RESEARCH BRIEF

The Impact of New Technology on the Healthcare Workforce

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MIT work OF THE FUTURE

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Abstract

Dramatic improvements in information technology have the potential to transform healthcare delivery, and a key question is how such changes will affect the healthcare workforce of the future. In this brief, we present the state of knowledge of the effects of health information technology on the workforce. We first lay out the rapidly changing healthcare landscape due to the greater availability and use of information and communication technology (ICT) followed by a description of the evolution of employment, wages, and education across the wide variety of occupations in the healthcare sector since 1980. The healthcare sector has outperformed the rest of the economy and has proven resilient to the multiple downturns over the last four decades, although some groups have done much better than others. Next, we review the literature on the effects of ICT on productivity in terms of patient health outcomes and resource use, as well as the effects on healthcare expenditure. We find that there is evidence of a positive effect of ICT (e.g., especially electronic health records) on clinical productivity, but (i) it takes time for these positive effects to materialize; and (ii) there is much variation in the impact, with many organizations seeing no benefits. Looking at the drivers of adoption, we find that the role of workers is critical, especially physicians' attitudes and skills. Privacy laws, fragmentation, and weak competition are also causes of slow adoption. There is very little quantitative work that investigates directly the impact of new technology on workers' jobs, skills, and wages, but what there is suggests no substantial negative effects. Our own analysis finds no evidence of negative effects looking at aggregate data and hospital-level event studies. These findings are consistent with studies outside of healthcare, which stress the importance of complementary factors (such as management practices and skills) in determining the success of ICT investments. We conclude that management initiatives to increase the skills of workers will be required if the healthcare workforce and society more generally are to substantially benefit from the adoption of these powerful tools.

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I. Introduction

During the coronavirus pandemic, the importance of health and healthcare as fundamental supports to daily activities became particularly stark. The healthcare workforce has taken center stage by taking personal risks to help stem the spread of COVID-19, and new communication technologies such as telehealth have become very widespread. Meanwhile, great hopes are placed on innovation to provide a solution in the form of therapies and vaccines. A longer-term question is how the future of technological development will affect the healthcare workforce. The aim of this research brief is to consider the state of knowledge on this question and offer a path forward to understand and be prepared for these coming changes.

It has long been recognized that healthcare holds enormous potential for the beneficial impacts of new technologies. Healthcare accounts for nearly one in every five dollars spent in America. Therefore, improvements in this sector have first-order effects on economic performance through sheer scale. Furthermore, like almost every other country, the proportion of national income absorbed by healthcare appears on an almost inexorable upwards trend. According to the National Health Expenditure Accounts, the fraction of GDP spent on healthcare has risen by about four percentage points every 20 years: from 5% in 1960 to 9% in 1980, 13% by 2000, and then to nearly 18% today. This is driven by the aging population, costs of new technologies, and a natural tendency for humans to increase the fraction of their budgets on health as they grow richer—after all, there are only so many consumer goods one can have (Hall and Jones, 2007).

The United States has long stood out from other Organisation for Economic Co-operation and Development (OECD) countries in that it spends a larger fraction of income on health. It also achieves relatively disappointing results for this high expenditure. For example, improvements in life expectancy in the United States appear to have stalled, in stark contrast to the experience of other nations (Case and Deaton, 2020).

In light of these trends, policymakers have stressed the use of information and communication technology (ICT) in healthcare as a mechanism to improve efficiency and clinical outcomes. In some sense, this culminated with the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, part of the Affordable Care Act (colloquially known as “Obamacare”), which spent around $30 billion to increase the take-up of electronic health records (EHRs). Although ICT has been used in healthcare since at least the early 1960s, fewer than 10% of hospitals (and fewer than 20% of physicians) were using EHRs prior to HITECH (Atasoy et al., 2019). By 2014, 97% of reporting hospitals had certified EHR technology (Gold and McLaughlin, 2016).

An aim of HITECH was to increase adoption rates by subsidizing ICT acquisition costs, changing reimbursement rules, and providing technical support. It emphasized the adoption of decision support capabilities and utilization at the point of care, formally referred to as "meaningful use." Jha et al. (2010) estimate that fewer than 2% of hospitals met the criteria of meaningful use prior to the Act, and the rise in health ICT capabilities provides an opportunity to investigate the effects of such subsidies on healthcare productivity in general and the workforce in particular.

There is some reason for optimism that ICT can substantially improve the productivity of healthcare. Apart from sheer scale, an advantage for tech applications is that healthcare is a knowledge-intensive industry characterized by fragmented sources of information (Atasoy et al., 2019). Therefore, in principle, it is perfect for the application of ICT. The enormous decline in the quality-adjusted price of ICT (approximately 15% per annum since 1980 and up to 30% per annum between 1995 and 2001) is therefore a boon to the sector (e.g., Bloom, Sadun, and Van Reenen, 2012). Indeed, after the success of IBM Watson's Artificial Intelligence computer on the television quiz show *Jeopardy*, the first commercial application announced was in healthcare (IBM Watson Health[1]). In a well-known RAND study, Hillestad et al. (2005) estimated that IT adoption could save between $142 billion and $371 billion over a 15-year period.[2] However, despite the enormous potential and investments, the results of the impact of health ICT have been disappointing. A subsequent RAND study by Kellermann and Jones (2013) shows that the predicted savings had not materialized due, in part, to a lack of information sharing across providers and a lack of acceptance by the workforce in an environment where incentives run counter to the goal of reducing healthcare costs. Lessons from other industries suggest that the *management* of new technologies is an important driver of ICT productivity gains, and there are serious issues of management quality in the healthcare sector (e.g., Bloom et al., 2020).

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The scale of healthcare is seen in the sheer number of jobs attributed to the healthcare sector: 11% of all U.S. employment (see Section III for a more detailed analysis). In addition to size, jobs in healthcare are generally regarded as "good jobs," even for relatively less skilled workers, with reasonable wage and nonwage benefits. One of the great fears of our age is the potential for machines to replace human jobs and lead to mass unemployment. Even if this were true in general, and history suggests that it is not, the growth in the number of jobs in healthcare means that new technologies in healthcare would primarily slow down the growth of employment rather than reduce it. In any event, the rise of new technologies in healthcare has the potential to benefit the workforce across a wide range of skills, but it will be important to manage the change brought on by innovations in the sector.

This research brief provides background on the latest developments in new information technologies and workforce trends in healthcare. We will consider lessons from other industries as well as findings specific to healthcare ICT adoption. We hope that this will provide a basis to understand the potential changes that will affect the workforce in the future, depending on how such changes are managed. One lesson from our review of the literature is that the current evidence on the impact of health IT on the workforce is very sparse indeed; we need a renewed emphasis to examine the impact of past (and more speculatively current and future) technologies on the healthcare workforce.

The structure of this brief is as follows: Section II provides a summary of the evolution of health IT and a summary of what is known about the effects of health IT on productivity. Section III provides the context of the evolution of the healthcare workforce since 1980 in terms of jobs, wages, and education. Section IV describes the findings of our literature review on the impacts of health IT on healthcare productivity and the workforce. In Section V, we present our own findings of the impact of health IT adoption on the workforce, and Section VI concludes.

II. The Recent Evolution of Health Information Technology

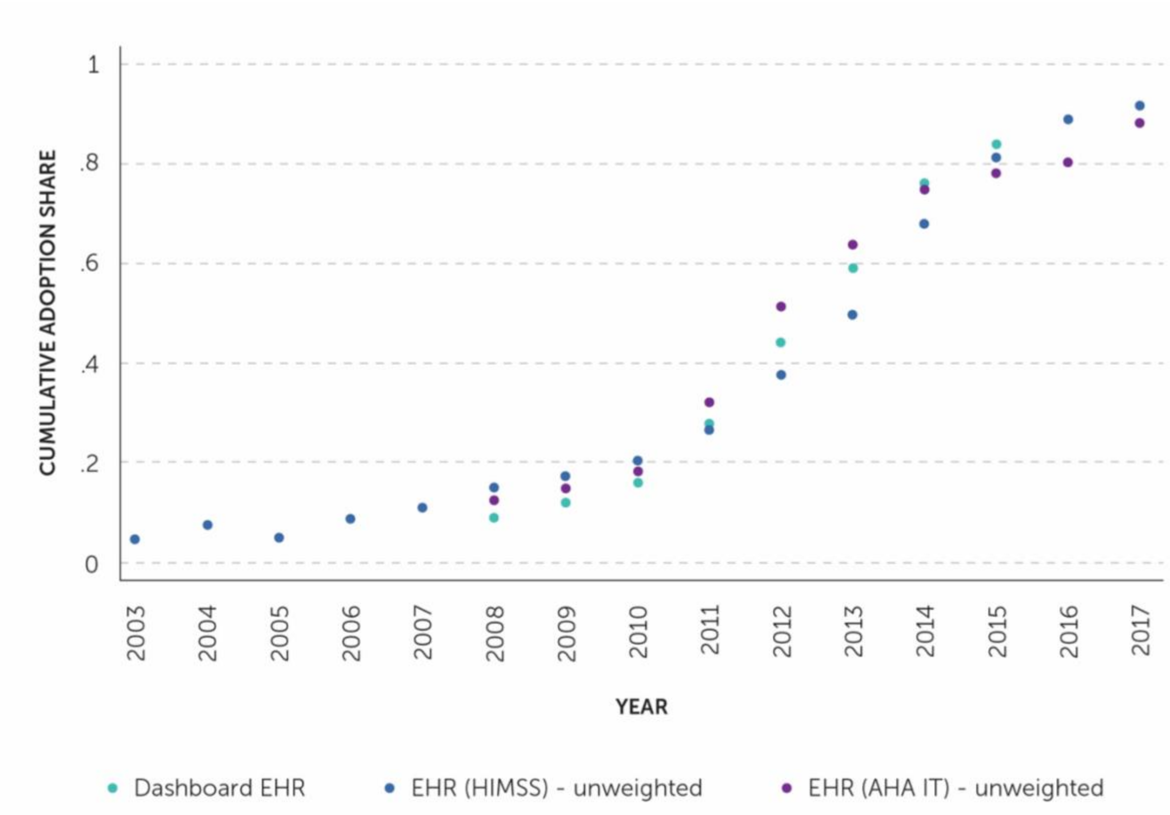
II.1. NEW HEALTH INFORMATION TECHNOLOGIES

II.1.1. Electronic Health Records

The electronic health record, or EHR, is, at its core, a digitized medical chart. Deriving value from this technology requires a broad array of functions that gather, manage, and share digital health information. This information can then be exploited to support medical decision-making and operations. Ideally, information gathering begins before a patient encounter: retrieving records from other providers or past patient encounters. This, and other information, is then updated at the beginning of the patient's interaction with the physician or nursing staff; additional data—such as lab values, images, and progress notes—are added as the encounter progresses. This data could, ideally, be made portable so that it may be shared with other providers or accessed via patient portals.

Figure 1 below shows how EHR adoption has dramatically increased over the 2003–2017 period, particularly after the HITECH Act. We report three series. First, the "official" measure from the Office of the National Coordinator for Health Information Technology, which presents the fraction of hospitals using EHR (with a correction for nonrandom sample response) from a large survey of hospitals, the American Hospital Association (AHA) Annual Survey Information Technology (IT) Supplement, or AHA IT Supplement Survey, from 2008 onwards.[3] Second, we present our own analysis of the AHA IT Supplement Survey, as well as (our third series) a similar definition using another large survey of hospitals carried out by the Healthcare Information and Management Systems Society (HIMSS), which allows us to cover a longer time series, from 2003 onwards. Although the precise levels of these series differ, the broad trends are similar, showing a strong increase in adoption over this period, with a particularly big boost after the HITECH Act, which was implemented in 2010.[4]

Figure 1: Cumulative Adoption of Electronic Health Records (EHRs)

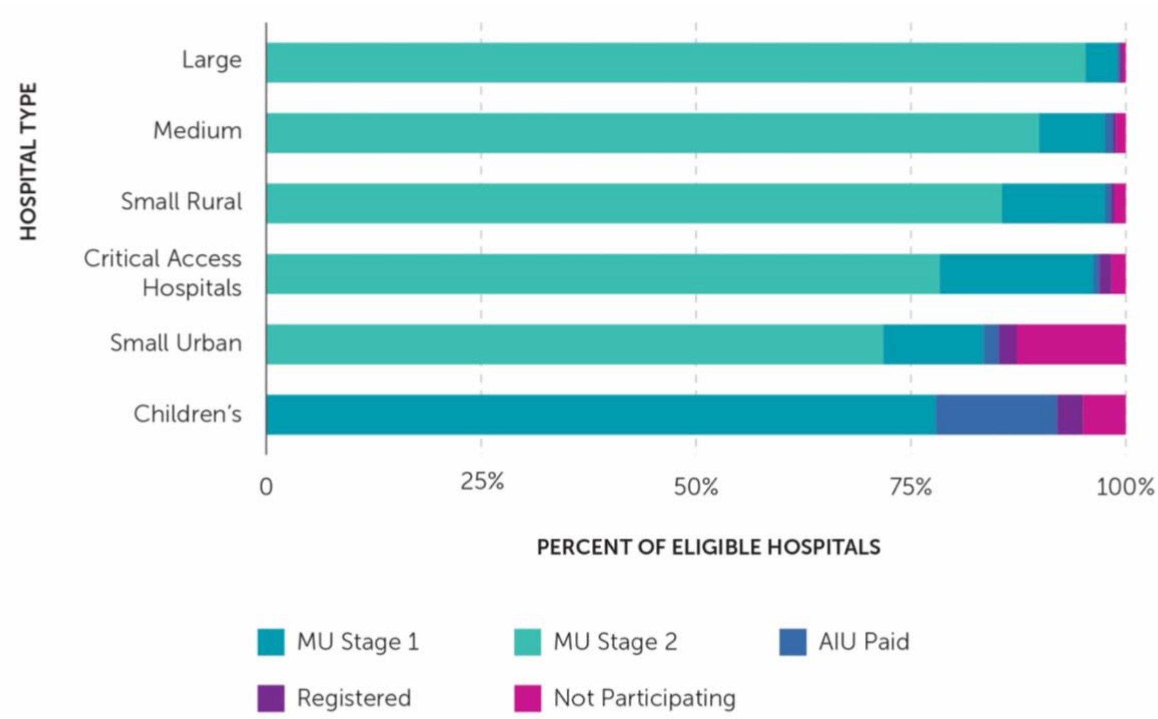


Notes: This figure presents estimates of the fraction of hospitals that were using "basic" EHRs (electronic health records) in the year indicated in different databases. The basic EHR is defined as the use of physician documentation and computerized physician order entry (CPOE). The squares are official estimates from the Office of the National Coordinator for Health Information Technology (re-weighted to correct for nonrandom sample response). The circles are our own estimates from the AHA IT Supplement Survey, and the triangles are our own estimates from HIMSS. The vertical axis is set so that 1 = 100% (complete adoption).

The HITECH Act's intention was to encourage hospitals to adopt and use EHRs meaningfully by committing around $30 billion in incentives (Wani and Malhotra, 2018).[5] The program is based on three main stages. Stage 1 established requirements for the electronic capture of clinical data. In order to achieve successful first-stage attestation, hospitals were required to enter medication orders electronically for at least 80% of their patients and have electronic discharge instructions and health records for 50% of them. These incentives were structured to encourage early adoption, as hospitals that achieved these benchmarks by 2011 received 100% of the incentive payment, which declined 25% each additional year until adoption. After 2015, penalties were imposed: Hospitals that still failed to achieve the benchmarks started to lose 1% of Medicare reimbursements each year. In order to achieve the goals, core technologies needed to be adopted, including electronic medication administration record (eMAR), clinical data registry (CDR), clinical decision support (CDS), and computerized physician order entry (CPOE).

The second and third stages elevate the benchmarks. Stage 2 focused on advancing clinical processes and encouraging health information exchange in a highly structured format. Stage 3 focused on using certified electronic health records to improve health outcomes. According to the Office of the National Coordinator for Health Information Technology (2017), as of 2016, over 95% of hospitals had achieved meaningful use of certified health IT, while nearly 90% of hospitals had reached Stage 2 certification. Figure 2 shows that achieving higher stages is correlated with hospital size.

Figure 2: Meaningful Use (MU) Certification by Size, Type, and Urban/Rural Location



Notes: This figure presents meaningful use attestation status by size/type and urban/rural location hospitals according to the health IT dashboard in 2016. The categories are hierarchical and mutually exclusive. Adopt, Implement, Upgrade (AIU) incentives are paid in the first year a hospital is part of the program, prior to attaining Stage 1 or Stage 2 performance. https://dashboard.healthit.gov/quickstats/pages/FIG-Hospital-Progress-to-Meaningful-Use-by-size-practice-setting-area-type.php

With such rapid, federally subsidized growth in health IT adoption, there is considerable policy interest in whether organizations are learning to use the new tools in ways that can improve healthcare productivity and how these new technologies are affecting the healthcare workforce.

II.1.2. Clinical Decision Support (CDS)

As noted above, EHRs may serve as a platform for decision support: Established clinical guidelines or best medical practices may be operationalized within the EHR software using patient-level data to prompt providers with suggestions or raise flags regarding potentially risky interventions or inappropriate imaging

(Doyle et al., 2019). These capabilities depend on detailed patient information and a provider interface at the point of care.

CDS can also support a broad range of functions, such as pre-specified order sets—a package of tests and subsequent procedures that can be chosen in an order-entry system with one click (e.g., common postoperative monitoring and care). These order sets, properly chosen by clinicians within health systems, may help implement evidence-based guidelines and best practice protocols, as well as reduce unwanted variation in practice across clinics or physicians.

There is evidence that CDS improves patient safety for medication prescribing (Campanella et al., 2016). For example, algorithms can check for drug allergies or drug-to-drug interactions and dosage errors through automated dosage calculators. These capabilities can improve medical adherence and reduce medication overuse (Atasoy et al., 2019).

Mirroring the overall concerns with ICT acceptance by the workforce, a key concern is alert fatigue and cognitive overload. Computer systems generate alerts when there is a suspected mistake (e.g., ordering too high a dosage of a drug), but if the thresholds are set too low, then the alerts may be too frequent. For EHR, most of the alerts appear to be overridden in practice. Ancker et al. (2017) find that the likelihood of acceptance of a best-practice advisory goes down by 10 percent with each 5% increment in within-patient repeats, while it goes down by 30% with each additional suggestion. Although overrides are frequently justified, they can be associated with medication errors and adverse events (including death) if clinically important information is advertently ignored.

II.1.3. New Communication Technologies: The Example of Telehealth

Miscommunication is common in a complex system like modern medicine. McCullough et al. (2010) explain that the U.S. healthcare system is often criticized for miscommunication that leads to preventable medical errors and wasteful allocation, including part of the estimated 44,000 deaths annually due to inpatient hospital errors. For example, a prescription requires a physician, a pharmacist, and a nurse to coordinate. EHR can resolve this in principle—likely a substantial improvement from the days of illegible handwriting. Similarly, computerized physician order entry (CPOE) offers a more efficient way for physicians to communicate orders that may help prevent mistakes. McCullough et al. (2010) report small but significant improvements in quality because of CPOE. While such systems likely reduce errors, continued management of these systems is necessary to ensure safety. A dramatic example was described by Wachter (2017) involving a series of mistakes caused by EHR that nearly led to the death of 16-year-old Pablo Garcia at the UCSF Medical Center in 2013.[6]

In addition, telemedicine provides a new platform to deliver healthcare at a distance. The coronavirus pandemic has seen rapid take-up of telemedicine in the United States and around the world, and this is likely to persist even after the pandemic has abated.[7] Often, large and sudden shocks can help the switch to a new adoption equilibrium as it gives multiple players simultaneous incentives to switch to using the new technology (e.g., physicians, patients, and hospital managers). In particular, the decision by Medicare to reimburse telehealth visits during the pandemic provides a valuable opportunity for providers to offer such care in lieu of in-person visits. Key players in this switch are federal and local regulators. The rapid changing of regulations to facilitate telemedicine suggests that regulatory barriers have been part of the reason for the slow diffusion of telemedicine and perhaps health ICT more generally (Cutler et al., 2020; Keesara et al., 2020).

Telehealth is particularly attractive for patients in hard-to-reach communities who can be treated via a video connection. Telemedicine allows physicians to receive consultations from specialists (Long et al., 2018). For example, Telestroke connects specialists to clinicians at the bedside of a stroke patient while transferring key clinical indicators in real time, which enables distant specialists to provide advice on treatment decisions. Baratloo et al. (2018) offer a review of 26 studies that analyze the program and argue that telemedicine can improve stroke care in regional areas with limited experience in thrombolysis.

II.1.4. Information Management and Healthcare Analytics

With information moving from paper to digital records, health IT opens new doors to manage and mine data with new powers of diagnosis and treatment recommendations. This is particularly relevant for complex patients with multiple comorbidities and those who require intensive monitoring and testing. Data can be more easily captured, organized, and analyzed. Furthermore, now that EHR adoption is widespread, these systems provide a basis for data analytics that may lead to large long-run gains in healthcare quality and efficiency, including better-informed policy design.

Diabetes serves as an example to illustrate many advantages of information technology. Rumbold, O'Kane, Philip, and Pierscionek (2020) explain that machine-learning algorithms can capture blood sugar measurements daily and help predict with greater confidence who will develop a complication. This allows treatment such as medication choice and dosing to be personalized to each patient. Moreover, technology now allows patients to carry their information on their cellphones, receive alerts and reminders of treatment, and track their health status. Such apps have the potential to improve treatment adherence.

Another prominent example of the use of healthcare analytics that benefits from the storage and analytical capabilities of health IT comes from the field of radiology. Machine learning in general has achieved substantial gains in image recognition, and allowing machine-learning algorithms to flag concerns in images provides a powerful tool that has the potential to increase the productivity of radiologists (and potentially lead to job displacement; see Section III). A related example is offered by Rumbold et al. (2020) who explain how machine-learning algorithms can improve the detection of diabetes complications from retinal images.

II.1.5. Health IT and Public Health Surveillance

From a public health surveillance viewpoint, Gamache, Kharrazi, and Weiner (2018) argue that the ability to capture where each case is happening and how the population characteristics are evolving allows governments to make more informed public policy choices. For example, O'Donovan and Bersin (2015) explain how technology can play a key role in mitigating an Ebola outbreak. By allowing free communication between the government and citizens, cellphones provided an effective way to track an epidemic and provide useful information to citizens on how to stay safe. In the midst of the current pandemic, an unprecedented effort on increasing surveillance capabilities has taken place worldwide as several governments use contact-tracing apps that help them identify potentially sick individuals. Countries such as South Korea, Singapore, and China have aggressively used track, trace, and testing to control the COVID-19 pandemic.

II.2. CHALLENGES AND DRIVERS OF ICT ADOPTION AND MEANINGFUL USE

Our review of the literature described below suggests that health IT appears to have had modest improvements in productivity measured by health outcomes and clinical quality, and mixed effects on healthcare spending. Meanwhile, the impacts of health IT on the workforce itself has been much less studied. To make further progress in understanding the effects of health IT on this range of outcomes, it is useful to understand what drives the diffusion of the technology.

The factors that affect the adoption of health IT are similar to those in the broader literature on technological diffusion (e.g., see Hall, 2005; for a survey). Complexity, cost, competition, and complementary factors (such as skilled labor) are all important. For example, given the high fixed costs of adoption, it is no surprise that larger organizations are more likely to adopt IT, while stand-alone hospital systems are less likely to adopt administrative and strategic health IT (Hikmet, Bhattacherjee and Kayhan, 2008).

This section builds on Gnanlet et al. (2019), which reviewed the literature covering 37 recent papers. We will discuss some of the broader issues affecting IT adoption, as well as healthcare-specific factors identified in the literature.

Patient Safety

Although health IT offers the potential to improve patient safety substantially (Bates and Gawande, 2003), there is a risk that errors may be introduced (Harrington et al., 2011). The initial adjustment costs in most industries as firms learn how to use IT are well documented, and this appears to be the case in healthcare as well. However, because patient safety may be affected by such a transition, there is a natural tendency toward greater risk aversion to all sorts of change, including technology in the health sector.

Patient Privacy

A common concern that affects health IT adoption revolves around privacy. Congress passed a federal law, the Health Insurance Portability and Accountability Act (HIPAA), in 1996 to aid in the sharing of health data by establishing some rules of the road. States also passed privacy laws, and the sheer complexity of legal obligations is thought to reduce the benefits of data sharing and, thus, health IT adoption (Schmit et al., 2017, 2018). Miller and Tucker (2009, 2011) investigated the role of state privacy laws following HIPPA. They argue that restricting hospital release of information reduced IT adoption by about 24%. The main reason they offer is that the gain to a network from adopting EHR is that systems can interoperate within the network across disparate hospitals and other providers. However, these interoperability benefits are undermined when privacy laws are very restrictive, so hospitals have much less incentive to adopt EHR.

Market Concentration

The EHR market features two dominant firms, Epic and Cerner. Many have argued that this lack of robust competition raises prices and thereby slows adoption. The effects of competition on the quality of EHR systems is more ambiguous, but if investing in raising quality is more costly than the improved revenues that would result from greater demand, then a lack of quality-improving investments is another way that adoption might be slowed. Improving interoperability standards could be a major area where government regulation could overcome the frictions that sustain market concentration.

On the demand side, a few large providers similarly dominate some healthcare markets. Zhivan and Diana (2012) argue that more inefficient hospitals are more likely to adopt EHR; so to the extent that more concentrated markets allow more inefficient firms to survive, that would work to speed the adoption.

Finally, there has been some concern that health ICT in general and the HITECH Act specifically have accelerated the consolidation of physician practices, as small practices have greater difficulty covering high fixed cost investments in ICT. These investments are increasingly rewarded, in the setting of HITECH Act incentive and penalty payments, as well as various pay for performance systems, including the Merit-based Incentive Payment System (MIPS) (Johnston et al., 2020). Case studies suggest that the need for EHR investment is a major motivation for small practices seeking to be acquired by a large integrated care system (Christianson et al., 2014). As a result, one indirect way that health ICT may reshape the healthcare workforce is by changing firm size and employment relationships.

Management

Many lessons can be learned from other industries when looking at the ICT revolution. For many decades, the Solow Paradox ruled: We could see computers everywhere apart from the productivity statistics. In the macroeconomic productivity numbers, we did not see serious impacts on productivity until after 1995, when there was a near doubling of U.S. productivity growth (at least through 2004), which was focused on the industries that intensively used or produced ICT (Oliner et al., 2007). And this lag in productivity gains from new technologies is nothing new. Economic historians like Paul David (1990) point to similarly long lags from other major technological revolutions such as electricity.

From the mid-1990s, the macroeconomic productivity improvements from ICT were becoming statistically visible; a large number of microeconometric studies were also uncovering large returns to ICT investments, albeit with long time lags. Digging deeper into these microstudies reveals that although on average there was a positive effect of ICT on firm performance, the impact was extremely heterogeneous (see the survey in Draca et al., 2007; Brynjolfsson and Hitt, 2000). Some firms could spend huge amounts on ICT and receive very little return. One important factor in explaining this variation were the bottlenecks that firms faced in best using the opportunities new technologies created. Particular bottlenecks were rigid organizations (poor management practices) and the wrong sort of skills (e.g., Bresnahan et al., 2002; Caroli and Van Reenen, 2001). The firms that were best able to exploit the new technologies were those that could adapt by changing their organization and skill mix.

A similar story reveals itself in healthcare. Gnanlet et al. (2019) argue that there are three inter-related stages of IT implementation: adoption, integration, and sustenance. Major impediments for success include provider resistance in the integration stage and lack of interoperability in the sustenance stage.

New technologies often create winners and losers—some are deskilled and some are reskilled; some might gain responsibility and remuneration while others might lose it (in the extreme case losing their jobs entirely). Having to change one's routines and learn complex new systems can be burdensome, to say the least (Gawande, 2018).[8] Kroth et al. (2018) report that 56% of doctors complained about excessive time spent on EHR. A recurring theme is that workers say they see little benefit from new IT systems. For example, Ancker et al. (2017) argue that there is some evidence of alerts overload from decision support systems. As noted above, the more alerts, the less likely physicians are to accept them. Physicians tend to dismiss alerts for the most complicated patients, which is potentially when they would help the most. On a brighter note, Adelman et al. (2019) find that there is no negative effect of allowing physicians to open more than one patient's records at the same time.

Many stakeholders can resist change, especially when there is asymmetric information between the IT decision-makers (senior managers) and those who are using the tools (medical staff). Physicians have been found to play a particularly important role here. Without buy-in from senior physicians, it had been found to be very hard to effectively diffuse IT in healthcare (Cohn, 2009). Compared to other industries, the physicians are powerful, high-human-capital workers who know much more about the delivery of care than senior managers (the asymmetry of information is severe—a doctor can easily claim, "This change will endanger patients' lives"). Case studies suggest that having a "Physician Champion" is very important (Cohn, 2009) to successful transitions. These are typically experienced doctors who conduct exercises and illustrative cases in their respective departments, which later lead to faster buy-in among other physicians and supporting clinicians. Beyond physicians, Hardiker et al. (2019) found that if nurses did not find the IT helpful, they swiftly found workarounds and did not use the technology. Meanwhile, Litwin (2011) describes engagement and cooperation with the workforce at Kaiser Permanente, which preserved employment (e.g., Kaiser Permanente had to provide alternative jobs for the chart room) while improving patient satisfaction. This evidence suggests that greater involvement of the workforce in adapting to the new capabilities of health IT could improve acceptance and speed productivity gains while mitigating negative effects on the workforce.

There is limited evidence that the ownership structure of providers is related to adoption. Lee, McCullough, and Town (2013) show that for-profit institutions have a different (slower) adoption pattern than not-for-profit ones (we will also see this in our own empirical analysis below). While for-profits have eventually caught up for basic EHR adoption, they have lagged on the intensity of IT services, such as CPOE.

Resistance to Change

A general point may be that healthcare workers, especially the more senior ones, are used to having a lot of autonomy in making choices about what is best for the patient. IT systems (such as Epic) take away some of this autonomy and leave healthcare workers with the feeling that they have lost the discretion to help their patients make the best choices. Whereas this may be true in a wide variety of places with automation, it is plausible such resistance is more effective in healthcare where the workforce is more accustomed to exercising their discretion and thereby requires greater negotiation to gain acceptance and effect change. An important way to overcome this is to engage employees in the process of designing and implementing technology and/or offer some degree of job protection and retraining. Employee engagement of this sort is a key part of the management practices emphasized by Bloom and Van Reenen (2007) as exemplified by hospitals such as Virginia Mason in Seattle.[9]

Misaligned Incentives

Cutler (2011) argues that healthcare is exceptionally inefficient in generating incentives for innovation and diffusion. First, despite recent payment reforms, most providers continue to operate on a basis where greater provision of care results in greater profits (“fee for service”), which means that there is little incentive to seek lower costs through health IT adoption and use.

Second, competition between hospitals is weak (and growing weaker—see Cooper et al., 2019), so the incentives to improve are blunted. Weak competition has been shown to be a force that is reducing efficiency in healthcare (e.g., Bloom et al., 2015).

Third, ICT-related coordination is hampered because of the different systems run by competing healthcare firms: From different providers, including physician groups that are not employed by hospitals, to different insurers, there is a wide array of players whose systems are not integrated. This lack of integration may be deliberate because many healthcare providers have incentives to avoid seamless information exchange by "locking in" their patients. Creating barriers to health information exchange may increase switching costs for patients. Lin et al. (2018) expands on this argument and provides suggestive evidence of the phenomenon. They find that for-profit hospitals and those operating in highly competitive markets are less likely to send summary of care records electronically (something that may offset the benefits from greater competition).

Government Influence

The government is heavily involved in healthcare IT in a number of ways. Most directly, the HITECH Act increased incentives to adopt technology. There is debate over whether it grew efficiently, however, and the Stage 2 regulations and targets over meaningful use have come in for a lot of criticism.

The government also directly runs many hospitals such as Veterans Administration (VA) and other public hospitals. The Veterans Administration's nationwide health IT infrastructure is often lauded for its interoperability across space. However, while adoption has been successful in some cases, Hasbrouck (2016) paints a grim picture for many local health departments, with nearly a third still using paper records and under a quarter reporting having a strategic plan for IT. Massoudi and Chester (2017) further argue that best practices for informatics are lacking in local health departments and that workforce development is rare. Despite these problems with government-run providers, it is not obvious that the profit motive is the key to IT adoption. For example, Hikmet, Bhattacherjee and Kayhan. (2008) found that for-profit hospitals adopt fewer IT systems than not-for profits.

Kellermann and Jones (2013) note that modern health systems are not interoperable and connected due in part to regulatory hurdles and software personalization. This lack of interoperability substantially limits the potential of efficiency gains.

Training

Poor training is frequently mentioned as a cause of inefficiency in IT use. Aron et al. (2011) performed a systematic study of multiple units in hospitals to identify factors that influence automation and help reduce medical error rates. They found that training of hospital staff in quality management and automation of control systems improves outcomes and reduces errors due to subjective decision-making. Mantzana et al. (2007) argue that management is critical in identifying who requires training and in determining the roles and responsibilities of the different healthcare employees when adopting and integrating health IT systems.

Summary on Adoption

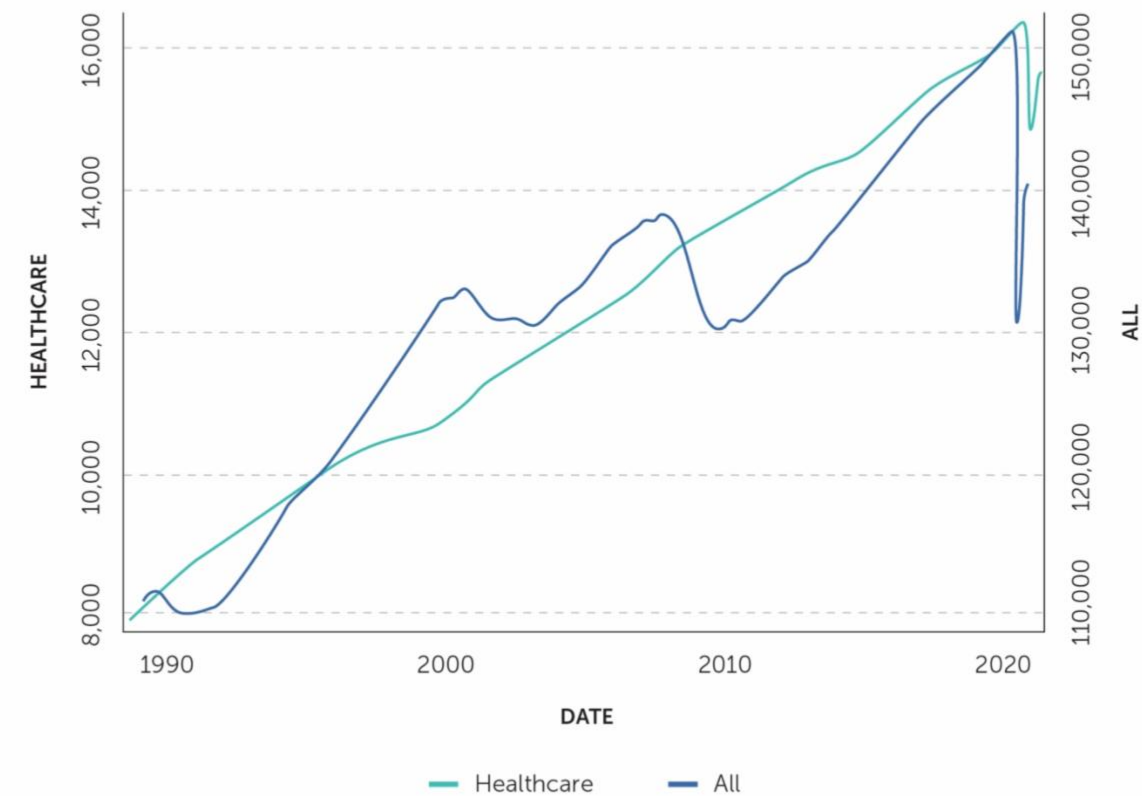
There are almost too many reasons to explain why adoption of IT is inefficient. Resistance on the part of the workforce appears particularly relevant in healthcare due to the high adjustment cost and potential risks to patients. The fragmented nature of the U.S. healthcare system also blunts incentives to share information smoothly, although the problems of IT adoption have been just as strong in the United Kingdom, which features the National Health Service, with $16 billion written off from a failed attempt at EHR in the mid-2000s.[10] The fact that this happened in a system without fee for service and a fully integrated insurer suggests more deep-rooted problems than the idiosyncrasies of the American healthcare system. If healthcare follows other industries, there continues to be substantial potential for productivity gains, but we also know that the understanding of how to use the new tools requires management changes and acceptance by the workforce.

III. The Evolution of the Healthcare Workforce

III.1 HISTORICAL LABOR TRENDS

The growth in healthcare spending over time is accompanied by growth in healthcare employment. Figure 3 shows growth in the healthcare workforce in the United States since 1990, as reported in the Federal Reserve Economic Data (FRED).[11] Healthcare workers are defined as those employed in the three main healthcare sectors: hospitals, ambulatory healthcare facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities.[12] Three things stand out. First, the number of healthcare workers has doubled from about 8 million to 16 million, rising from just over 7% to almost 11% of all workers. This continues a longer-run trend of increasing healthcare employment. Second, healthcare jobs appear to be largely recession proof. Indeed, the growth of the healthcare workforce appears like a straight line, rising year after year despite the total number of workers falling during the recessions of the early 1990s, early 2000s, and the Great Recession of 2008–09. The only time there has been a big fall is during the COVID-19 pandemic of 2020, but even this fall in healthcare jobs has been much lower than the workforce in general. The resilience of the healthcare workforce is not surprising, as the demand for healthcare rises steadily, even in economically strained times. Finally, there is not much discernible impact of the 2009 HITECH Act in Figure 3. To the extent that the Act, or ICT more broadly, did influence employment, it is not easily detectable in the overall headline numbers (we will drill down further below).

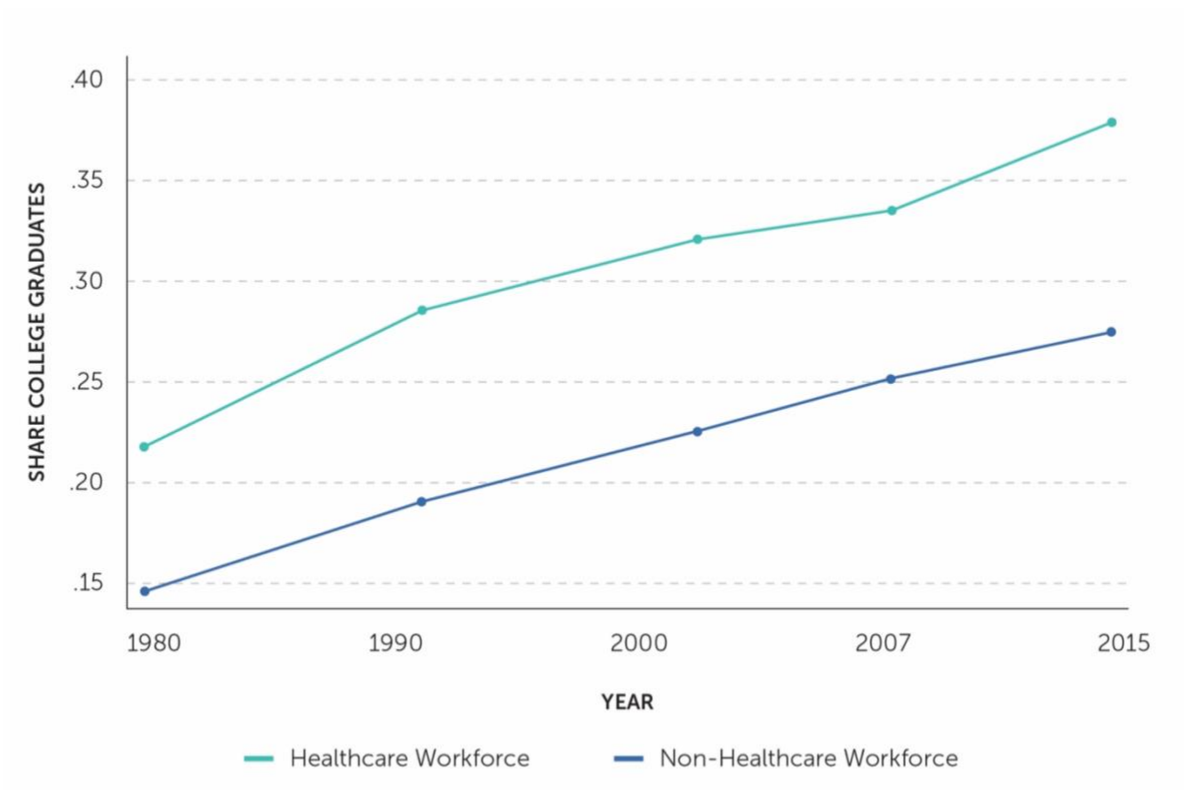
Figure 3: Healthcare Workers and Total Workforce (thousands)



Notes: This figure presents total non-farm employees and healthcare employees (in thousands) from a monthly time series provided by FRED. U.S. Bureau of Labor Statistics, All Employees, Health Care [CES6562000101], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CES6562000101, July 16, 2020. U.S. Bureau of Labor Statistics, All Employees, Total Nonfarm [PAYEMS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PAYEMS, July 16, 2020.

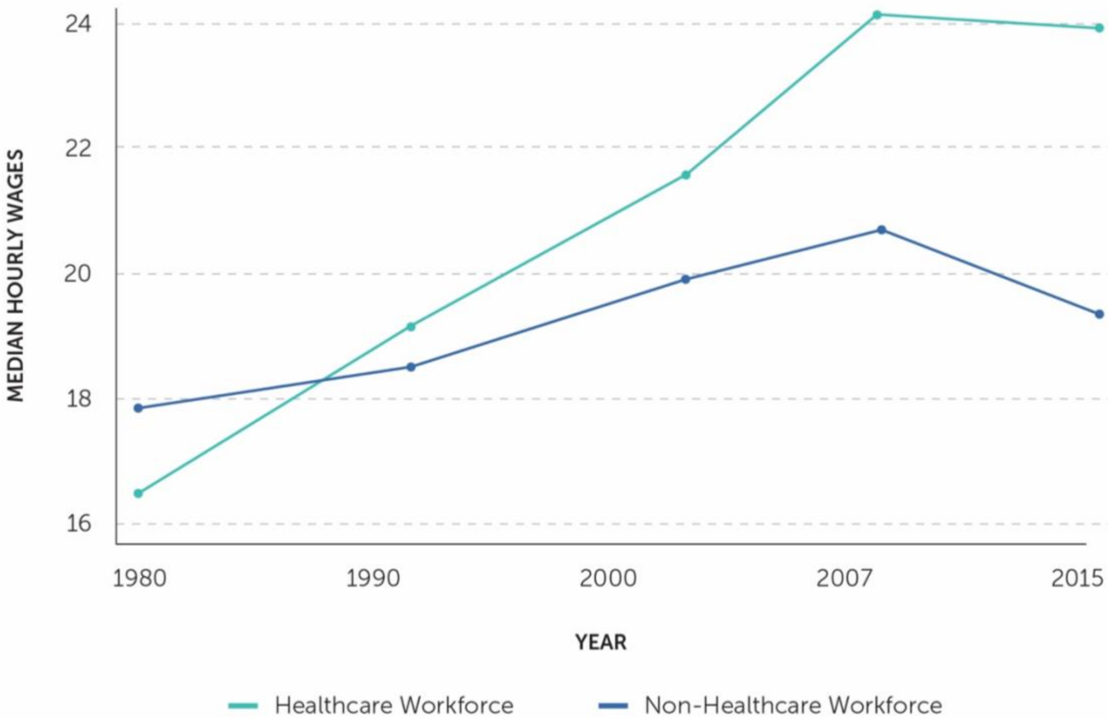
There is a similar story in terms of average wages and education for healthcare workers. We compiled data from the U.S. Census of Population from 1980 onwards and the American Community Survey (ACS). In Figure 4, the increase in average education and wages has been steeper for healthcare workers than for non-healthcare workers. Healthcare workers have always been more educated: About 22% had a college degree or higher in 1980 compared to 15% in the working population. By 2015, about 38% of healthcare workers had a college degree, compared with 28% of the rest of the population. Interestingly, despite their higher education, Figure 5 shows that healthcare workers were actually paid a slightly lower median hourly wage in 1980 than the rest of the economy (just $16.50 per hour compared to $18 per hour in 2015 US$). By the end of our sample period, however, the position had reversed with healthcare workers on $24 per hour compared with $19.50 for non-healthcare workers. We also see the greater resilience of the sector to downturns noted above: There were falls in median real wages between 2007 and 2015 for non-healthcare workers, but not for healthcare workers.

Figure 4: Share of College Graduates in the Healthcare and Non-Healthcare Workforce



Notes: This figure presents the share of college graduates between the ages of 16 and 66 who are reported in the Census and ACS data for each year. The figure is constructed using U.S. Census of Population data for 1980, 1990, and 2000 and American Community Survey (ACS) data for "2007" (actually years 2006, 2007, and 2008 pooled) and "2015" (2014, 2015, and 2016 pooled), sourced from IPUMS (Ruggles et al., 2018). Healthcare workers are those employed in hospitals, ambulatory healthcare facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities (see text).

Figure 5: Median Hourly Wages in the Healthcare and Non-Healthcare Workforce



Notes: This figure presents the median hourly wage for workers between the ages of 16 and 66 who are reported in the Census and ACS data for each year. The figure is constructed using U.S. Census of Population data for 1980, 1990, and 2000 and American Community Survey (ACS) data for "2007" (actually years 2006, 2007, and 2008 pooled) and "2015" (2014, 2015, and 2016 pooled), sourced from IPUMS (Ruggles et al., 2018). Healthcare workers are those employed in hospitals, ambulatory healthcare facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities (see text). The chain-weighted (implicit) price deflator for personal consumption expenditures deflates real wages to 2015 dollars.

The healthcare workforce is composed of a very diverse set of occupations and industries that are likely to be affected differently by technologies and other changes. In terms of industries, the fastest growing part of healthcare is ambulatory healthcare facilities (e.g., physicians' offices) compared to hospitals and nursing homes. This is consistent with the global shift to try to deliver healthcare through the primary sector rather than through inpatient care. In order to describe the composition of the healthcare workforce by broad occupation, Table 1 breaks down the fraction of the healthcare workforce into eight occupational groups. We show some example "sub-occupations" within the broader groups as well as their employment, education, and wages. Looking at 2015, the largest group is healthcare assistants, who accounted for around a quarter of the healthcare workforce. Nurses are the second largest group (17%) followed by clerical workers with 13%. Physicians and healthcare managers as well as professionals associated with medicine (PAM) were smaller groups accounting for 5.8%, 7.7%, and 5.4%, respectively.

This employment distribution across healthcare occupations is fairly stable over time. For example, the nurse fraction was 15.5% in 1980 compared to 17.1% in 2015. However, there are some changes. Clerical workers have fallen from 16% to 13%, which is similar to the hollowing out of jobs involving routine tasks that we have seen elsewhere in the economy (Acemoglu and Autor, 2011). By contrast, we see an increase in the share of PAMs from 3.8% to 5.4%, managers up from 5.1% to 7.7%, and a rise in the share of technicians from 6.5% to 8%.

A diverse set of occupations naturally requires different qualifications for each job. Table 1 and Figure 6 present the education distribution within each occupation for 2015. For example, all physicians had a bachelor's degree or higher in 2015, whereas only 18% of clerical workers did; 58% of healthcare managers had a bachelor's degree, compared with 12% of healthcare assistants.

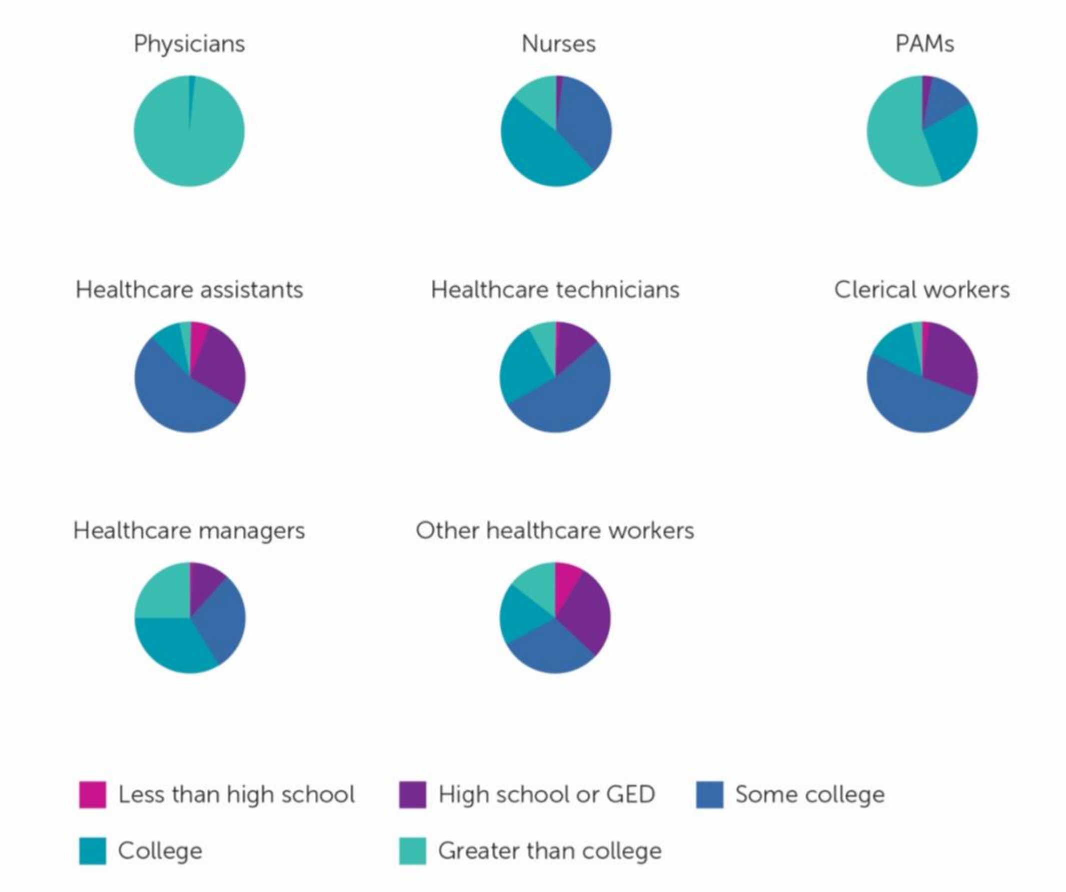
In Figure 7 (and Table 1), we plot the median real hourly wage (2015 prices) by occupation over the past three decades. Physicians, nurses, managers, and PAMs make substantially more than the average non-healthcare workers, while clerical workers, healthcare assistants, technicians, and the "other" category make less. In terms of the changes over time, physicians have had the fastest increase: more than doubling their hourly wages between 1980 and 2015. For example, they are the only occupational group that did not see a fall in their wages between 2007 and 2015. Nurses and PAMs have also had relatively faster real wage growth than other healthcare occupations. Wage growth for the other groups was slightly better, but not much more so compared to the average non-healthcare worker, as shown in Figure 5.

Table 1: Some Characteristics of the Healthcare Workforce

Broad Occupation	Example of sub-occupations (2015 definitions)	Share of occupation with college or more, 1980	Employment share in healthcare workforce, 1980	Median hourly real wage, 1980	Share of occupation with college or more, 2015	Employment share in healthcare workforce, 2015	Median hourly real wage, 2015
Physicians	Physician Surgeons	96.4%	7.2%	$27.65	99.8%	5.8%	$68.77
Nurses	Registered Nurses Nurse Anesthetists	32.5%	15.5%	$19.08	61.5%	17.1%	$31.16
PAM	Chiropractors Dieticians	59.1%	3.8%	$18.50	82.6%	5.4%	$31.77
Healthcare assistants	Dental Hygienists Licensed Vocational Nurses	5.2%	27.7%	$11.06	12.1%	23.6%	$14.79
Healthcare technicians	Diagnostic-Related Technologists Medical Records Technicians	28.4%	6.5%	$15.87	33.2%	8.0%	$20.58
Clerical workers	Bill and Account Collectors Customer Service Representatives	7.6%	16.2%	$12.00	18.1%	12.8%	$15.06
Managers	General and Operations Managers Medical and Health Service Managers	38.5%	5.1%	$19.55	57.7%	7.7%	$28.66
Other	Other Teachers and Instructors Transportation Security Screeners	16.1%	18.2%	$13.05	30.9%	19.6%	$15.92

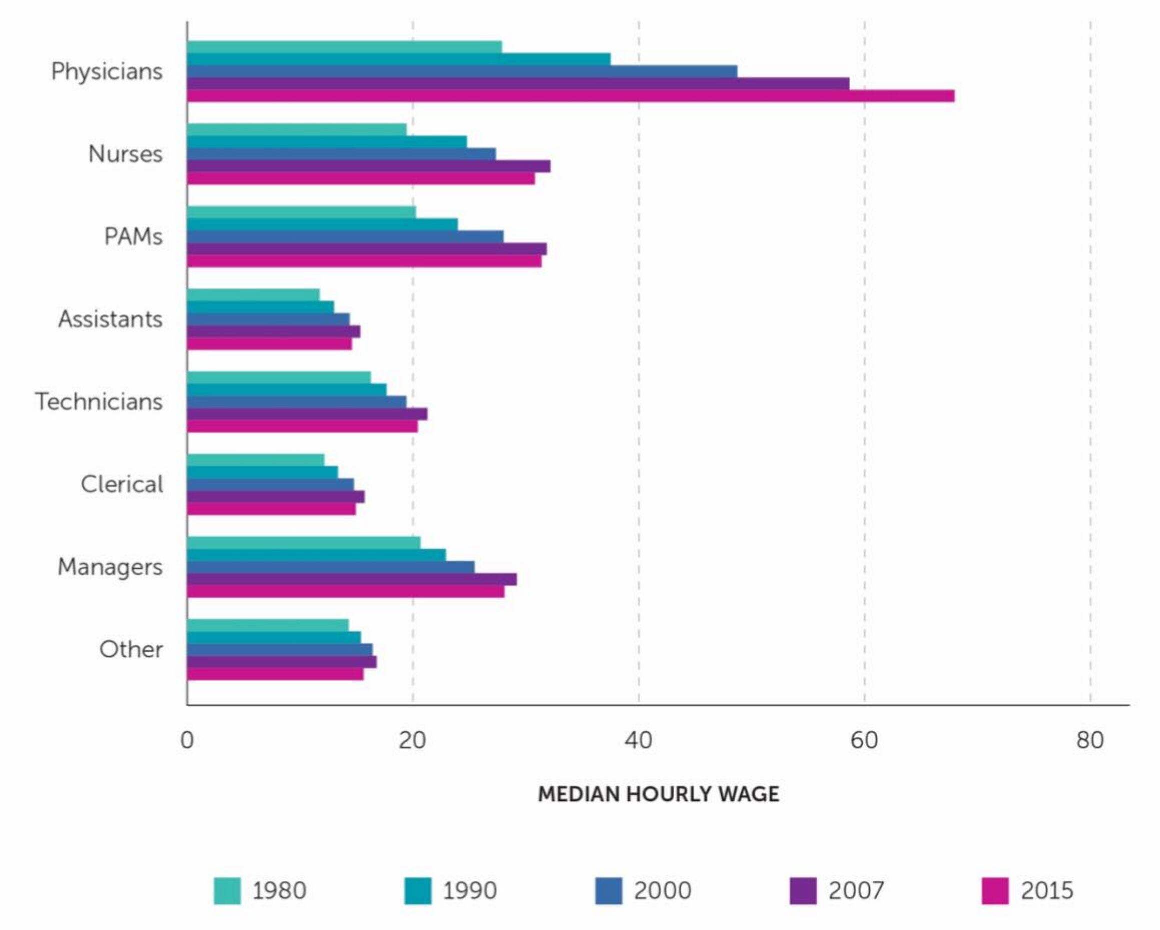
Notes: The table is constructed using U.S. Census of Population data for 1980 and "2015" (2014, 2015, and 2016 pooled), sourced from IPUMS (Ruggles et al., 2018). Healthcare workers are those employed in hospitals, ambulatory healthcare facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities (see text). The chain-weighted (implicit) price deflator for personal consumption expenditures deflates real wages to 2015 dollars.

Figure 6: Education Distribution by Broad Occupation



Notes: This figure shows education distribution by occupation. The figure is constructed using U.S. Census of Population data for "2015" (2014, 2015, and 2016 pooled), sourced from IPUMS (Ruggles et al., 2018). Healthcare workers are those employed in hospitals, ambulatory healthcare facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities (see text).

Figure 7: Median Hourly Wages by Broad Occupation



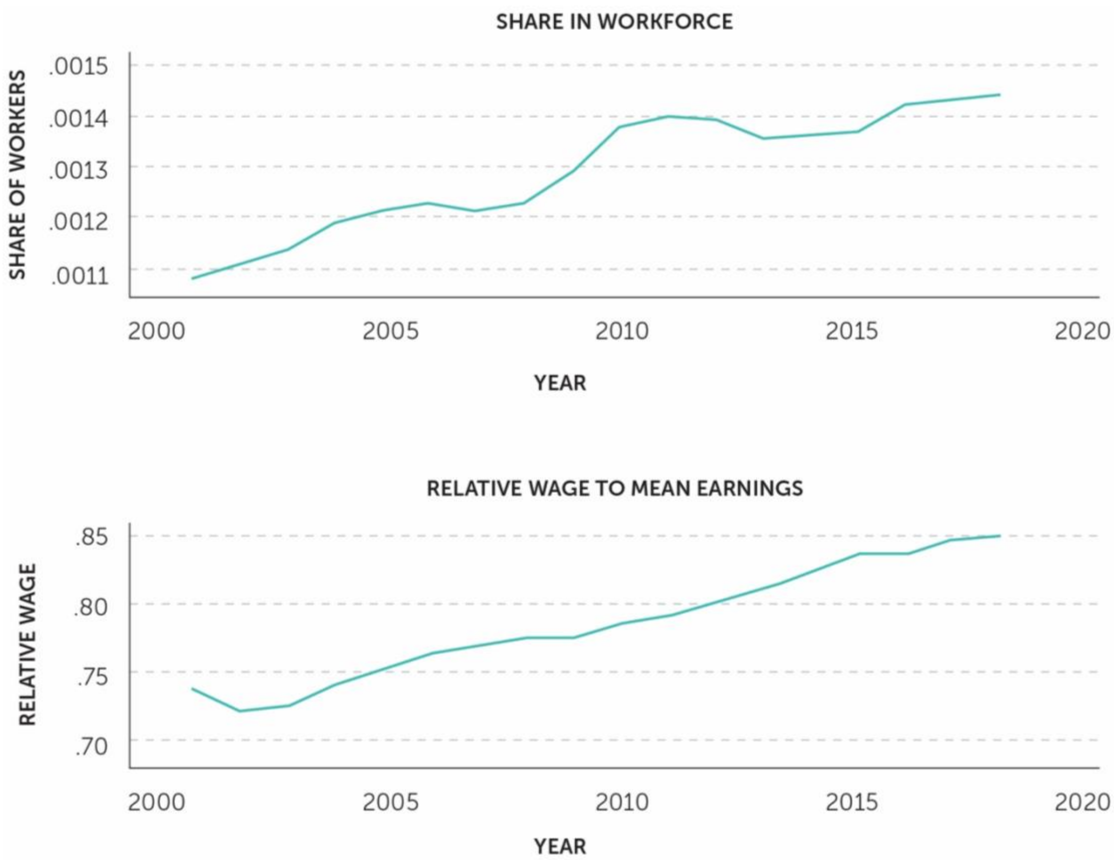
Notes: This figure presents the median hourly wage between the ages of 16 and 66 who are reported in the Census and ACS data for each year by occupation. The figure is constructed using U.S. Census of Population data for 1980, 1990, and 2000 and American Community Survey (ACS) data for "2007" (actually years 2006, 2007, and 2008 pooled) and "2015" (2014, 2015, and 2016 pooled), sourced from IPUMS (Ruggles et al., 2018). Healthcare workers are those employed in hospitals, ambulatory healthcare facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities (see text). The chain-weighted (implicit) price deflator for personal consumption expenditures deflates real wages to 2015 dollars.

The samples in the ACS are not large enough to look at very detailed healthcare occupations. To analyze specific occupations before and after the HITECH Act, we return to the Occupational Employment Statistics from the Bureau of Labor Statistics, which has consistent, detailed breakdowns since 2000. Figures 8 to 11 show the evolution of employment (top panel) and wages (bottom panel) relative to employment and wages in the United States as a whole for four groups: nurses, health IT technicians, medical transcriptionists, and radiographers and radiologists. Comparing Figures 8 and 9, it is clear that health IT workers are doing better than nurses in both their employment growth and (especially) their pay growth over the past 15 years. The relative wage of nurses is relatively constant while the relative wage of IT workers grew by over 10%. To the extent that these trends were driven by ICT, it is consistent with the plausible idea that health IT technicians are a complement to IT.

Figure 8: Relative Employment and Wages of Nurses

Notes: This figure presents the evolution of nurses' share in the total workforce and their average wage relative to the average in the working population. Data is based on Occupational Employment Statistics data provided by the Bureau of Labor Statistics. https://www.bls.gov/oes/tables.htm

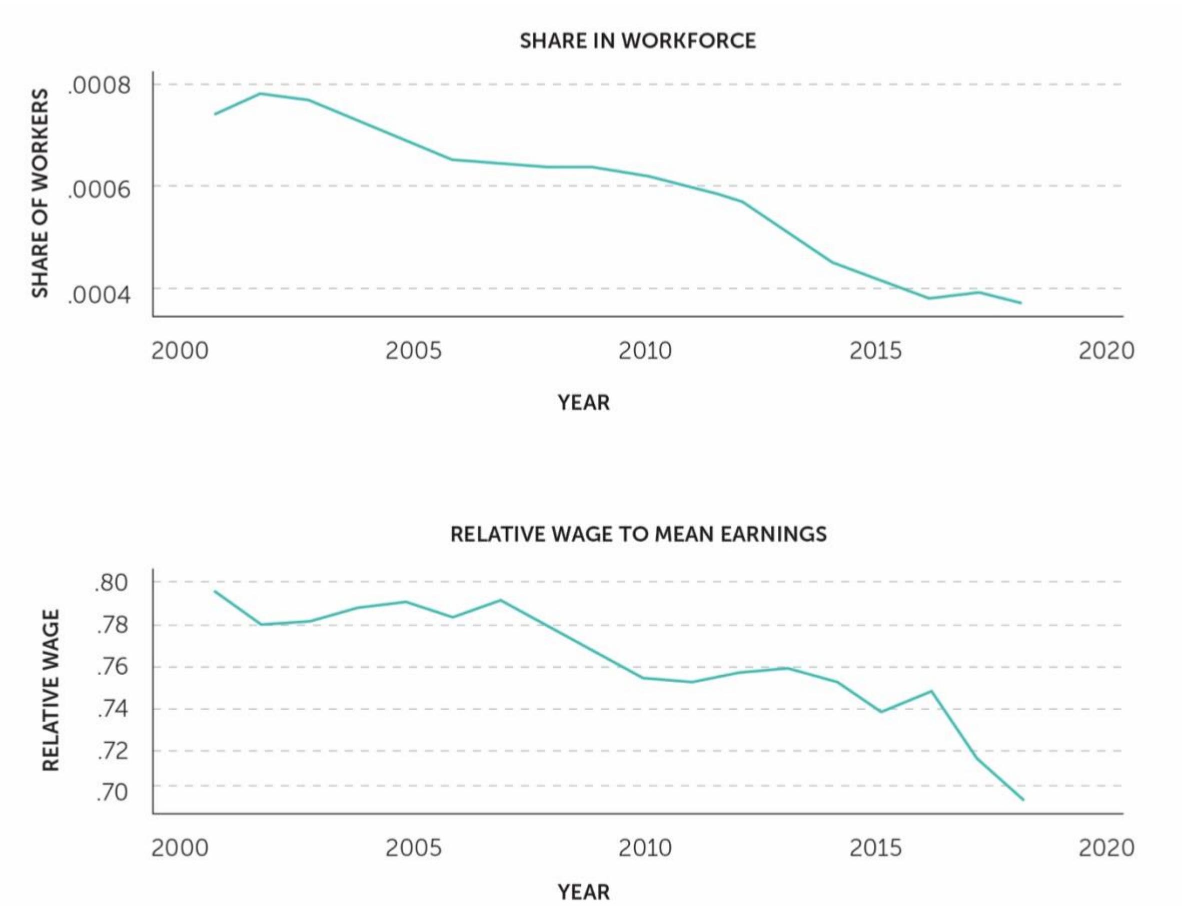
Figure 9: The Relative Employment and Wages of Health Information Technicians



Notes: This figure presents the evolution of health information technicians' share in the total workforce and their average wage relative to the average in the population. Data is based on Occupational Employment Statistics data provided by the Bureau of Labor Statistics. https://www.bls.gov/oes/tables.htm

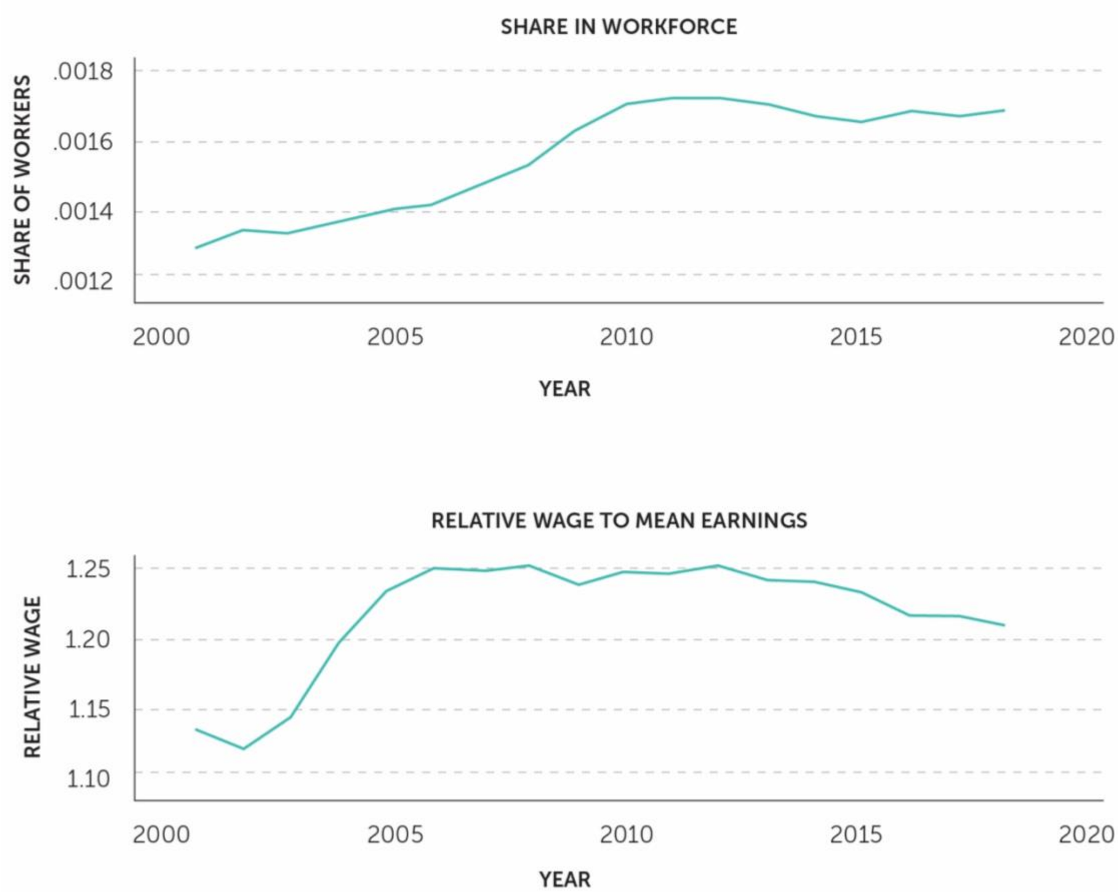
By contrast, demand for medical transcriptionists in Figure 10 appears to be falling as their relative employment and relative wages are both going down, which is consistent with IT being a substitute for this role. Finally, Figure 11 shows that demand for radiographers and radiologists has held up, although there may be a sign of falling demand in recent years, which could be an early effect of artificial intelligence, which is having a strong effect on reading and interpreting clinical images.

Figure 10: The Relative Employment and Wages of Medical Transcriptionists



Notes: This figure presents the evolution of medical transcriptionists' share in the total workforce and their average wage relative to the average in the population. Data is based on Occupational Employment Statistics data provided by the Bureau of Labor Statistics. https://www.bls.gov/oes/tables.htm

Figure 11: The Relative Employment and Wages of Radiographers and Radiologists



Notes: This figure presents the evolution of radiographers' and radiologists' share in the total workforce and their average wage relative to the average in the population. Data is based on Occupational Employment Statistics data provided by the Bureau of Labor Statistics. https://www.bls.gov/oes/tables.htm

In summary, the historical trends in employment show robust growth in employment and wages within the healthcare sector at the same time that health IT adoption has been strongly growing. Given the many other changes occurring in the healthcare landscape, we do not regard this positive correlation as definitive about the role of IT as a driver of job creation. Nevertheless, the growth in employment is an important backdrop to any transition that might occur as providers adopt new technologies.

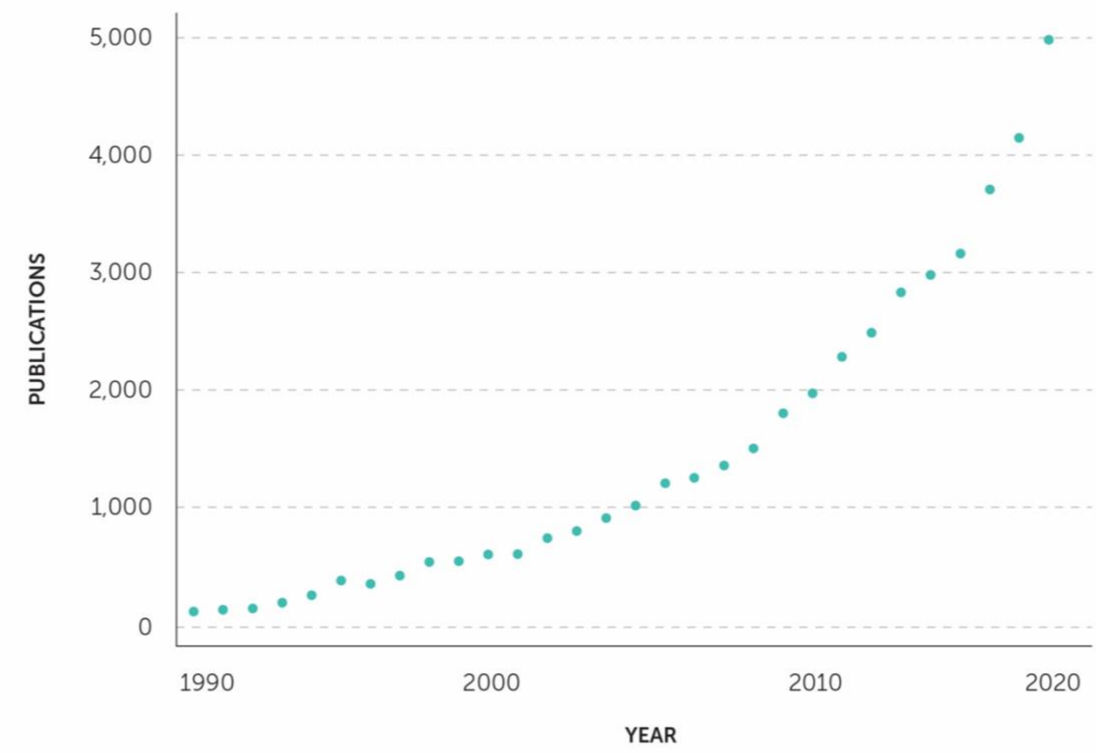
IV. The State of the Literature: Effects of Health IT on Productivity and the Workforce

IV.1. METHODOLOGY

For our literature review, we focused on reviews from the medical literature and on economics papers related to health IT adoption and its effects, with a special focus on the impact on the health workforce. More details can be found in Appendix B. In total, we reviewed 975 papers, and we read and summarized 58 in detail for our literature review. From these papers, 20 are related to IT adoption, implementation, and meaningful use; 14 concern the healthcare workforce (although most are speculative); and 25 focus more on productivity outcomes and cost effects.[13]

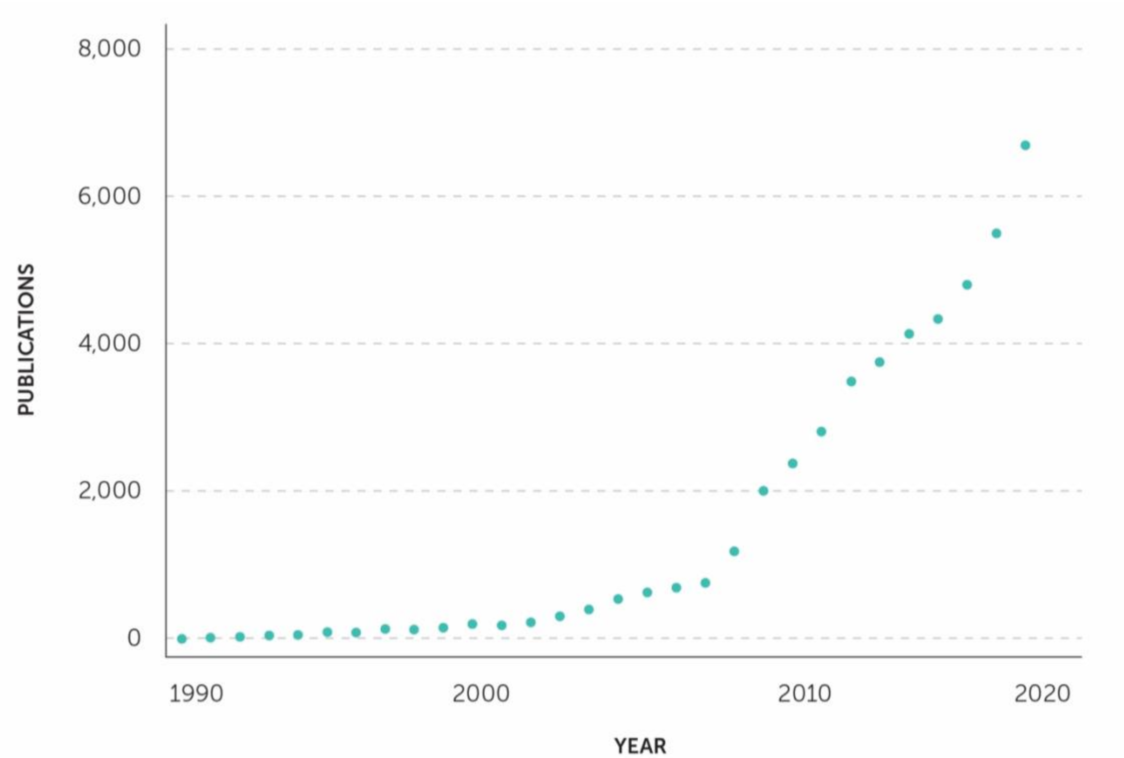
The increase in papers on health IT over time has been remarkable, particularly since the HITECH Act. Figure 12 shows the number of publications per year with "Health Information Technology" in the title or abstract of the paper. This rose from 118 in 1990 to 3,556 in 2018. A good part of this growth is the increased interest in electronic health records. Figure 13 shows that the flow for papers with "Electronic Health Records" in the title or abstract grew from three in 1990 to 3,989 in 2018. The growth after the HITECH Act was passed is particularly impressive, with the number in the year before the Act in 2008 at only 568.

Figure 12: Health Information Technology in the Title or Abstract



Notes: This figure presents the number of publications with "Health Information Technology" in the title or abstract according to the dimensions app.
https://app.dimensions.ai/discover/publication?search_text=Health%20Information%20technology%20&search_type=kws&search_field=text_search

Figure 13: Electronic Health Records in the Title or Abstract



Notes: This figure presents the number of publications with "Electronic Health Records" in the title or abstract according to the dimensions app.
https://app.dimensions.ai/discover/publication?search_text=Electronic%20health%20records&search_type=kws&search_field=text_search

IV.2. IMPACT OF HEALTH ICT ON HEALTH OUTCOMES AND PRODUCTIVITY

Medical Meta-Reviews

The medical literature has, quite reasonably, focused on the impact of technology on patient outcomes. Atasoy et al. (2019) provide a concise overview of the reasons why IT should have a positive effect on healthcare quality, focusing on EHR. As they point out, it is now a vast literature—there are several meta-studies of the papers and even reviews of reviews. The four reviews below cover papers between 1995 and 2017 and do not overlap, covering a total of 637 papers.

Kruse and Beane (2018) is the most recent study covering papers published between 2011 and 2017. They find very encouraging results. Of the 37 papers they examined, 30 found significantly positive effects of health IT, and only seven found null results. No negative results were found in their review.

Buntin et al. (2011) reviewed 154 papers published somewhat earlier, between 2007 and 2010. Of these, 62 were statistical studies and 45 were descriptive studies that included some quantitative findings (the remaining studies were qualitative); 100 of the total were in the United States, and 60% found significantly positive effects of health IT on patient outcomes (compared to over 80% in Kruse and Beane, 2018). A further 30% were inconclusive, and just under 10% found negative impacts of IT.

Goldzweig et al. (2009) reviewed 179 papers between 2004 and 2007. Many of the applications studied focused on patient care. They concluded that there are positive effects on average, but they noted concerns over a “paucity of meaningful data on the cost-benefit analysis of actual IT implementation.”

Chaudhry et al. (2006) is the earliest large-scale review, examining 257 studies between 1995 and 2004. These were both qualitative and quantitative studies and revealed mixed evidence, but the overall tenor of the findings was still positive: Improvements in health IT tended to result in better patient outcomes by increasing adherence to guidelines, enhancing disease surveillance, and decreasing medication errors. The authors cautioned that their results come mostly from single-site studies within a very limited set of institutions (fully one-quarter were from four leading academic hospitals), so whether other institutions could achieve similar results was not clear at that time. As discussed, the subsequent reviews suggested that the positive results could be generalized.

To summarize, the reviews of the medical literature suggest that there is an overall positive effect of IT on patient outcomes and healthcare productivity, on average. However, it does seem that later reviews, where a longer time period can be observed between adoption and outcomes, tends to find more positive effects than the earlier reviews, consistent with the idea that there is learning over time and a long lag between adoption and productivity increases. Finally, although the mean effect is positive, there is a lot of heterogeneity, with a non-trivial fraction of inconclusive studies and some even finding negative effects (particularly in the earlier years).

Economics Literature

Work in the economics literature tends to use modern empirical methods developed to estimate how inputs are transformed to outputs (“production functions”) and sources of variation in the use of IT that come from natural experiments. Such “experiments” are naturally occurring contexts where adoption by some hospitals (but not by others) is argued to be effectively random, so this design provides estimates that plausibly measure the causal effect of adoption. Taken as a whole, this literature tends to find less positive effects compared to the reviews of the medical literature discussed in the previous subsection.

McCullough has a series of papers carefully examining the impact of IT. Overall, the findings suggest that IT improves patient safety, increases guideline adherence, and reduces the likelihood of death. Parente and McCullough (2009) look at three technologies: EHR, picture archiving and communication systems (PACs), and nurse charts. They find that only EHR has a clear, statistically significant effect on improving patient safety. McCullough, Casey, Moscovice, and Prasad (2010) investigate EHR and computerized physician order entry (CPOE) and find that these have a small positive effect on the proportion of correct medications provided. Meanwhile, McCullough, Parente, and Town (2016) consider a large range of technologies using IT adoption surveys from HIMSS and Medicare claims data from 1998–2007. In particular, they look at patient outcomes across four conditions: acute myocardial infarction (AMI), congestive heart failure (CHF), coronary atherosclerosis (CA), and pneumonia (PN). There is a positive effect for patients with more complex conditions (apart from AMI) reducing more than one death per 100 admissions, but no impact was found for the typical patient. The significant effects found for the high-severity patients is suggestive that the gain from EHR technology comes from treating complex patients who require coordination across multiple clinical specialties, intensive monitoring, and information management.

Lee, McCullough, and Town (2013) estimate a more standard production function-based approach on 309 Californian hospitals using Office of Statewide Health Planning and Development (OSHPD) data combined with HIMSS data over the period 1998–2007. The outcome they study is value added defined as revenue minus intermediate inputs (supplies, linens, clothing, etc.) from hospital accounts data. They use proxy-based methods (e.g., Olley and Pakes, 1996; and Ackerberg et al., 2015) as well as dynamic panel data models (e.g., Arellano and Bond, 1993). They find very high returns to IT (both labor and capital), which suggests (i) good returns to IT and (ii) barriers to investment (hence the high marginal returns).

Hitt and Tambe (2016) examine the impact of EHR in 304 New York State nursing homes. Using difference-in-differences approaches, they find 1% higher productivity and 3% greater efficiency following EHR system implementation. Facilities that are one standard deviation higher on a work-organization scale—composed of practices that encourage employee collaboration, decision-making, suggestions, and problem-solving—are associated with a productivity increase of 1.5% or more when health IT is adopted. This is consistent with many of the studies from other industries suggesting an important role for complementary investments to IT, such as managerial skills (e.g., MacDuffie, 1995; Bresnahan et al., 2002; or Bloom et al., 2012).

Agha (2014) uses an event study approach that tracks outcomes over time across different providers with different dates of EHR adoption, to examine its early impact, between 1998 and 2005. Like McCullough et al. (2016), who exploit Medicare admission data from 1998–2007, she finds no effect on patient mortality or readmission on average.[14] By contrast, Lin et al. (2018) studied Medicare claims from 2008–2013 and found that adopting additional EHR features reduced mortality, but only after a maturation period. This suggests that IT applications may be improving and that there may be important learning effects: In the short run, there are little/no effects, but after several years (presumably when learning has happened) the effects do show some positive results. McKenna et al. (2018) also find reductions in mortality after the introduction of IT in New York State. They look before and after the HITECH Act, which plausibly increased incentives to adopt IT, although the main assumption for the results is that differential adoption rates over time are solely due to HITECH incentives, which is a strong assumption.

Miller and Tucker (2011) employ a particularly novel set of empirical strategies to estimate plausibly causal estimates of the early effects of health IT. They focus on all births in U.S. hospitals from 1995–2006 and identify technology adoption using the 2007 release of the HIMSS Analytics Database (HADB); 38% of their 3,764 hospitals have EHR by the end of the period in 2006. Their main approach uses changes in privacy laws to generate some exogenous variation in the adoption of IT (building on their results in Miller and Tucker, 2009, which suggests 24% lower IT adoption in states with tougher privacy laws). The privacy law, HIPPA, governs sharing of patient information at the federal level. Their argument is that IT systems are less attractive when there are additional privacy laws at the state level that make it harder to share patient information. They show that hospitals in states that toughened privacy laws (11 states introduced these enhancements over the 12-year period they studied) had a smaller increase in IT adoption than other states. Their results suggest that health IT reduces infant mortality by 5% when comparing hospitals that adopted at different times, and the estimate grows somewhat larger when they focus on IT adoption differences that stem from privacy law enhancements; 5% is smaller than some of the earlier literature, but still a nontrivial effect (26 fewer neonatal deaths per 100,000 births). Since there may be other state-level effects confounding their analysis, they go one step further and look within hospital networks: They examine the impact of IT adoption in hospital A stemming from many other hospitals in the same network being located in states adopting tougher privacy laws, and they show that the results are similar when focusing on this as the driver of adoption differences across hospitals.

Summary

Overall, the literature suggests modest improvements in productivity following IT adoption, with plenty of heterogeneity across studies. The results of the literature suggest a few themes. First, it can take time for health IT to generate improvements in productivity, likely due to the learning that needs to take place. Second, the results likely differ across patient groups, with evidence suggesting that more complex patients see benefits of the new technologies. One question that requires better understanding is how health IT affects a wider array of different types of patients.

IV.3. IMPACT OF ICT ON HEALTHCARE COSTS

Healthcare costs are typically measured in two ways: healthcare expenses paid by payers such as insurance companies and government programs such as Medicare and Medicaid, or input costs incurred by providers including labor and capital expenses. The former is also the revenue received by healthcare providers, and a concern is that health IT has enabled providers to bill payers more effectively (e.g., through automated coding that maximizes revenue for providers). This clearly creates more profits for providers and might be a more accurate and systematic recording than before the IT was introduced. However, if the main effect were to “upcode” patients’ health, IT would inflate healthcare spending.

Healthcare Expenses Paid by Providers

Many of the papers (particularly those in the economics literature) look at costs as well as quality. While the Agha (2014) study discussed above found no effect on quality from IT adoption, she did find a 1.3% increase in billing. Indeed, modern IT could be a complement to other new technologies, such as personalized medicine or diagnostics for novel devices or treatments that have higher marginal costs compared to legacy technologies.

Further, modern IT systems may be successful at increasing provider revenue rather than lowering payers' spending. Health IT can change the ability to code diagnoses and procedures in ways that increase bills for tasks that previously went uncompensated or undercompensated. There are many anecdotes of upcoding. Most famously perhaps is the epidemic of Kwashiorkor. In January 2014, the U.S. Office of the Inspector General found that two Catholic community hospitals had overcharged Medicare by $236,000 for cases billed as Kwashiorkor, the rare belly-bloating form of malnutrition found largely among children in sub-Saharan Africa. Medicare had paid out $700 million in hospital bills in 2010 and 2011 for cases listing Kwashiorkor as one of the diagnoses. The audits showed that none of the 217 cases in the two community hospitals actually had the disease.

In hospital billing, insurers pay based on the complexity of diagnoses, number of patient history and facts (like cough, belly pain, and patient history), and organs examined. EHR can maximize the billing for such indications even if the disease is highly unlikely. Hence, when patients registered malnutrition and low blood protein, the system would prompt coders or doctors to "Kawshiorkor" because of its high reimbursement rate.

In terms of more systematic evidence, Ganju et al. (2016) and Li (2014) found evidence that EHR adoption led to upcoding, although Adler-Milstein and Jha (2014) did not. Gowrisankaran et al. (2016) found that EHRs lead to higher codes for medical (but not surgical) claims following a 2007 Medicare payment reform that raised the standards to document complications that result in higher payment. This is an example where the EHR may have facilitated higher billing by providers. The authors did not find that the increase in documented severity was correlated with higher financial returns, however, which might suggest the change was due to increased accuracy rather than upcoding.

Operating Costs

While comparing similar hospitals that adopt at different times can yield causal estimates of the effects of IT, a concern is that hospitals may choose to adopt depending on changing market conditions that can also affect healthcare productivity. Recall from the summary above that Zhivan and Diana (2012) found that inefficient hospitals are more likely to adopt IT. This will confound any estimated effects of IT when using empirical strategies that fail to consider this nonrandom adoption.

Dranove et al. (2014) offer a number of empirical strategies with the aim of overcoming such spurious correlations. In addition to considering the different timing of IT adoption across providers, the authors have three empirical strategies to focus on variation in adoption that can yield plausibly causal estimates. These designs are: (a) focusing on hospital systems and adoption of IT by hospitals within the system in other markets (similar to Miller and Tucker, 2011); (b) focusing on adoption by competitors to hospitals within the same system; and (c) using the fact that hospitals based farther from major EHR vendors (like Epic) are slower to adopt. These sources of variation in IT adoption yield less precise estimates, but they all tell a similar story; namely that there were large *increases* in costs immediately after EHR adoption. The authors stress that over time these costs start to decline, which suggests some positive learning effects on productivity. Furthermore, the paper tests the idea that the cost impact depends on whether the local labor market has an elastic supply of IT professionals. In counties where this is the case, there is actually a fall in costs. This is consistent with a complementarity between IT workers and adoption, or more simply that EHR implementation will be more costly when relative wages of IT workers are higher.

Summary on Healthcare Spending

The potential for health IT to lower healthcare spending is immense. As noted above, the widely cited Hillestad et al. (2005) estimated that the adoption of interoperable EHR systems could produce efficiency and safety gains of $142 billion to $371 billion over 15 years. The literature yields evidence on healthcare spending that is more mixed, however, especially compared to the literature that considers clinical outcomes. Overall, IT adoption tends to be associated with an increase in costs, at least in the initial years (Dranove et al., 2014), and the barriers for successful adoption described in Section II provide some guidance on the frictions that can impede progress.

IV.4 IMPACT OF ICT ON THE HEALTHCARE WORKFORCE

There have been relatively few studies on the effect of IT on the healthcare workforce, with most publications describing qualitative concerns rather than providing quantitative support. Masys (2002) is one of the first papers to argue how health IT may revolutionize the market, with especially large changes among less skilled members of the workforce. Medical staff may use the health IT to become more capable of managing and analyzing data, while doctors will need to offer advice to internet-savvy patients. More recently, Zeng (2016) argues that clinical informatics and data scientists are important to exploit the benefits of IT while, unsurprisingly, every position based on paperwork will become obsolete.

McFarlane, Dixon, Grannis, and Gibson (2019) analyze the public health workforce interests and needs from 2014 to 2017 and conclude that the share of informatics workers remained stable and very low. Moreover, it appears that informatics workers are not leading analytics improvements, as they report that they perform low-skilled tasks while non-informatics workers report the opposite.

While the skills required to perform a job may shift because of IT, the way that potential workers can learn changes as well. IT allows workers to get online training, which potentially lowers the cost of education and allows for personalized programs. Car et al. (2019) use the gold-standard Cochrane method to construct a systematic review of randomized controlled trials (RCTs) on the effectiveness of digital versus traditional learning. Based on a pooled-analysis of nine RCTs involving 890 healthcare professionals, they find no difference in knowledge after digital education when compared to traditional strategies. Furthermore, an effort to broaden healthcare workers' skill sets is visible in some institutions. Herath et al. (2017) review 65 studies related to interprofessional education (IPE) and find that, while there is a need to broaden adoption of such programs, the benefits are starting to show.

Even with greater education and training, regulatory constraints can create inefficiencies. Nancarrow (2015) argues that a major rethinking of healthcare provision and the structure of the workforce is necessary to successfully adopt IT. She suggests that positions should be filled on a "skill basis" instead of "titles basis" and that regulatory barriers may explain the lack of success of IT, leading to overtraining in some skills and undertraining in others. If this were true, one would expect worker turnover to be on the rise as there is increasing skill mismatch. There is some evidence of this as Rosenbaum (2018) finds that the healthcare workforce turnover rate increased from 15.6% in 2010 to 20.6% in 2017, a greater rate than comparable occupations. Lopes et al. (2017) argue that there is a lot of variation in healthcare workforce turnover, with less specialized positions—who are potentially more affected by IT—being more likely to exit.

Bullard (2016) argues that there is an oversupply of just-graduated nurses, and that having additional nurses who specialize in systems can substantially lower the costs of IT implementation. However, if they will be specialized in systems and how to use them, do they need to have a full clinical training? Understanding the role that certifications play in the healthcare workforce's ability to adapt IT is an interesting area for future research.

There have also been some microstudies analyzing the effects of IT implementation on workers and staffing decisions. Bharghava and Mishra (2014) point out that the effect of IT is not the same for all physicians. They explain that the ratio of information entered versus information used might explain whether or not a physician benefits from IT. They then exploit the different timing of health IT implementation at 12 clinics involving 87 physicians across a wide range of productivity measures to show that family doctors and pediatricians, who must enter a lot of information to the system, do worse with IT. Meanwhile internists, who use a lot of information that was previously captured, benefited from the IT implementation. For example, they show that internal medicine doctors increase their work relative value units (wRVUs) by 1%, while pediatricians and family doctors reduce their wRVUs by 2% and 5%, respectively, after the implementation phase.

In terms of management training, Webb (2019) argues that the number of Physician CEOs is on the rise, but the average tenure is just 3.5 years. She argues that these leaders should have training in finance and leadership to improve performance and extend tenure. Bloom et al. (2020) find that hospital quality and management performance is improved by the joint provision of business and clinical skills (using a hospital's proximity to co-located business and medical schools).

In the related setting of nursing homes, Lu, Rui, and Seidmann (2018) argue that most facilities are at capacity and that they achieve higher revenue by attracting higher-paying customers through quality differentiation. Thus, a key decision for nursing homes in attracting higher-paying patients is the number of nurses they hire. They analyze decisions by nursing homes and predict through their model that nursing homes that usually attract high-paying patients will reduce the number of nurses since they can achieve the same high-quality service with fewer nurses due to IT. Meanwhile nursing homes lower on the quality spectrum will increase the number of nurses they hire because the return to an additional nurse becomes much higher, thanks to complementarities between nurses and IT. That is, the substitution effect between IT and workers among the more financially successful nursing homes dominates, while the complementarity channel dominates the decision of firms that had more room for improvement. They show their predictions hold empirically as lower-quality nursing homes increase staff 7.6%, while higher-quality nursing homes decrease it by 5.8%, following IT implementation.

Finally, the event studies by Agha (2014) on EHR between 1998 and 2004 also have a small section on the impact on the workforce. She finds that adoption leads to just over 1% increases in nurse employment and total employment, but this effect is statistically insignificant. We will examine similar specifications on more recent data in Section V below (and reach a similar conclusion).

Summary

Micro-evidence on the effect of IT adoption on the workforce is scarce, and it is important to note that in these few studies it is not clear whether IT adoption is driving the changes in workforce or whether other characteristics might be driving both.

IV.5 IMPACT OF ICT ON HEALTH EQUITY

In principle, ICT could affect inequality through differential effects on different occupations. For example, there is much evidence from other industries that new technologies increase the demand for more highly skilled people on average ("skill-biased technical change"). There is no strong evidence of this in healthcare, however, as discussed in the previous subsection.

As noted above, telemedicine may be a force for reducing inequality in access to health. This may be important because Khullar et al. (2020, especially Table 3) show that providers serving lower-income patients have less advanced ICT capabilities, on average. Second, there are concerns that algorithmic approaches to targeting healthcare resources can replicate racial inequities in care delivery (Obermeyer et al., 2019).

IV.6. LESSONS FROM OTHER INDUSTRIES

Productivity

There is a vast literature on the impact of ICT on economic outcomes outside of healthcare, and this in turn is a subset of the vast field of the impact of technological change on the economy. A broad motivation in macroeconomics has been the slowdown in productivity growth since the mid-1970s. This is worrisome because, in the long run, productivity growth is the determinant of real wage growth.

As noted earlier, the Solow Paradox is that this productivity slowdown has coincided with the ICT revolution. One bit of good news was that subsequently to Solow's Paradox, there was a pick-up in U.S. productivity growth between 1995 and 2004. Quality-adjusted prices of IT fell even more swiftly (30% per year on some measures in the late 1990s compared to 15% per annum before). As Stiroh (2002) first showed, increases in productivity were particularly strong in the industries that intensively produce ICT (such as semiconductors) or that used IT intensively (such as retail, wholesale, and finance). This result has been confirmed by other authors in the United States and in other OECD countries (e.g., Draca et al., 2007). Unfortunately, productivity growth slowed in the mid-2000s and has been even more lackluster following the Great Recession (Van Reenen, 2020).

Many explanations have been put forward for the paradox, such as mis-measurement and the greater difficulty of innovating as ideas become harder to find. However, one leading hypothesis is that it takes a long time between the invention of a major new general-purpose technology (like the computer) and how it feeds through to greater productivity (David, 1990). This was the case for the invention of electricity in the 19th century—it took decades before organizational and social changes were made to make effective use of electricity in industry (e.g., the 24-hour-a-day multi-shift Fordist assembly-line factory). With ICT, many complementary investments in workplace organization and management also need to be made to make best use of the new opportunities. And by extension, the most recent waves of radical technologies such as artificial intelligence may also take some time before they show up in productivity improvements (Brynjolfsson, Rock, and Syverson, 2020).

Microeconomic evidence is more compelling than evidence based on macroeconomic data. Much of this is summarized in McAfee and Brynjolfsson (2016. In short, the studies of firms suggest:

i) A positive and significant association between organizational productivity and the use of ICT.

ii) Although this correlation is on average quite large, it is extremely heterogeneous between studies. In addition, even within studies, the effects are generally quite variable across different firms.

iii) When researchers can look at data over many years, it is clear that the positive effects do not take place immediately, but typically are only revealed after several years.

These findings lend credence to the "organizational complementarity" story whereby just spending a lot of money on technology can be quite ineffective. Firms take time to learn the most effective way to use this technology, and there is much ex ante uncertainty about the optimal way to use ICT, which is why the returns are so variable and slow to happen. In particular, many other types of investment must be made, not least of which is changing the structure of organizations. This might require decentralization—for example, changing the power structure so that more decisions are made lower down in the hierarchy.

Some papers have also used more direct tests of the organizational complementarity explanation by collecting information on the inner workings of firms—for example, their degree of workplace decentralization, HR management practices, and use of teams.[15] These have all found important roles for strong complementarities between ICT and organization change that help explain the variety of impacts of ICT on productivity.[16]

Effect of ICT on Labor Market Outcomes

The literature on the effects of technology on the labor market is also vast. A useful survey is Acemoglu and Autor (2011). The focus of the literature has been on the impact of ICT on the demand for different types of skills. The broad picture here is that, on average, ICT has increased the demand for the highly skilled—those with a college degree or higher. Hence, as Jan Tinbergen argued, wage inequality can be seen as a race between technologies that increase skill demand pushing inequality up versus the supply of education that will pull inequality down. Autor et al. (2020) show that the slowdown in years of schooling for cohorts entering the labor market since the late 1970s has been a major cause of the rise in the premium to having more education.

More recent work suggests that ICT has a more nuanced effect. Computers tend to replace routine work. For example, tasks traditionally undertaken by low-skilled manual workers on car assembly lines have been largely automated away by robots. However, routine tasks by middle-educated workers doing clerical work were also automated away (e.g., automated teller machines), whereas low-skilled workers doing non-routine work like cleaning have been less affected by ICT. Hence, ICT may have the largest negative impact on middle-skilled workers and lead to polarization of the workforce.

Summary

Our sense from the literature is that ICT has two central tendencies: to raise productivity and to increase the demand for more educated/skilled workers. However, the impact is highly variable and mediated by specific features of the environment into which the technology is placed. In particular, the finding that the impact is contingent on organization and management is consistent with our review of studies focusing on healthcare.

V. New Empirical Evidence

In addition to the nationwide trends in IT adoption and healthcare employment shown above, we have investigated the adoption of health IT over the past decade using the American Hospital Association (AHA) Annual Survey Information Technology (IT) Supplement from 2008–2017 (see Appendix C for more details).

V.1. THE DETERMINANTS OF EHR ADOPTION

In the cross section, it is no surprise that larger hospitals are more likely to adopt ICT. EHR has a significant fixed cost, so being able to spread this over a larger scale is an advantage. Furthermore, due to the uncertainty over the benefits of EHR and its high cost, larger hospitals were the early adopters. Figure 14 plots the median size of adopters in the AHA IT Supplement Survey as measured by the number of beds. Although adopting hospitals are larger than non-adopters on average, the magnitude of this gap declines over time, as smaller hospitals start adopting. It is striking that the decline in median bed size accelerated rapidly after the introduction of the HITECH Act. This suggests that the subsidies included enabled some smaller hospitals to adopt EHR.

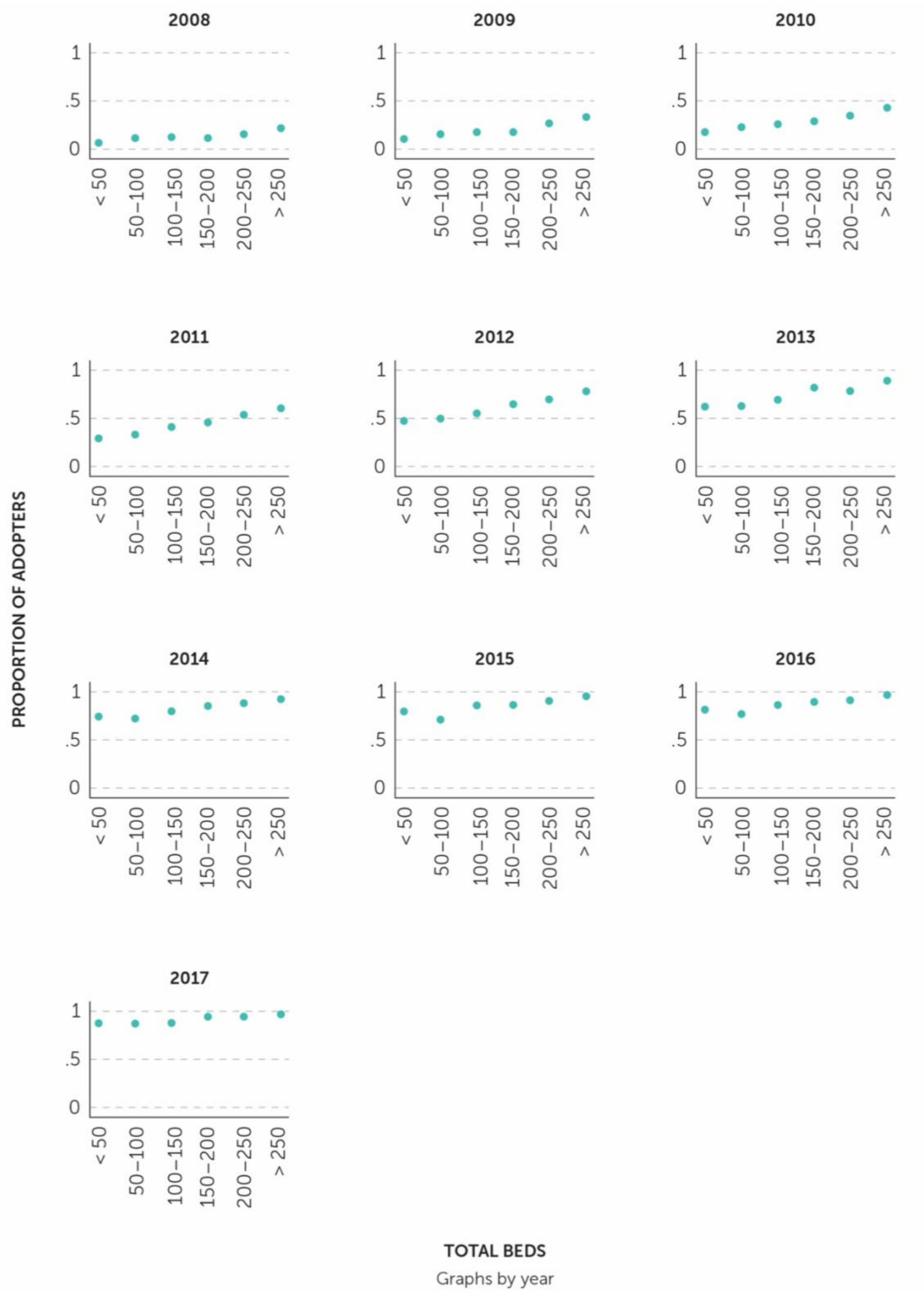
Figure 14: Average Size of Adopters (number of beds) Over Time

Notes: This figure presents average size of hospitals in terms of numbers of beds that reported acquiring EHR for the first time in an AHA IT Supplement Survey.

Another way to see this is through the proportion of hospitals that had adopted by each year by size groups (Figure 15). We divided hospitals into six groups of increasing size. In 2008, there is the steepest gradient by size: Almost none of the smallest hospitals have adopted EHR, whereas about a fifth of the largest ones had. By 2017, there was no difference. Further, we can see that although there is an uptick in adoption for large hospitals, the main effect of the HITECH Act is concentrated on smaller hospitals that had virtually no adoption prior to the introduction of the subsidies.

A similar story is visible when looking at other measures of hospital size such as the total number of patients, staff members, and revenue.

Figure 15: The Average Size of Hospitals with EHR



Note: This figure presents the proportion of hospitals that have adopted EHR as a function of hospital size (measured by number of beds) in the AHA IT Supplement Survey.

V.2 THE IMPACT OF EHR ADOPTION ON WORKERS

In order to look at the potential impact of EHR on the workforce and hospital outcomes, we conducted a preliminary empirical study using an event study methodology (see Appendix C for methodological details). This follows the same hospitals before and after they adopted EHR compared to a control group. Our main approach is to follow hospitals up to six years before adoption and four years afterwards. We found that hospitals typically were trending in different ways prior to adopting (i.e., adopters were growing less quickly than non-adopters), so we allowed for pre-trends when looking at the adoption impact.[17] Effectively, we are comparing adopters to non-adopters in the same year after allowing for differential growth rates.

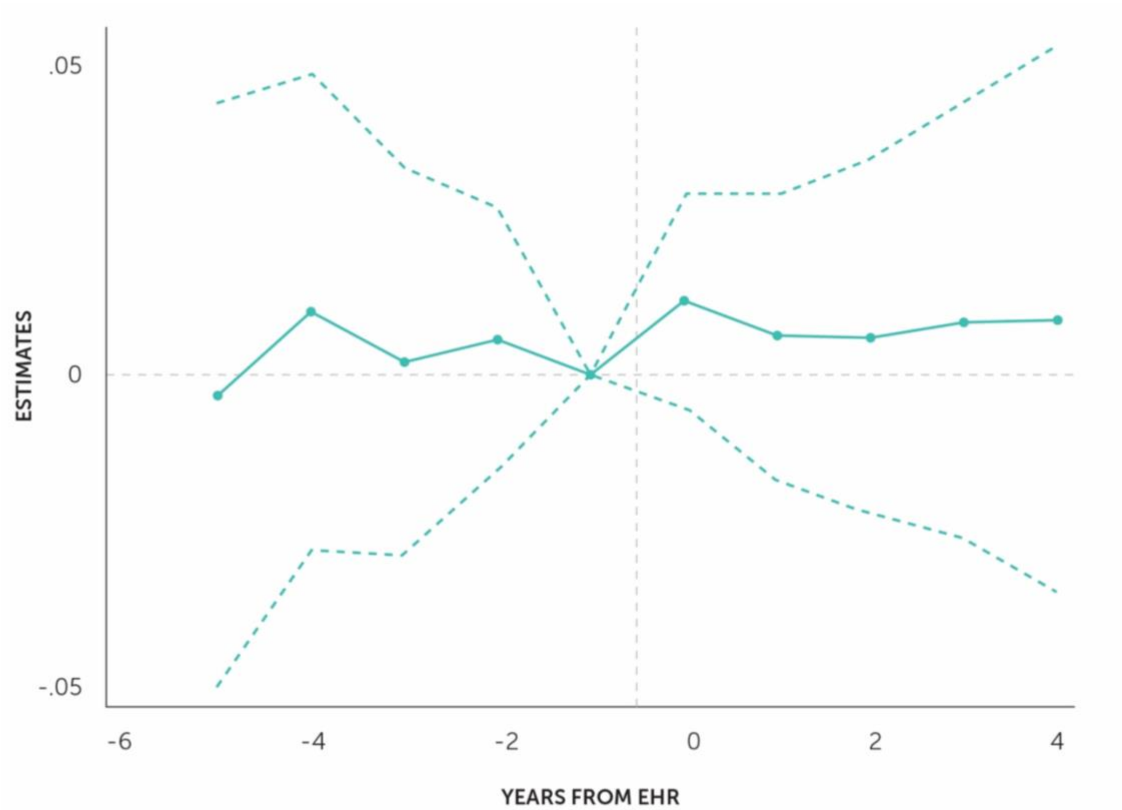
Figure 16 presents the results for hospital capacity as measured by the number of beds. Each dot reflects the impact of EHR in the indicated year after adoption relative to the year before adoption ("t-1"). The positive value of the dot in the year of adoption ("t = 0") indicates that there was a positive impact of EHR adoption on the number of beds compared to the previous year, but it was small—less than a one percent increase in size. This impact falls very slightly in subsequent years. Not only is the effect small in magnitude, it is not statistically significantly different from zero as indicated by the 95% confidence intervals. Similarly, looking prior to adoption, we find that adopting hospitals look like non-adopters (after controlling for the time trends). This suggests little impact of ICT on hospital capacity.

Figure 17 implements the same event study analysis but uses total employees as an outcome. The point estimates suggest that there is little effect in the year of adoption, but by four years after adoption, total employment is about 3% higher, and this effect is significant at the 10% level. Figure 18 uses the total number of nurses as an outcome, one of the largest occupational groups in a hospital.[18] It shows a similar increase in the total number of employees of around 3%, with smaller confidence intervals, which is a statistically significant effect at the 5% level by a year after adoption.

Taken as a whole, these results imply that there is no evidence that this new technology had a large negative impact on jobs in the hospital sector. If anything, there appears to be an increase in jobs (similar to the findings of Agha, 2014, on an earlier period), both overall and nurses in particular.

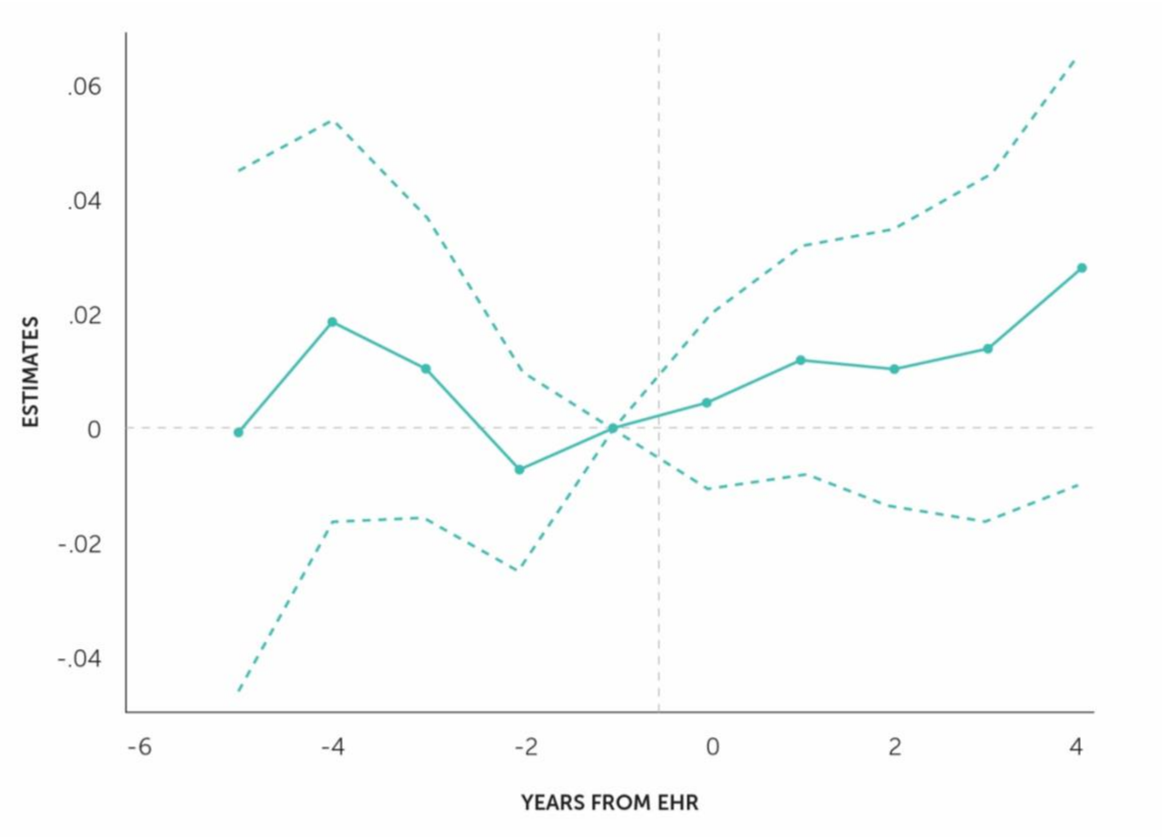
In Appendix C, we show that this conclusion is robust to other ways of implementing the event studies, such as looking only at adopters and exploiting the differential timing of adoption amongst this group.

Figure 16: Event Study of the Impact of Adopting EHR on Capacity as Measured by the Log (number of beds)



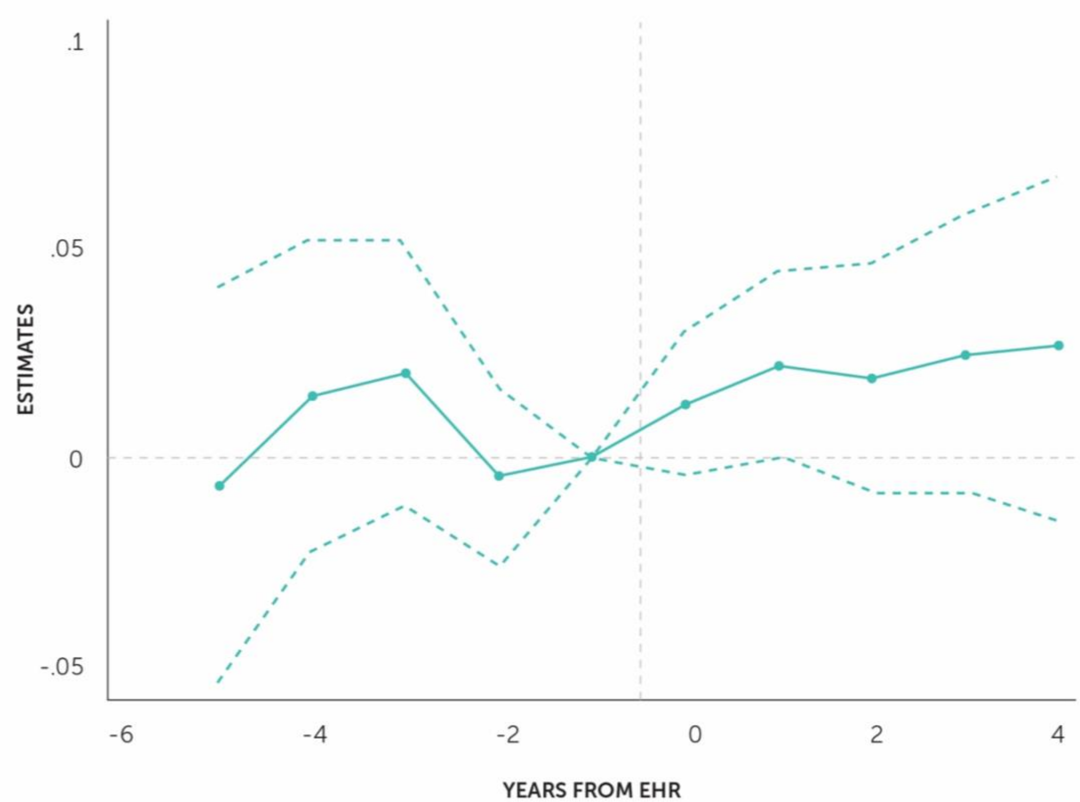
Notes: This is an event study graph examining the impact of hospital adoption of EHR (in year zero) on hospital capacity (the number of beds). The dotted lines are the 95% confidence intervals for the coefficients we obtain from a trend adjusted regression (controlling for state by year dummies and hospital fixed effects). (See Appendix C for details.)

Figure 17: Event Study of the Impact of Adopting EHR on the Log (total employees)



Notes: This is an event study graph examining the impact of hospital adoption of EHR (in year zero) on the total number of employees (Full-Time Equivalents). The dotted lines are the 95% confidence intervals for the coefficients we obtain from a trend adjusted regression (controlling for state by year dummies and hospital fixed effects). (See Appendix C for details.)

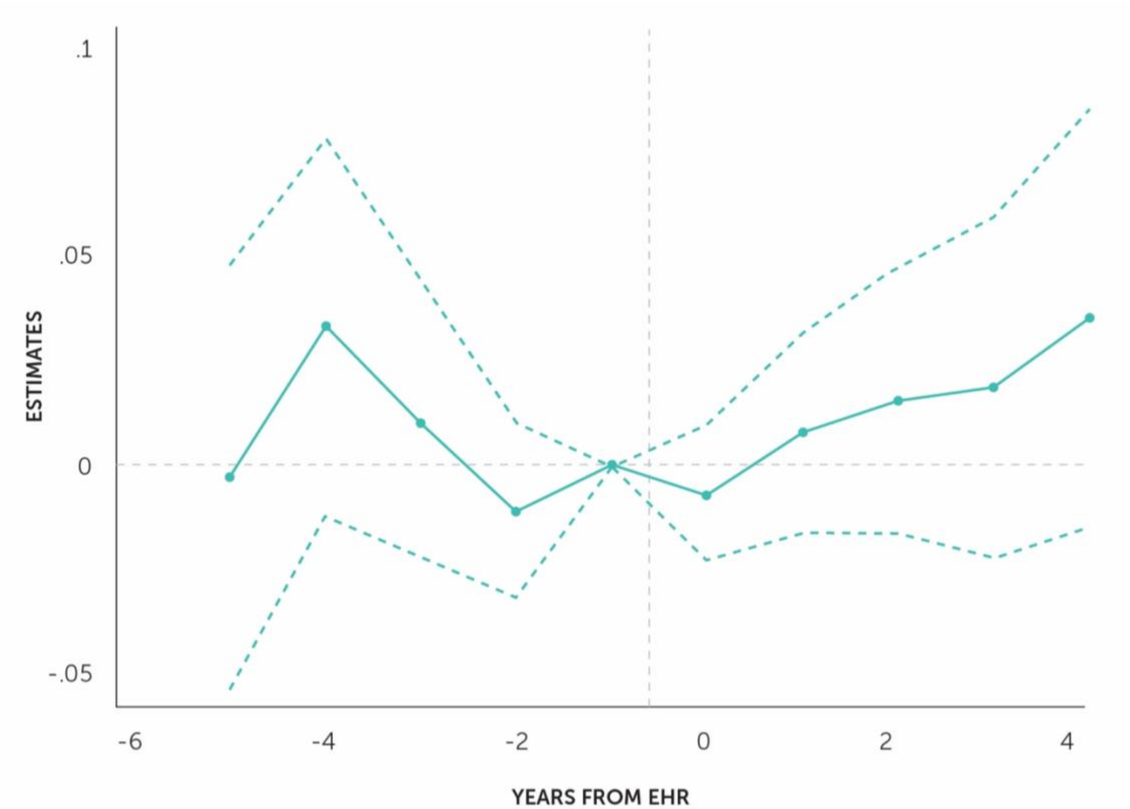
Figure 18: Event Study of the Impact of Adopting EHR on the Log (number of nurses)



Notes: This is an event study graph examining the impact of hospital adoption of EHR (in year zero) on the number of nurses. The dotted lines are the 95% confidence intervals for the coefficients we obtain from a trend adjusted regression (controlling for state by year dummies and hospital fixed effects). (See Appendix C for details.)

The increase in employees could reflect that EHR improves the efficiency or attractiveness of a hospital, enabling it to expand admissions relative to capacity; or it might reflect an inefficient increase in workforce without improvements in performance. Deteriorating productivity could be reflected in a falling number of admissions. Figure 19 examines admissions as an outcome. We see an (insignificant) increase in admissions. Admissions per bed and payroll costs per bed are both essentially flat (not shown). This suggests that the increase in employment numbers does not reflect big falls in efficiency, but neither does it imply large increases in efficiency. The absence of cost savings is somewhat disappointing given the hopes in the HITECH Act. However, it is consistent with the literature review, and the good news is that employment tends to rise.

Figure 19: Event Study of the Impact of Adopting EHR on the Log (inpatient admissions)



Notes: This is an event study graph examining the impact of hospital adoption of EHR (in year zero) on the number of admissions. The dotted lines are the 95% confidence intervals for the coefficients we obtain from a trend adjusted regression (controlling for state by year dummies and hospital fixed effects). (See Appendix C for details.)

Summary

Our empirical analysis rejects the idea that EHR technology has displaced frontline healthcare workers. If anything, there are positive impacts on the number of workers (which does not come from a decrease in efficiency). While we are utilizing a demanding specification by controlling for general state by time shocks (e.g., legal and political changes), the usual caveats apply, as it is possible that there are omitted factors we have not controlled for that could be driving the results. Nevertheless, the absence of large displacement effects is an optimistic message.

VI. Conclusion

This brief has shown some key facts when considering the future of health IT and its potential effects on the workforce. We hope that the studies we have compiled provide a valuable resource for future researchers. First, health IT has only recently arrived as a tool used by most providers. The lag in the time to adopt IT in healthcare compared to other industries is in part due to a failure of the management of these systems to adopt the new technology due to hurdles specific to healthcare. These hurdles include a hesitant workforce and the high stakes of failure, including patient health and privacy that leads to a more cautious approach to IT investment. The role of management appears critical in stimulating employee engagement and overcoming any resistance to change. In the United States, there is the additional hurdle of a fragmented system of competing providers and payers with incentives that do not encourage data integration.

Second, as we look ahead, we know from the experience of other industries that it takes time and effort to learn how to employ such new technologies. The same factors that slowed the adoption of IT can slow the learning that takes place once the IT is in place. Nevertheless, the literature suggests modest improvements in healthcare quality and evidence that points to IT leading to higher healthcare spending in the near term following IT adoption. The $3 trillion question is whether that relationship can be reversed as we learn how to use the new technology to become more effective at improving health and preventing illness.

In terms of the healthcare workforce, the fundamentals are strong due to growing demand for services over time. This is evident in the growth of healthcare jobs over the past decades. In our empirical analysis at the hospital level, we actually found that EHR adoption tended to (weakly) increase demand for healthcare workers, rather than displace it. We expect the growth to continue, and it remains to be seen whether new technologies will slow that growth. Intriguingly, analytics tools could enable lower-skilled workers to benefit rather than suffer from these innovations as they can provide in-person services guided by recommendations from the technology itself or from remote interactions with physicians in the form of telemedicine. The underlying labor economics suggests that for lower-skilled workers to benefit from these technologies, greater investment in their skills should be a priority.

Given substantial investments in health IT over the past decade, we are at a moment where new analytics may yield insights. Indeed, health IT has the potential to transform healthcare to improve patient health and lower healthcare costs. The form of the transition and the speed with which the new IT tools generate value will depend on the strength of management to guide the use of new technologies.

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Appendices

Appendix A: Methodology of Review

We incorporate relevant papers from diverse searches on PUBMED, dimension app, and Google Scholar, as well as references found within those papers[19]. To achieve this, we started by searching on PUBMED. We searched with keywords: information technology, health, and labor. We found several thousand results and reviewed the abstracts from the 100 most recent articles and the 100 best matches according to PUBMED's search algorithm. As a second effort, we searched with keywords: "health" and "information technology" and "workforce" and filters: "review." This resulted in 34 articles in the last five years. Our third effort consisted of searching for economics papers on the "effect of health information technology." As before, we scanned the 100 most recent papers and the 100 most relevant. As a fourth effort, we used the dimension app to filter papers since 2015 and using the following keywords: "health" and "technology" and "workforce" resulting in 541 articles. Overall, this effort, including related works discovered from the search-engine results, left us with 975 papers to review.

To narrow down our search, we focused on peer-reviewed journals and empirically oriented projects for every outcome. The exception is that we reviewed all of the articles specifically about the workforce. In total, we read and summarized 58 papers for our literature review. From these papers, 20 are related to IT adoption, implementation, and meaningful use; 14 concern the health workforce (although most are speculative); and 25 focus more on productivity outcomes and cost effects.

Appendix B: Spreadsheet of Studies

As an additional attachment, we include a spreadsheet (lit review for paper 1.xls) with a summary of the key points of the 58 papers we analyzed in detail. Our intention is to provide the reader with the ability to quickly screen the main points discussed in each paper and be able to quickly find additional information on any point that is not discussed in detail in the main text. On such a spreadsheet, one can find the title, authors, journal, year of publication, and a link to the online publication of the paper. Moreover, we include the following eight sections that describe the main points of each paper: 1) main research question, 2) main results, 3) data, 4) institutional background, 5) intervention, 6) empirical strategy, 7) identification evidence, and 8) robustness.

Appendix C: Methodology and Data Underlying Adoption and Event Studies

In this Appendix, we describe the methodology utilized for the empirical results presented above. Our results are based on the AHA survey and the AHA IT Supplement Survey from 2008–2017. This dataset provides an unbalanced panel with 33,651 hospital-year observations and 5,999 different hospitals. At first, we attempted to estimate our regressions on the panel as is, controlling for state-year and hospital fixed effects. However, adopting hospitals seemed to be growing more slowly than non-adopters which invalidated our empirical strategy.

In order to improve our specification, we decided to control for a hospital-specific pre-adoption linear trend in the outcome of interest. In order to achieve this, we followed the following steps for each event study:

1. Restricted the sample to hospitals that had at least two observations prior to adoption of EHR (we removed adopters in 2008 or 2009 as we cannot fit a pre-adoption linear trend with less than two pre-adoption data points). This step left us with 23,076 hospital-year observations from 3,648 different hospitals in an unbalanced panel.[20]
2. We ran a regression for each hospital on the desired outcome on a linear time trend, only considering the pre-adoption observations. Since there are 3,648 different hospitals, we adjusted 3,648 different models. The regression is:
$$y_t = \alpha + \beta * year_t$$
Where y_t represents the outcome of interest in year t, $year_t$ represents the year of each observation, and β captures the linear trend we are after.
3. We predict the values of such a model for each hospital for the whole sample and then calculate the residuals (deviations) from the real values to the predicted values of the model $(y - \hat{y})$. Thus, a positive value means that the real value is higher than what the model would have predicted.
4. We adjust our event study specifications utilizing the residuals from the previous step as our independent variable. The model we adjust is:
$$Y_{res_{ijt\tau}} = \alpha + \Gamma_i + \Omega_{jt} + \sum_{\tau \neq -1} \beta_\tau + \epsilon_{ijt\tau}$$
Where $Y_{res_{ijt\tau}}$ represents the residual from the above procedure for hospital i in state j on year t and with relative time to adoption τ. Γ_i captures hospital fixed effects, Ω_{jt} captures state-year fixed effects, and β_τ captures the coefficients of interest, which we plot in the above graphs. We cluster standard errors at the hospital level.

In order to check robustness from our previously presented results and the potential bias that may arise from negative weights in our two-way fixed effects specifications, we replicate our results through a stacking procedure like the one presented in Deshpande and Li (2019). In sum, we want to compare adopters with one another and exploit the timing of adoption to see their evolution after EHR adoption. The identifying assumption here is that eventual adopters were on a similar trend, and the stacking procedure eliminated the bias from the negative weights that may arise from running an event study specification when the treatment happens at different times for different units. In order to achieve this procedure, we do the following process:

1. Generate a dataset that contains hospitals that adopted in year i and those that adopted at least 3 years after that. Keeping only datapoints from 3 years prior to adoption until 3 years after.
2. Generate a relative time variable τ.
3. Define the treatment group as those that adopted in year i.
4. Replicate this process for all years (we do 2011–2014).
5. Stack all datasets.

Once we have our dataset ready, we run the following model:

$$Y_{ijt\tau} = \alpha + \Gamma_i + \Omega_{jt} + \mathrm{K}_\tau + \sum_{\tau \neq -1} \beta_\tau (Relyear_\tau * T) + \epsilon_{ijt\tau}$$

Where $Y_{ijt\tau}$ represents the outcome of interest for hospital i in state j on year t and with relative time to adoption τ. Γ_i captures hospital fixed effects, Ω_{jt} captures state-year fixed effects, K_τ captures relative time to implementation fixed effects, and β_τ captures the coefficients of interest, which come from the interaction from the relative year dummies and the treatment dummy. We cluster standard errors at the hospital level.

Endnotes

1 See https://www.techrepublic.com/article/ibm-watson-the-inside-story-of-how-the-jeopardy-winning-supercomputer-was-born-and-what-it-wants-to-do-next/.

2 See also Long (2018), on the broad applicability of IT from training to providing access and improving patient safety; Ippollitti (2017) and Harper (2012) on how data improves assignment of the health workforce and ramps up efficiency; and Gamache et al. (2018) on how big data better informs public policy. As a specific example, Rumbold et al. (2019) show how big data can dramatically improve service provision for diabetics.

3 https://dashboard.healthit.gov/quickstats/pages/FIG-Hospital-EHR-Adoption.php.

4 We also developed our own sampling weights based on an inverse probability rule from the AHA population (similar to the methodology used in the official statistics (the official weights are not reported). This led to qualitatively similar results, so we just present the simpler unweighted versions here.

5 https://www.healthit.gov/sites/default/files/hitech_act_excerpt_from_arra_with_index.pdf.

6 Pablo Garcia had a rare genetic disease called NEMO syndrome. However, he was in UCSF for a routine colonoscopy and had been given Septra, a standard antibiotic the night before the procedure. However, after he felt unwell at 3am with numbness and tingling, it was discovered by the chief resident that six hours earlier Pablo had not taken the normal one Septra pill, but had been administered over 38½ pills by the nurse. The nurse had followed the instructions given to her by the EHR system, but there had been multiple mistakes with the human-machine interaction, which compounded into the disastrous decision to give an overdose. The first major error was a confusion in the original order between weights (mg/kg). Another part of the problem was that the Epic system produced so many alerts, that the culture was just to override them without thinking. Pablo's pediatrics resident was Jenny Lucca: "With her task list brimming with dozens of unchecked boxes and more sick kids in need of her care and attention, Lucca assumed this was yet another nuisance alert with no clinical significance, so she clicked out of it. With that, the order for 38½ Septras was now live." The pharmacist, Benjamin Chan, filled the order and also got an alert but he clicked out of his alert screen, too—the combination of alert fatigue, friendship with Jenny Lucca, and the extreme degree of interruption and multitasking in the hospital pharmacy all contributed to this. Finally, a robot arm faultlessly filled the order electronically from UCSF's Mission Bay campus (unlike a more urgent request or the pre-robot days when there would have been a human technician to do this and potentially spot the error).

7 For a recent take see https://freakonomics.com/podcast/telehealth/.

8 https://www.newyorker.com/magazine/2018/11/12/why-doctors-hate-their-computers.

9 The Harvard Business School case study of Bohmer and Ferlins (2008) describes practices such as the "Tuesday Stand Up" where all staff meet to discuss data on performance tracking and targets. This helps with engagement and understanding of how well the hospital is managing with productivity, quality, and implementation of new technologies.

10 For example, see the UK government's 2011 review of the National Programme for IT in the NHS (https://publications.parliament.uk/pa/cm201012/cmselect/cmpubacc/1070/107003.htm) that was launched in 2002. Interestingly, Wachter (2017) describes that Clive Granger, the head of the UK program, was influential in getting George W. Bush interested in a similar U.S. initiative as the precursor of the HITECH Act.

11 U.S. Bureau of Labor Statistics, All Employees, Health Care [CES6562000101], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CES6562000101, July 16, 2020. U.S. Bureau of Labor Statistics, All Employees, Total Nonfarm [PAYEMS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PAYEMS, July 16, 2020.

12 These are defined on the basis of industry codes: NAICS 621, 622, and 623. Of course, many of the workers here are not healthcare occupations (e.g., there are janitors, cooks, security guards, general managers, etc.). In addition, some healthcare occupations will be outside these sectors (a nurse employed by a school or corporation, for example). However, the vast bulk of health occupations are in these industries. For example, only 5% of physicians and 10% of nurses work outside our three healthcare sectors. In addition, the trends are broadly similar on other definitions of the healthcare workforce.

13 One paper is classified as both workforce and effect of IT.

14 She does not look at whether there is a positive effect of EHR on more complex cases, as McCullough et al. (2016) find. She also finds increases in costs over five years, like Hitt and Tambe (2016).

15 For example, Bresnahan et al. (2002) for the United States; Caroli and Van Reenen (2001) for the United Kingdom and France; and Bloom et al. (2012) for seven OECD countries.

16 For a review of the case study evidence, see Kochan et al. (2020). Examples include Batt (1999), Cutcher-Gershenfeld (1991), Kochan and Gershenfeld (2007), or MacDuffie (1995).

17 In the main method, we estimated a time trend for each hospital using pre-adoption data (which required having at least two observations prior to adoption). Our outcomes were adjusted for this trend in the pre- and post-adoption periods. For the non-adopters, we estimated a trend over the whole period.

18 As shown in Section III, Health Care Assistants are an even larger group, but the data does not break this group out in a consistent way across hospitals.

19 PUBMED is a scientific search engine organized by the National Institutes of Health. Dimension app is an AI-powered search engine for publications, grants, datasets, publications, patents, and policy documents.

20 For each specification, the number of observation varies slightly due to some missing values.