neighbor with some probability generally depending on the edge strength between the nodes. Independent cascades are more appropriate for settings where information or contagion is short lived.

[12] A related question is whether EHR adoption decisions are affected by neighbors' characteristics. Such effects were termed by Manski *exogeneous peer effects*. I currently abstract from such effects. Including them in the analysis is left for future work.

are correlated with the network structure. Second, detailed network structure means that the reference group varies even among individuals that are connected. The main identifying assumption is that $\mathrm{Cov}(\varepsilon_{it}, G_i Y_{t-1}) = 0$: individual unobserved shocks are uncorrelated with the previous adoption by peers. It is implied by the stronger assumption that $\varepsilon_{it}$ and $\varepsilon_{jt'}$ are independent when $t \neq t'$.

### 4.3 Estimation

If the individual threshold $\varepsilon$ is i.i.d. and Gumbel distributed, the linear threshold model is a latent-variable model that yields a logit specification:

$$\Pr(Y_{it} = 1 | \tau_i \geq t, Y_{t-1}, X_i, G) = \frac{\exp(b_{it})}{1 + \exp(b_{it})} \tag{2}$$

Alternatively, I also estimate a Cox model where hazard rates are assumed to be proportional and given by:

$$\lambda(t) = \lambda_0(t)\exp(\beta_1 G_i^1 Y_{t-1} + \beta_2 G_i^2 Y_{t-1} + \gamma X_i) \tag{3}$$

Estimation is complicated by the survival bias that may arise because only annual snapshots are available, so events that appear simultaneous in the data may have in fact occurred sequentially. With only end-of-year snapshots observed, $(Y_t)_{t \in \mathcal{T}_0 \subsetneq \mathcal{T}}$, the data does not distinguish providers $i$ and $j$ who adopted together, say during the same month, from $i$ and $j$ who adopted in the consecutive month. This might be a problem as the adoption process in (2) give rise to survival bias. For example, if men are more likely to adopt early (as would be captured by $\gamma$), the population at risk would be increasingly feminine over time. Observing infrequent snapshots means some changes of the population occur within interim periods so that some of the interim changes might not be estimated correctly, and mis-attributed to the population composition during the last snapshot observed. Specifically, within-year changes in adoption rates within each peer group are imprecisely observed.[13]

[13]For example let $T$ be set of consecutive periods and, let $p_T|r = Pr(\tau \in T | \tau \geq r, Y_r, X)$ be the

To overcome these challenges, I use indirect inference (Gourieroux et al., 1993; Smith, 2008). This method estimates the parameters by minimizing the distance between data simulated from the model (2) and the actual data, where the metric used is the weighted difference between estimates of a separate auxiliary model, fitted to both actual and model-simulated data. The rest of this section described the procedure in more detail.

Indirect inference estimates the parameters of a fundamental model indirectly, by simulation data and estimating an auxiliary model. Recall that the fundamental model is a mapping from $G, X$ to a distribution on the set of possible $Y_t$, with parameters which we collectively referred to here as $\beta$, and a stochastic residual $\varepsilon$. An auxiliary model is a possibly misspecified such mapping with parameters denoted $\theta$. Let $Z$ denote the actual data $(G, X, Y)$, let $\theta(Z)$ denote estimates of the auxiliary model parameters $\theta$ using data $Z$, and let $\tilde{Z}(\beta, \varepsilon) = (\tilde{Y}(\beta, X, G, \varepsilon), X, G)$ denote data simulated using the fundamental model with parameters $\beta$, the actual exogenous variables $G$ and $X$, and a random draw of residuals $\varepsilon$ from their postulated distribution. The estimation is performed in three steps:

1. Estimate the auxiliary parameter using actual data $\hat{\theta} = \theta(Z)$.
2. Draw residuals of the fundamental model $\tilde{\varepsilon}$
3. Pick $\beta$ that produces simulated data with the associated auxiliary parameters closes to actual ones, that is

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left(\tilde{\theta}(\tilde{Z}(\beta, \tilde{\varepsilon})) - \hat{\theta}\right)' W \left(\tilde{\theta}(\tilde{Z}(\beta, \tilde{\varepsilon}))) - \hat{\theta}\right) \tag{4}$$

The third step is implemented using numeric minimization using iterated sub-steps. In

probability of adoption during any of these periods. If the model in (2) is estimated using snapshots from every *odd* period, the probability of adoption between observed snapshots is:

$$\overbrace{p_{t,t+1|t}}^{\tilde{p}} = p_{t|t} + p_{t+1|t} = p_{t|t} + (1 - p_{t|t})p_{t+1|t+1} > \overbrace{p_{t|t}}^{p}$$

A logit estimate treating the process as fully observed is going to be biased since

$$\tilde{p} > p \iff ln(\tilde{p}/(1-\tilde{p})) > ln(p/(1-p)) \iff X'\tilde{\beta} > X'\beta$$

each such step, data $\tilde{Z}(\beta, \tilde{\epsilon})$ is simulated using the fundamental model, and the auxiliary model estimates $\tilde{\theta}(\tilde{Z})$ calculated using the simulated data are compared against the estimates $\hat{\theta}$ calculated using the actual data. This process is repeated until it converges to a stable solution.[14] The weighting matrix $W$ used is the inverse of the estimated variance-covariance matrix of the coefficients of the auxiliary model, which approximates the Fisher information.

Indirect inference estimates the parameters of a fundamental model indirectly, by simulation data and estimating an auxiliary model. Recall that the fundamental model is a mapping from $G, X$ to a distribution on the set of possible $Y_t$, with parameters which we collectively referred to here as $\beta$, and a stochastic residual $\varepsilon$. An auxiliary model is a possibly misspecified such mapping with parameters denoted $\theta$. Let $Z$ denote the actual data $(G, X, Y)$, let $\theta(Z)$ denote estimates of the auxiliary model parameters $\theta$ using data $Z$, and let $\tilde{Z}(\beta, \varepsilon) = (\tilde{Y}(\beta, X, G, \varepsilon), X, G)$ denote data simulated using the fundamental model with parameters $\beta$, the actual exogenous variables $G$ and $X$, and a random draw of residuals $\varepsilon$ from their postulated distribution. The estimation is performed in three steps:

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The third step is implemented using numeric minimization using iterated sub-steps. In each such step, data $\tilde{Z}(\beta, \tilde{\epsilon})$ is simulated using the fundamental model, and the auxiliary model estimates $\tilde{\theta}(\tilde{Z})$ calculated using the simulated data are compared against the

[14] In the implementation, the Bound Optimization BY Quadratic Approximation, BOBYQA, numerical optimization algorithm is used, starting from logit estimates of (2) with annual frequency as the initial parameter.

estimates $\hat{\theta}$ calculated using the actual data. This process is repeated until it converges to a stable solution.[15] The weighting matrix $W$ used is the inverse of the estimated variance-covariance matrix of the coefficients of the auxiliary model, which approximates the Fisher information.

In the current context, indirect inference allows for simulation of the fundamental model in frequency greater than the one observed, so that the population composition could vary within interim, unobserved periods. Simulated snapshots that match the observed frequency are then used in the estimation of the auxiliary model. The auxiliary mode used is again the one described in (2), but specified at annual frequency—the frequency observed in the actual data. Standard errors are bootstrapped parametrically, by simulating multiple times, each time using a separate draw of residuals (Step 2. above), and calculating the standard deviation of the sample of estimates derived from such distinct simulations.

# 5 Results

Adoption of EHR is highly correlated with previous cumulative adoption by neighbors, suggesting the presence of significant peer effect. Table 2 shows results of logistic and Cox proportional hazards estimation of (2). Without any controls, there is a correlation between the rate of EHR adoption by providers and the adoption of EHR in previous years by peers with whom they have common patients (Column 1). Correlation in adoption with practice-group peers explains only part of this correlation (Column 2). Moreover, the conditional effect of peers—the main parameter of interest—are stronger when gender, experience, specialty, and period effects are accounted for (Column 3). The odds ratio of adopting EHR within a year increase almost twofold (coefficient 0.568; odds ratio 1.764; 95% CI [1.625, 1.916]) when (all) peers with common patients adopt. Note that since year dummies are included, this effect is not mechanically driven by the progression of adoption over 2011–2014. High correlation in adoption times also exists within group

[15] In the implementation, the Bound Optimization BY Quadratic Approximation, BOBYQA, numerical optimization algorithm is used, starting from logit estimates of (2) with annual frequency as the initial parameter.

practices, which is to be expected given the likelihood that group practice member coordinate EHR adoption. Mid-career providers are most likely to adopt, as suggested by the quadratic experience term. Specialty is a major factor in adoption decisions, although estimates partly reflect data limitations (providers' eligibility is determined in part by whether or not they mostly work in a hospital setting, which is highly correlated with specialty). The estimated effects of gender are small and turn insignificant once flexible interactions of gender and experience are included (Column 4), suggesting EHR adoption is not determined by gender per se, but rather by differences in the trajectory of the impact of experience on adoption rates, combined with the fact males are more experienced on average. Cox proportional hazard estimates yield a similar picture (Columns 6 and 7, corresponding to specifications analogous to Columns 3 and 4, respectively). Column 5 shows that including a single control for specialty—the average adoption rate in each specialty in 2011—does not matter much. Such single control for specialty is used in the numeric estimation of indirect inference estimates instead of multiple specialty dummies, for computational simplicity.

The estimated effects of peer adoption are stronger when peer adoption only during the previous year—not the cumulative adoption to date—is considered. Table 3 shows logistic estimates of (2) with this alternative measure of peer adoption. The signs of all effects are unchanged, but the estimated effects of adoption by peers of either type are larger (coefficient 0.99; odds ratio 2.7; 95% CI [2.428, 3.001]). These findings suggest that influence of peers adopting the technology is strongest shortly after they do so, and decays over time.

Table 2: Peer Effects in EHR Adoption

| | *Dependent variable: Adopt EHR* | | | | | | |
|---|---|---|---|---|---|---|---|
| | *logistic* | | | | | *Cox prop. hazards* | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Pct Peers Adopted (Common Patients) | 0.315*** | 0.249*** | 0.568*** | 0.568*** | 0.573*** | 0.493*** | 0.493*** |
| | (0.036) | (0.037) | (0.042) | (0.042) | (0.041) | (0.036) | (0.036) |
| Pct Peers Adopted (Group) | | 0.646*** | 1.520*** | 1.520*** | 1.510*** | 1.230*** | 1.230*** |
| | | (0.031) | (0.036) | (0.036) | (0.035) | (0.028) | (0.028) |
| Male | | | −0.069*** | 0.034 | −0.022 | −0.061*** | 0.030 |
| | | | (0.018) | (0.066) | (0.018) | (0.016) | (0.060) |
| Experience | | | 0.095*** | 0.104*** | 0.093*** | 0.084*** | 0.093*** |
| | | | (0.003) | (0.005) | (0.003) | (0.002) | (0.005) |
| Experience2 | | | −0.002*** | −0.002*** | −0.002*** | −0.001*** | −0.002*** |
| | | | (0.0001) | (0.0001) | (0.00005) | (0.00005) | (0.0001) |
| Male x Experience | | | | −0.012** | | | −0.011** |
| | | | | (0.006) | | | (0.006) |
| Male x Experience2 | | | | 0.0003** | | | 0.0003** |
| | | | | (0.0001) | | | (0.0001) |
| Specialty (Baseline) | | | | | 6.370*** | | |
| | | | | | (0.165) | | |
| Constant | −1.720*** | −1.800*** | −2.330*** | −2.400*** | −3.120*** | | |
| | (0.009) | (0.010) | (0.104) | (0.112) | (0.039) | | |
| Specialty | *N* | *N* | *Y* | *Y* | *N* | *Y* | *Y* |
| Year | *N* | *N* | *Y* | *Y* | *Y* | *N/A* | *N/A* |
| Providers | 57,575 | | | | | | |
| Events | 25,665 | | | | | | |
| Observations | 128,331 | | | | | | |

*Notes:* Estimation results of logit and Cox proportional hazard models using annual data. Pct Peers Adopted is the cumulative adoption rate by peers up until the previous year. Common Patients peers are peers with at least 11 common patients. Group peers are peers with at least one common practice group affiliation. Experience is years since graduation (Experience2 is squared Experience). Male is a male provider dummy. Specialty (Baseline) is the mean adoption rate by specialists of the same specialty as the providers in 2011. *p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered by provider.

Table 3: Peer Effects in EHR Adoption (Peer Adoption in Previous Year Only)

| | | *Dependent variable: Adopt EHR* | | |
|---|---|---|---|---|
| | | *logistic* | | |
| | | (1) | (2) | (3) |
| Pct Peers Adopted Recently (Common Patients) | | 1.240*** | 0.993*** | 1.010*** |
| | | (0.051) | (0.054) | (0.053) |
| Pct Peers Adopted Recently (Group) | | 1.470*** | 1.660*** | 1.680*** |
| | | (0.048) | (0.050) | (0.050) |
| Male | | | −0.071*** | −0.022 |
| | | | (0.018) | (0.018) |
| Experience | | | 0.089*** | 0.088*** |
| | | | (0.003) | (0.003) |
| Experience2 | | | −0.002*** | −0.001*** |
| | | | (0.0001) | (0.00005) |
| Specialty (Baseline) | | | | 6.480*** |
| | | | | (0.165) |
| Constant | | −1.430*** | −2.270*** | −3.080*** |
| | | (0.011) | (0.104) | (0.038) |
| Specialty | | *N* | *Y* | *Y* |
| Year | | *N* | *Y* | *Y* |
| Providers | 57,575 | | | |
| Events | 25,665 | | | |
| Observations | 128,331 | | | |

*Notes:* Estimation results of logistic regressions using observed (annual) data. Pct Peers Adopted Recently is the adoption rate by peers up until the previous year. Common Patients peers are peers with at least 11 common patients. Group peers are peers with at least one common practice group affiliation. Experience is years since graduation (Experience2 is squared Experience). Male is a male provider dummy. Specialty (Baseline) is the mean adoption rate by specialists of the same specialty as the providers in 2011. *p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered by provider.

Indirect estimates further suggest that peer effect estimates do not exhibit survival bias (Table 4). Estimates of peer effects obtained from simulations of model (2) at various frequencies are virtually identical to the ones obtained from the observed annual frequency. The exception is the estimated constants (baseline probability of adopting), which are lower for higher frequencies. This is to be expected because at higher frequencies each period is shorter. For example, consider the constants estimated from simulations with quarterly and semi-annual frequencies ($\alpha_Q = -5.26$, and $\alpha_S = -4.5$, respectively; Columns 2 and 3 of Table 4. The approximate baseline probability of adoption during the simulated period (assuming all other covariates are zero) is $p(\alpha) = \exp(\alpha)/(1 + \exp(\alpha))$, yielding $p_Q = 0.52\%$, and $p_S = 1.1\%$. But this doubling of the baseline probability is to be expected when moving from quarterly to semi-annual frequency, where each period is twice as long: $p_S \approx p_Q + (1 - p_Q)p_Q \approx 2p_Q$. A similar relationship exists between estimated $p_S$ and $p_A$, the baseline probability of adoption with annual frequency.

Table 4: Indirect Inference Estimates of Peer Effects

| | *Dependent variable: Adopt EHR* | | | | | |
|---|---|---|---|---|---|---|
| | *indirect inference simulation frequency* | | | | | |
| | Annual | | Semi-Annual | | Quarterly | |
| | (1) | s.e. | (2) | s.e. | (3) | s.e. |
| Pct Peer Adopted (Common Patients) | 0.574 | 0.001 | 0.574 | 0.001 | 0.572 | 0.001 |
| Pct Peer Adopted (Group) | 1.510 | 0.0004 | 1.510 | 0.001 | 1.510 | 0.0005 |
| Male | -0.023 | 0.001 | -0.022 | 0.001 | -0.021 | 0.001 |
| Experience | 0.093 | 0.001 | 0.094 | 0.001 | 0.093 | 0.0005 |
| Experience2 | -0.002 | 0.00002 | -0.002 | 0.00002 | -0.002 | 0.00004 |
| Specialty (Baseline) | 6.380 | 0.003 | 6.380 | 0.001 | 6.380 | 0.001 |
| Constant | -3.550 | 0.002 | -4.500 | 0.001 | -5.260 | 0.054 |
| Year | Y | | Y | | Y | |
| Observations | 57,575 | | | | | |
| Simulations | 50 | | | | | |

*Notes:* Indirect inference estimates are mean estimates of the model simulated at different baseline frequencies and matched with data at annual frequency using an auxiliary logit model; coefficient shown are means across simulation. Standard errors are parametrically bootstrapped. Since computational intensity increases in the number of parameters, Specialty (Baseline): adoption rate by specialty (in 2011) is used in lieu of specialty dummies.

# 6 Conclusion

This study addressed the question of whether peer effects exists in the adoption of EHR by U.S. providers. I estimated a linear threshold model, where the technology is adopted if the fraction of peers adopting surpasses an individual stochastic threshold that depends on individual characteristics. Data on EHR adoption from Medicare and California Medicaid during 2011–2014 were combined with information on the networks of interaction between providers through common patients and common affiliations. Results suggest significant peer effects exit in EHR adoption. All else being equal, providers are increasingly more likely to adopt EHR as more peers they have patients in common with adopting EHR themselves. This effect is significant even for peers that are not within the same practice group (where adoption decisions are likely coordinated). Flexible period dummies and simulations of the model in different frequencies both show that estimated peer effects do *not* reflect a spurious correlation resulting mechanically from the fact that over time adoption rates increase in general, and thus they also increase within individual peer groups. Neither estimated peer effects are due to the variation over time in incentive payments for adoption.

Remaining concerns include network endogeneity. If, for example, the network exhibits homophily (a tendency to connect more with similar others) on unobserved dimensions that are also correlated with adoption, outcomes could be correlated because of inherent similarities in their characteristics rather than as a consequence of their interactions (Aral et al., 2009). This may bias current estimates upwards. Studying network endogeneity is a clear next step for this research. Other directions for future research include extending these results using data on Medicaid adoption from other states (once it becomes available), using alternative definitions of the peer networks, and exploiting the same methods to study the adoption of other technologies in medicine.

Results reveal that new opportunities are available to policymakers interested in inducing or, more generally, affecting technology diffusion in medicine. To the extent providers are influenced by their peers, policies affecting behaviors of individual providers then have an indirect effect on others as well. Such effects have already been shown to exist in other settings (Banerjee et al., 2013), and harnessing knowledge of peer effects to maximize influence is a widely studied theoretical problem with surprising feasibility results (Kempe et al., 2003). Furthermore, the fact network degrees are distributed very unevenly (Figure 2 shows they approximately follow a power law distribution) means that some nodes have the potential to be more influential than others. Policies targeting central individuals could, therefore, achieve better influence than policies that treat all nodes uniformly. More research is needed to corroborate the external validity of current estimates and to study more fundamental mechanisms that determine peer adoption. But results suggest that there might be room for concrete policy improvements based on utilizing networks data. Such potential uses may not be limited to EHR adoption, and policies aimed, for example, at inducing adherence to guidelines or at enhancing the use of cost efficient technologies could benefit from it as well. Using networks data appears to be a promising—and feasible—direction for the study of technology adoption in healthcare.

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# A Appendices

Table A1: Distinct Practice Groups per Physicians

| | Groups per Provider | Providers | Percent | Cumulative Percent |
|---|---|---|---|---|
| 1 | 0 | 5,568 | 0.097 | 0.097 |
| 2 | 1 | 45,380 | 0.788 | 0.885 |
| 3 | 2 | 5,424 | 0.094 | 0.979 |
| 4 | 3 | 939 | 0.016 | 0.995 |
| 5 | 4 | 167 | 0.003 | 0.998 |
| 6 | 5 | 56 | 0.001 | 0.999 |
| 7 | 6 | 27 | 0.0005 | 1.000 |
| 8 | 7 − 11 | 14 | 0.0001 | 1 |

*Notes:* Groups per Provider is the number of group practices each provider is affiliated with. Providers is the number of providers in the sample with such affiliation. The majority of providers, 45,380, are affiliated with exactly one practice group. Data source: CMS Physician Compare.

Table A2: EHR Meaningful Use by Specialty

| | Primary_Specialty | Overall_Adoption_Rate | N | In Sample |
|---|---|---|---|---|
| 1 | INTERVENTIONAL CARDIOLOGY | 0.869 | 122 | Yes |
| 2 | HEMATOLOGY | 0.815 | 81 | Yes |
| 3 | CARDIAC ELECTROPHYSIOLOGY | 0.734 | 128 | Yes |
| 4 | ENDOCRINOLOGY | 0.667 | 519 | Yes |
| 5 | RHEUMATOLOGY | 0.663 | 469 | Yes |
| 6 | HEMATOLOGY/ONCOLOGY | 0.653 | 822 | Yes |
| 7 | CARDIOVASCULAR DISEASE (CARDIOLOGY) | 0.648 | 1,943 | Yes |
| 8 | GASTROENTEROLOGY | 0.646 | 1,308 | Yes |
| 9 | NEPHROLOGY | 0.626 | 835 | Yes |
| 10 | GYNECOLOGICAL ONCOLOGY | 0.612 | 80 | Yes |
| 11 | SPORTS MEDICINE | 0.612 | 49 | Yes |
| 12 | MEDICAL ONCOLOGY | 0.603 | 229 | Yes |
| 13 | PULMONARY DISEASE | 0.574 | 859 | Yes |
| 14 | UROLOGY | 0.571 | 950 | Yes |
| 15 | FAMILY PRACTICE | 0.561 | 8,371 | Yes |
| 16 | PEDIATRIC MEDICINE | 0.546 | 683 | Yes |
| 17 | GERIATRIC MEDICINE | 0.546 | 141 | Yes |
| 18 | NEUROLOGY | 0.533 | 1,429 | Yes |
| 19 | OBSTETRICS/GYNECOLOGY | 0.524 | 2,801 | Yes |
| 20 | SURGICAL ONCOLOGY | 0.518 | 85 | Yes |
| 21 | OTOLARYNGOLOGY | 0.511 | 994 | Yes |
| 22 | INTERVENTIONAL PAIN MANAGEMENT | 0.507 | 136 | Yes |
| 23 | ALLERGY/IMMUNOLOGY | 0.492 | 358 | Yes |
| 24 | HAND SURGERY | 0.490 | 102 | Yes |
| 25 | VASCULAR SURGERY | 0.477 | 327 | Yes |
| 26 | COLORECTAL SURGERY (PROCTOLOGY) | 0.472 | 108 | Yes |
| 27 | ORTHOPEDIC SURGERY | 0.465 | 2,314 | Yes |
| 28 | GENERAL PRACTICE | 0.461 | 865 | Yes |
| 29 | RADIATION ONCOLOGY | 0.461 | 445 | Yes |
| 30 | PODIATRY | 0.459 | 1,500 | Yes |
| 31 | OPHTHALMOLOGY | 0.450 | 2,173 | Yes |
| 32 | CERTIFIED NURSE MIDWIFE | 0.444 | 63 | Yes |
| 33 | DERMATOLOGY | 0.442 | 1,544 | Yes |
| 34 | NEUROSURGERY | 0.442 | 484 | Yes |
| 35 | GENERAL SURGERY | 0.428 | 1,861 | Yes |
| 36 | PAIN MANAGEMENT | 0.426 | 176 | Yes |
| 37 | OSTEOPATHIC MANIPULATIVE MEDICINE | 0.419 | 62 | Yes |
| 38 | INTERNAL MEDICINE | 0.369 | 11,968 | Yes |
| 39 | INFECTIOUS DISEASE | 0.366 | 541 | Yes |
| 40 | UNDEFINED PHYSICIAN TYPE (SPECIFY) | 0.357 | 70 | Yes |
| 41 | THORACIC SURGERY | 0.347 | 190 | Yes |
| 42 | PLASTIC AND RECONSTRUCTIVE SURGERY | 0.304 | 563 | Yes |
| 43 | CARDIAC SURGERY | 0.298 | 171 | Yes |
| 44 | PREVENTATIVE MEDICINE | 0.292 | 65 | Yes |
| 45 | PHYSICAL MEDICINE AND REHABILITATION | 0.289 | 700 | Yes |
| 46 | OPTOMETRY | 0.270 | 2,778 | Yes |
| 47 | HOSPICE/PALLIATIVE CARE | 0.258 | 66 | Yes |
| 48 | MAXILLOFACIAL SURGERY | 0.244 | 41 | Yes |
| 49 | CRITICAL CARE (INTENSIVISTS) | 0.223 | 301 | Yes |
| 50 | DIAGNOSTIC RADIOLOGY | 0.216 | 3,015 | Yes |
| 51 | PSYCHIATRY | 0.208 | 2,537 | Yes |
| 52 | SLEEP LABORATORY/MEDICINE | 0.737 | 19 | - |
| 53 | PERIPHERAL VASCULAR DISEASE | 0.714 | 7 | - |
| 54 | GERIATRIC PSYCHIATRY | 0.500 | 28 | - |
| 55 | ADDICTION MEDICINE | 0.429 | 14 | - |
| 56 | NEUROPSYCHIATRY | 0.400 | 5 | - |
| 57 | NUCLEAR MEDICINE | 0.192 | 104 | - |
| 58 | ORAL SURGERY (DENTIST ONLY) | 0.160 | 181 | - |
| 59 | CHIROPRACTIC | 0.157 | 3,705 | - |
| 60 | INTERVENTIONAL RADIOLOGY | 0.152 | 263 | - |
| 61 | ANESTHESIOLOGY | 0.141 | 4,117 | - |
| 62 | NURSE PRACTITIONER | 0.138 | 2,967 | - |
| 63 | EMERGENCY MEDICINE | 0.075 | 2,577 | - |
| 64 | PATHOLOGY | 0.050 | 1,050 | - |
| 65 | CLINICAL NURSE SPECIALIST | 0.048 | 21 | - |
| 66 | PHYSICIAN ASSISTANT | 0.017 | 117 | - |
| 67 | CERTIFIED REGISTERED NURSE ANESTHETIST | 0.005 | 645 | - |
| 68 | CLINICAL SOCIAL WORKER | 0.001 | 1,377 | - |
| 69 | CLINICAL PSYCHOLOGIST | 0.0004 | 2,839 | - |
| 70 | PHYSICAL THERAPY | 0 | 4,472 | - |
| 71 | AUDIOLOGIST | 0 | 389 | - |
| 72 | REGISTERED DIETITIAN OR NUTRITION PROFESSIONAL | 0 | 188 | - |
| 73 | OCCUPATIONAL THERAPY | 0 | 378 | - |
| 74 | SPEECH LANGUAGE PATHOLOGIST | 0 | 96 | - |

*Notes:* Data sources: Medicare and Medi-Cal. Rates of EHR adoption via the Meaningful Use incentive program by 2015. N is number of providers overall, as reported via Physician Compare. Sampled are all specialties with at least 30 providers and 2015 adoption rate of at least 20%, to crudely account for the fact providers billing 90% or more in inpatient settings, and providers of certain specialties are not eligible to participate in the program.

Table A3: Share of Payments Through Medicare, not Medicaid

| | Primary Specialty | Medicare |
|---|---|---|
| 1 | PODIATRY | 1 |
| 2 | SURGICAL ONCOLOGY | 0.977 |
| 3 | DERMATOLOGY | 0.972 |
| 4 | INTERVENTIONAL CARDIOLOGY | 0.972 |
| 5 | SPORTS MEDICINE | 0.967 |
| 6 | VASCULAR SURGERY | 0.962 |
| 7 | COLORECTAL SURGERY (PROCTOLOGY) | 0.961 |
| 8 | PAIN MANAGEMENT | 0.960 |
| 9 | OPTOMETRY | 0.944 |
| 10 | RADIATION ONCOLOGY | 0.941 |
| 11 | HOSPICE/PALLIATIVE CARE | 0.941 |
| 12 | UROLOGY | 0.928 |
| 13 | CARDIAC ELECTROPHYSIOLOGY | 0.926 |
| 14 | HEMATOLOGY | 0.924 |
| 15 | CARDIAC SURGERY | 0.922 |
| 16 | MEDICAL ONCOLOGY | 0.920 |
| 17 | HAND SURGERY | 0.920 |
| 18 | RHEUMATOLOGY | 0.920 |
| 19 | GYNECOLOGICAL ONCOLOGY | 0.918 |
| 20 | INTERVENTIONAL PAIN MANAGEMENT | 0.913 |
| 21 | PULMONARY DISEASE | 0.913 |
| 22 | CRITICAL CARE (INTENSIVISTS) | 0.910 |
| 23 | GASTROENTEROLOGY | 0.910 |
| 24 | THORACIC SURGERY | 0.909 |
| 25 | ORTHOPEDIC SURGERY | 0.905 |
| 26 | OPHTHALMOLOGY | 0.905 |
| 27 | CARDIOVASCULAR DISEASE (CARDIOLOGY) | 0.902 |
| 28 | HEMATOLOGY/ONCOLOGY | 0.894 |
| 29 | OTOLARYNGOLOGY | 0.890 |
| 30 | ENDOCRINOLOGY | 0.887 |
| 31 | ALLERGY/IMMUNOLOGY | 0.886 |
| 32 | NEUROSURGERY | 0.883 |
| 33 | NEUROLOGY | 0.879 |
| 34 | PLASTIC AND RECONSTRUCTIVE SURGERY | 0.877 |
| 35 | PHYSICAL MEDICINE AND REHABILITATION | 0.871 |
| 36 | GERIATRIC MEDICINE | 0.870 |
| 37 | NEPHROLOGY | 0.870 |
| 38 | DIAGNOSTIC RADIOLOGY | 0.860 |
| 39 | GENERAL SURGERY | 0.818 |
| 40 | INTERNAL MEDICINE | 0.807 |
| 41 | PREVENTATIVE MEDICINE | 0.737 |
| 42 | FAMILY PRACTICE | 0.726 |
| 43 | INFECTIOUS DISEASE | 0.692 |
| 44 | UNDEFINED PHYSICIAN TYPE (SPECIFY) | 0.680 |
| 45 | OSTEOPATHIC MANIPULATIVE MEDICINE | 0.654 |
| 46 | OBSTETRICS/GYNECOLOGY | 0.606 |
| 47 | GENERAL PRACTICE | 0.536 |
| 48 | PSYCHIATRY | 0.423 |
| 49 | MAXILLOFACIAL SURGERY | 0.300 |
| 50 | PEDIATRIC MEDICINE | 0.155 |
| 51 | CERTIFIED NURSE MIDWIFE | 0 |

*Notes:* Percent of EHR incentive payments claimed through Medicare (as opposed to Medicaid), out of all claimants, by specialty. Participation through Medicaid is only available for providers whose patient share in Medicaid is 30% or more.