

settings.<sup>1</sup> 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.<sup>2</sup> 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 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 et al., 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

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

<sup>2</sup>The Health Information Technology for Economic and Clinical Health (HITECH) Act was part of the Recovery and Reinvestment Act of 2009.

## Seeded Content – **The Robo-Doctor Will See You Now**

<https://www.asme.org/engineering-topics/articles/robotics/robo-doctor-will-see-you-now>

A technological idea born in science fiction is a promising answer to the challenging realities of modern health care.

With fewer doctors to meet the growing health-care needs of our aging population, hospitals and health systems are investing in robotic systems for surgery and telemedicine that increase their patient capacity and geographic reach. Machines like the da Vinci Surgical System (Intuitive Surgical Systems, Sunnyvale, CA) and the RP-7i Remote Presence medical robot (InTouch Health, Santa Barbara, CA) connect patients who need specialized care with physicians who can help them – even if they are an ocean apart.

In Robert A. Heinlein's popular 1942 science-fiction story "Waldo," a physically disabled but mechanically gifted man builds a set of automated "hands" that gave him super-human strength and dexterity. Waldo Farthingwaite-Jones could control his Synchronous Reduplicated Pantograph to duplicate his exact hand motions in numerous then-fictitious applications, including cellular-level microsurgery.

But fiction soon collided with reality when the nuclear industry invented a real gadget, nicknamed a Waldo, for the safe manipulation of radioactive materials from a remote location, and a new industry was born.

Seventy years later, medical robots are still an emerging technology. But forces such as health-care reform, the shortage of doctors and nurses, and the skyrocketing costs of hospital care are driving its acceptance like never before.

But it's about more than just saving money. Advocates of robotic surgery, for example, claim the [da Vinci](#) surgical robot achieves significantly better outcomes than either radiation or traditional surgery in delicate procedures such as radical prostatectomy for prostate cancer. They say robotic surgery can remove more cancerous tissue with less disruption of adjacent nerve endings than other methods, helping to reduce cancer recurrence and retain sexual function. That's why some 85% of men undergoing prostate cancer surgery are choosing medical centers that offer robotic surgery.

Introduced in 1999, the da Vinci system remains the standard robotic system for complex operations in cardiac, colorectal, gynecologic, thoracic, urologic, and head and neck surgeries. The U.S. Food & Drug Administration continues to approve its use in additional surgical applications.

"From Day One, when I sat down at that robotic console, I knew we would give patients a better outcome," said Florida surgeon Vipul Patel in a *New York Times* interview. "I have not seen anyone who has done a good amount of robotic surgery go back (to traditional methods)," he said.

The guts of the system include four robotic arms, a high-definition 3-D viewing system with up to 10x magnification, and a novel family of specialized instruments with Intuitive Surgical's proprietary "EndoWrist" technology. Traditional devices such as forceps, scalpels, retractors, and suture drivers have been reimaged for the robotic age, with seven degrees of freedom, a large range of motion, and less risk from surgeon hand tremors.

The system's robotic and computer technologies work together to scale, filter, and translate the surgeon's hand movements into micro-movements that guide the instruments, not unlike the Waldo of science fiction. Seated at a viewing and control console located in or near the operating room, the surgeon uses hand controls to manipulate surgical instruments through tiny incisions. The instruments move like high-precision puppets with each motion of the surgeon's hand, wrist, or finger.

[Robotic surgery](#) has its critics, especially among those concerned about its comparatively high cost and the worry that hospitals will over-hype the technology to lure patients and recoup their investments.

Catherine Mohr, director of medical research at Intuitive Surgical, acknowledged that a typical system "will cost you about as much as a solid gold surgeon. It's a fairly big capital investment, but once you've got it, your procedure costs do come down."

For Mohr, the next challenges in robotic surgery are to make the technique faster and easier to use in more complex operations, which is key to their eventual routine, cost-effective use. She said she is working with prototype designs that eliminate the need to move the robot to reach additional areas of the body and add

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 Flickr 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%]).<sup>3</sup> Overall, peer effects 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 et al.,

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<sup>3</sup>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%.

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).<sup>4</sup>

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 diffusion rates (Baker, 2001), and the impact of economic incentives on innovation (Kremer and Snyder, 2003; 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.,

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<sup>4</sup>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.

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.

## 2.2 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.<sup>5</sup> 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.<sup>6</sup> 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 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

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<sup>5</sup>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.

<sup>6</sup>Data source: EHR Incentive Program - CMS, <https://www.cms.gov/regulations-and-guidance/legislation/ehrincentiveprograms/eligibility.html>, Accessed March 2016



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.<sup>7</sup> 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 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.

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<sup>7</sup>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](https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/downloads/MU_Stage1_ReqOverview.pdf), Accessed March 2016

- Einav, Liran, Amy Finkelstein, and Jonathan Levin (2010b), “Beyond testing: Empirical models of insurance markets.” *Annual Review of Economics*, 2, 311.
- Ellis, Randall P et al. (2000), “Risk adjustment in competitive health plan markets.” *Handbook of Health Economics*, 1, 755–845.
- Geruso, Michael (2013), “Selection in employer health plans: Homogeneous prices and heterogeneous preferences.”
- Hackmann, Martin B, Jonathan T Kolstad, and Amanda E Kowalski (2012), “Health reform, health insurance, and selection: Estimating selection into health insurance using the massachusetts health reform.” *The American Economic Review*, 102, 498–501.
- Hackmann, Martin B, Jonathan T Kolstad, and Amanda E Kowalski (2015), “Adverse selection and an individual mandate: When theory meets practice.” *The American economic review*, 105, 1030.
- Handel, Ben, Igal Hendel, and Michael D Whinston (2015), “Equilibria in health exchanges: Adverse selection versus reclassification risk.” *Econometrica*, 83, 1261–1313.
- Handel, Ben, Igal Hendel, and Michael D Whinston (2016), “The welfare impact of long-term contracts.” *Unpublished manuscript*.
- Handel, Benjamin R (2013), “Adverse selection and inertia in health insurance markets: When nudging hurts.” *The American Economic Review*, 103, 2643–2682.
- Heiss, Florian, Adam Leive, Daniel McFadden, and Joachim Winter (2013), “Plan selection in medicare part d: Evidence from administrative data.” *Journal of Health Economics*, 32, 1325–1344.
- Kolstad, Jonathan T and Amanda E Kowalski (2012), “Mandate-based health reform and the labor market: Evidence from the massachusetts reform.” *NBER Working Paper*.
- Marzilli Ericson, Keith M (2014), “Consumer inertia and firm pricing in the medicare part d prescription drug insurance exchange.” *American Economic Journal: Economic Policy*, 6, 38–64.
- McGuire, Thomas G, Jacob Glazer, Joseph P Newhouse, Sharon-Lise Normand, Julie Shi, Anna D Sinaiko, and Samuel H Zuvekas (2013), “Integrating risk adjustment and enrollee premiums in health plan payment.” *Journal of Health Economics*, 32, 1263–1277.
- Rice, Thomas, Marcia L Graham, and Peter D Fox (1997), “The impact of policy standardization on the medigap market.” *Inquiry*, 106–116.

## 3.A Appendix