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The Impact of Health Information and Communication Technology on Clinical Quality, Productivity, and Workers

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Abstract

The adoption of health information and communication technology (HICT) has surged over the past two decades. We survey the medical and economic literature on HICT adoption and its impact on clinical outcomes, productivity, and the health care workforce. We find that HICT improves clinical outcomes and lowers health care costs; however, (*a*) the effects are modest so far, (*b*) it takes time for these effects to materialize, and (*c*) there is much variation in the impact. More evidence on the causal effects of HICT on productivity is needed to improve our analytical understanding and to guide further adoption. There is little econometric work directly investigating the impact of HICT on labor market outcomes, but the existing literature suggests that there are no substantial negative effects on employment and earnings. Overall, although health care is in many ways exceptional, we are struck by the similarities of our conclusions to the wider findings

on the relationship between productivity and information and communication technologies, which stress the importance of complementary factors (e.g., management practices and skills) in determining the impact of these new technologies.

1. INTRODUCTION

Health care delivery revolves around information gathering, inference, and communication across providers and with patients. As a result, it has long been recognized that health information and communication technology (HICT) holds enormous potential to improve productivity. In the United States, it has now been about a decade since there was a sharp rise in the adoption of HICT, especially in the now widespread use of electronic health records (EHRs). Recently, the COVID-19 pandemic further spurred growth in the use of innovations such as telehealth. This article reviews the medical and economic literature addressing the drivers of HICT adoption and usage, and it analyzes their effects on health care productivity (including clinical quality and costs) and the health care workforce. Our aim is both to consider the state of knowledge on these questions and to suggest paths forward to deepen our understanding.

The impacts of HICT could be enormous. Health care accounts for nearly one in every five dollars spent in the United States, and improvements in this sector have first-order effects on economic performance through sheer scale. Furthermore, in almost every country, the proportion of national income absorbed by health care appears to be on an almost inexorable upward trend. According to the National Health Expenditure Accounts, the fraction of US GDP spent on health care has risen by about four percentage points every 20 years: from 5% in 1960 to 9% in 1980, to 13% in 2000, and then to nearly 18% in 2020. This is driven by an aging population, the cost of new technologies, and a natural tendency for humans to increase the fraction of their budgets spent on health as they grow richer (Anderson et al. 2003, Hall & Jones 2007).

Apart from sheer scale, an advantage for tech applications is that health care 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 information and communication technology (ICT), and the enormous decline in the quality-adjusted price of ICT over the last 40 years should have been a great boon to the sector (e.g., Bloom et al. 2012).[1] In a well-known RAND study, Hillestad et al. (2005) estimated that ICT adoption could save the US health care sector between $142 billion and $371 billion over a 15-year period.[2]

The United States has long stood out from other Organization for Economic Co-operation and Development (OECD) countries in spending a much larger fraction of GDP on health but achieving relatively disappointing results (Papanicolas et al. 2018). For example, life expectancy in the United States is lower than in many European countries, and indeed it appears to have fallen in recent years (Case & Deaton 2020).

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[1]Indeed, after the success of IBM Watson's Artificial Intelligence computer on the television quiz show *Jeopardy*, the first commercial application announced was in health care (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]Readers may also consult Long et al. (2018) on the broad applicability of information technology (IT) from training to providing access and improving patient safety, Ippoliti & L'Engle (2017) and Harper (2012) on how data improve assignment of the health workforce and ramp up efficiency, and Gamache et al. (2018) on how big data better inform public policy. As a specific example, Rumbold et al. (2020) show how big data can dramatically improve service provision for diabetics.

In light of these trends, policy makers in the United States have stressed the use of HICT as a mechanism to improve both efficiency and clinical outcomes. This culminated in the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, which allocated around $30 billion to increase adoption of HICT by subsidizing acquisition costs, changing reimbursement rules, and providing technical support. The Act emphasized the adoption of decision support capabilities and their utilization at the point of care, formally referred to as "meaningful use." The rise in HICT installation across hospitals and doctors' offices has been impressive. Although HICT has been used in health care since at least the early 1960s, fewer than 10% of hospitals (and fewer than 20% of physicians) were using EHRs prior to the HITECH Act (Atasoy et al. 2019). In contrast, by 2014, 97% of reporting hospitals had certified EHR technology (Gold & McLaughlin 2016).

Understanding the consequences of such a rapid expansion of technology services into the health care sector is more important than ever, as the presence of HICT is evident in almost any part of the sector and the trends suggest this is just the beginning.

Despite the enormous level of investment in HICT and its undoubted potential, its impact has been disappointing (Sahni et al. 2017). A RAND study by Kellermann & Jones (2013) shows that the predicted savings largely have not materialized due to a lack of information sharing across providers and to a lack of acceptance by the workforce in an environment where incentives run counter to the goal of reducing health care 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 health care sector (e.g., Bloom et al. 2020b).

It will take time for the sector to learn how to use the new tools provided by HICT, and it will be crucial to understand the effects of HICT and the innovations it makes possible on health and health care costs in order to guide future policy and practice. Jha et al. (2010) note that fewer than 2% of hospitals met the criteria of meaningful use prior to the HITECH Act, and the rise in HICT capabilities provides an opportunity to investigate the effects of such subsidies on health care productivity in general and the workforce in particular. This review aims to provide a foundation to capitalize on this opportunity.

We first describe the evolution of recent HICT, especially EHRs, in section 2. We then turn to the impact of HICT on patient outcomes, productivity, and costs in Section 3. Section 4 looks at the impact on the workforce, starting with some new material on broad trends before looking at the (smaller) academic literature. Section 5 compares our findings on the impact of ICT in the health care sector with findings on the impact of the new technology in other industries. Finally, Section 6 offers some conclusions and areas for future research.

2. THE RECENT EVOLUTION OF HICT

2.1. New forms of HICT

In this section, we describe new forms of HICT that have the potential to drive substantial improvements in health care productivity. We begin by describing EHRs, which are the basis for almost any IT application, and then move on to highlight the most common applications of HICT. As mentioned above, the HICT sector is booming, and several firms and startups are developing innovative ways of delivering health care, exploiting medical information, and automating parts of the process.

2.1.1. Electronic health records. The 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

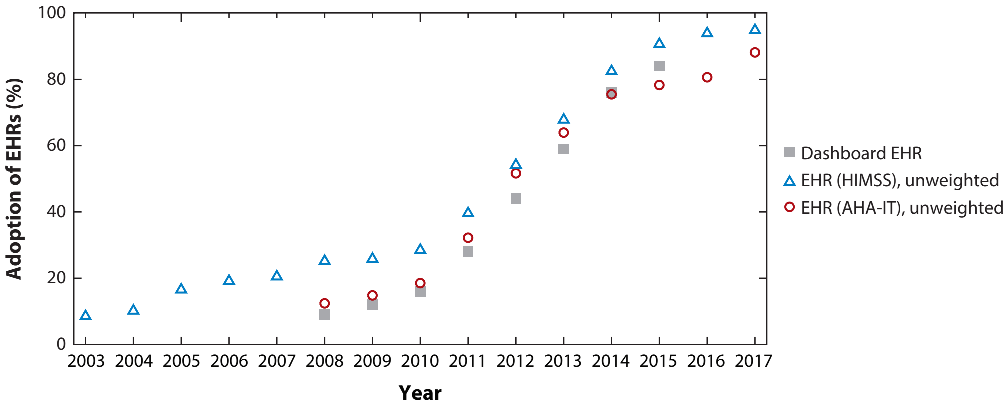

Figure 1

Cumulative adoption of electronic health records (EHRs). This figure presents estimates of the fraction of hospitals that were using "basic EHR without clinician notes" in the year indicated in different databases. The squares are official estimates from the Office of the National Coordinator of Health Information Technology (reweighted to correct for nonrandom sample response). The circles are our own estimates from the AHA (American Hospital Associations) IT supplement, and the triangles are our own estimates from HIMSS (Healthcare Information and Management Systems Society) data. The **Supplemental Appendix** describes these definitions in detail.

Supplemental Material >

making and operations. Ideally, information gathering begins before a patient encounter with 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. These data can be made portable so that they may be shared with other providers or accessed via patient portals.

Figure 1 shows how the adoption of EHRs has dramatically increased over the 2003–2017 period in the United States. The diffusion graph follows the traditional sigmoid pattern (e.g., Swan 1973), with an inflection point after the implementation of the HITECH Act.

2.1.2. Clinical decision support. EHRs may serve as a platform for decision support: Established clinical guidelines or best medical practices may be operationalized within the EHR software by using patient-level data to prompt providers with suggestions or to 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.

Clinical decision support (CDS) can also support a broad range of functions, such as prespecified order sets—that is, packages 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 by communicating to physicians the priorities of clinical leaders and by reducing the cost of adherence through ease of use. One marker for success is the reduction in unwanted variation in practice across clinics or physicians (Tsugawa et al. 2017). Ultimately, greater adherence to best practices could provide further evidence of the effectiveness of the guidelines themselves. Another potential for CDS stems from algorithms that can provide warnings—for example, about drug allergies or drug-to-drug interactions—and alerts about dosage errors through automated dosage calculators. As with any warning system, attention to the acceptance of the warnings and concerns over "alert fatigue" will need to be managed (Ancker et al. 2017).

2.1.3. New communication technologies. Miscommunication is common in a complex system like modern medicine, and McCullough et al. (2010) argue that it accounts for a substantial part of the estimated 44,000 annual deaths in the United States due to inpatient hospital errors. For example, a prescription requires a physician, a pharmacist, and a nurse to coordinate. EHRs can resolve this in principle—likely a substantial improvement from the days of illegible handwriting. Computerized physician order entry (CPOE) offers a more efficient way for physicians to communicate orders that may help prevent mistakes and coordinate different players in the system.

In addition, telemedicine provides a new platform to deliver health care at a distance and has expanded enormously under the COVID-19 pandemic due to the need for social distancing.[3] Physicians can receive consultations from specialists (Long et al. 2018). Telemedicine can also aid health equity, as it is particularly attractive for patients in hard-to-reach communities who can be treated via a video connection. 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 (Akbik et al. 2017, Baratloo et al. 2018).

2.1.4. Information management and health care analytics. With information moving from paper to digital records, HICT enables data to be more efficiently captured, stored, organized, and analyzed, which in turn generates better diagnosis and treatment recommendations. This is particularly relevant for patients with multiple comorbidities and those who require intensive monitoring and testing. For example, Rumbold et al. (2020) consider diabetes and show how machine-learning algorithms can capture blood sugar measurements daily and help predict with greater confidence who will develop a complication. This allows treatment options such as medication choice and dosing to be personalized to each patient. Moreover, technology allows patients to carry their information on their cell phones, receive alerts and reminders of treatment, and track their health status. Such apps have the potential to improve treatment adherence.

A second example would be in public health (see Gamache et al. 2018). O'Donovan & Bersin (2015) showed how cell phones helped mitigate the Ebola outbreak. During the COVID-19 pandemic, an unprecedented effort on increasing surveillance capabilities has enabled many governments to effectively use contact-tracing apps to identify potentially sick individuals (Altmann et al. 2020).

2.1.5. Health care equity and algorithmic fairness. HICT can affect equity in health care access and delivery for marginalized populations. On the one hand, digital health can significantly reduce access barriers, as the digital transportation cost is close to zero, and more experienced doctors can easily give advice to less educated practitioners remotely. On the other hand, the fact that telehealth requires higher-quality technology and human capital can further deepen disparities in access. McCullough et al. (2021) use the Coronavirus pandemic to understand the consequences of new technologies on the digital divide. In a difference-in-differences model, they compare telehealth utilization rates in 2019 and in 2020 using data from a large commercial insurer. They show (*a*) a positive correlation between broadband penetration and the share of patients who shifted to telehealth after the pandemic started; (*b*) that individuals with more comorbidities, and therefore at a higher risk of dying from COVID-19, were less likely to shift to digital delivery; and (*c*) that patients with an established relationship with a provider or a higher income used digital visits more. These findings suggest an increase in health inequalities.

[3]The CDC reports a 154% increase in telehealth visits in March 2020 relative to March 2019 (**https://www.cdc.gov/mmwr/volumes/69/wr/mm6943a3.htm**).

Relatedly, new technologies can improve equity by reducing inherent bias in treatment decisions, but they can also make things worse if the algorithms used produce biased estimates. There is some evidence of both. On the one hand, Ganju et al. (2020) exploit the staggered adoption of CDS systems by hospitals and compare the treatment of black and white patients before and after adoption. They show that the disparities in treatment of complicated diabetes were reduced after adoption, as black patients were more likely to be revascularized (a procedure that allows one to keep their limb) instead of amputated. Moreover, they show that no harm was done because of this change, as the delayed amputation rates remained the same. On the other hand, Obermeyer et al. (2019) show the biased nature of an algorithm aiming to identify who would benefit the most from a program designed to help patients with complex medical needs. They show that black patients who are identified as being at a very high risk of high utilization have on average 26% more chronic illnesses than their white counterparts. They further explain that the difference arises because of the decision to estimate risk of utilization through predicted costs: Although the algorithm works well in terms of cost predictions, the fact that whites receive relatively more care, and thus spend more, induces the bias.

This discussion highlights the ambiguous effects of HICT on equity. Policy making must be context specific and not assume that HICT will always reduce the large existing inequities without intervention.

2.2. Drivers of HICT Adoption and Meaningful Use[4]

The factors that affect the adoption of HICT are similar to those described by the broader literature on technological diffusion [see the survey by Hall (2005)]. Leading drivers include complexity, cost, competition, and complementary factors (such as human capital). For example, given the high fixed costs of adoption, it is no surprise that larger organizations are more likely to adopt IT. This subsection describes factors that are particularly relevant to health care.

2.2.1. Patient safety. Although HICT offers the potential to improve patient safety substantially (Bates & Gawande 2003), it also carries the risk of introducing errors (Harrington et al. 2011). The initial adjustment costs in most industries as firms learn how to use ICT are well documented (Brynjolfsson & Hitt 2000, Brynjolfsson et al. 2021), and this appears to be the case in health care 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 in health care (Harrington et al. 2011, Raposo 2015).

2.2.2. Patient privacy. A common concern that affects HICT adoption revolves around privacy. In 1996 the US Congress passed a federal law, the Health Insurance Portability and Accountability Act (HIPAA), with the expressed aim of helping the sharing of health data by establishing national rules. There are concerns that organizations may cite HIPAA in an effort to reduce the sharing of information with competitors (Adler-Milstein & Pfeifer 2017). States also passed privacy laws, and the sheer complexity of legal obligations is thought to have reduced the benefits of data sharing and, thus, HICT adoption (Schmit et al. 2017, 2018).

Miller & Tucker (2009, 2011) investigate the role of state privacy laws following HIPAA in order to see whether HICT systems are less attractive when there are additional state privacy laws.

[4]For more details, readers are referred to Gnanlet et al. (2019), who reviewed the literature covering 37 recent papers. We discuss here some of the broader issues affecting IT adoption as well as health care–specific factors identified in the literature.

The authors argue 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 restrictive, and therefore hospitals have less incentive to adopt. Their main evidence in support of this relationship between privacy and adoption is that every additional hospital that adopts EHRs within a health service area increases the likelihood of adoption of a neighboring hospital by 7%, but the effect is weakened when states have more stringent privacy protections.

Miller & Tucker (2009) find that hospitals in states that toughened their privacy laws (11 states introduced these enhancements over the 12-year period they studied) reduced IT adoption by about 24%. Similar findings emerge when they instrument for privacy law changes using variation in the political mix of the states' legislatures. Another set of instruments includes measures of the value of privacy in the state, such as the proportion of the state that joined a do-not-call registry that prevents telemarketers from calling people's homes and the state's openness to immigration verification systems when obtaining drivers licenses. These checks bolster the claim that privacy attitudes and laws are drivers of HICT adoption.

2.2.3. Fragmentation. Coordination is hampered because of the different systems run by competing health care 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 (Cebul et al. 2008, Agha et al. 2020). In contrast, in the United States the nationwide HICT infrastructure of the government-run Veterans Administration (VA) is often lauded for its interoperability across units (Chan et al. 2020).

Fragmentation is one reason for the slow adoption of HICT, but it is part of broader reasons that are not unique to the United States. One example is the United Kingdom's National Health Service (NHS), which spent $16 billion on a failed attempt at promoting EHRs in the mid-2000s. The fact that this happened in a system without fee for service and a fully integrated insurer suggests deeper problems than the idiosyncrasies of the US health care system.[5]

2.2.4. Resistance to change and management. In this environment with concerns over patient safety and privacy among fragmented providers, many stakeholders can resist change, especially when there is asymmetric information between the IT decision makers (the senior managers) and those who are using the tools (the medical staff). Physicians have been found to play a particularly important role, because without their buy-in it is very hard to effectively diffuse IT (Cohn 2009). Compared to workers in many other industries, clinicians are powerful, high-human-capital workers who know much more about the delivery of care than senior managers do. Hardiker et al. (2019), for example, found that if nurses did not find the IT helpful, they would swiftly find workarounds and would not use the technology.

Employee engagement is a key part of the management practices emphasized by Bloom & Van Reenen (2007), and health care provider buy-in has been found to be important for the successful adoption of HICT (Bohmer & Ferlins 2008).[6] It appears that in health care, negotiation and cooperation are important drivers of acceptance that are necessary to effect change. Litwin

[5]See the UK government's 2011 review of the National Program for IT in the NHS that was launched in 2002 (**https://publications.parliament.uk/pa/cm201012/cmselect/cmpubacc/1070/107003.htm**). Interestingly, Wachter (2017) argues that Clive Granger, the head of the UK program, was influential in getting George W. Bush interested in a similar US initiative that would then become the HITECH Act.

[6]Bohmer & Ferlins (2008) describe practices at the Virginia Mason Medical Center in Seattle, such as the Tuesday Stand Up in which all staff meet to discuss data on performance tracking and targets. This helps with engagement and understanding of how well the hospital is managing productivity, quality, and the

(2011) describes how Kaiser Permanente managers meaningfully engaged and cooperated with their workforce, which helped preserve employment (e.g., by providing alternative jobs for the chart room) and improve patient satisfaction. Training also seems to be critical. 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 health care employees when adopting and integrating HICT systems.

2.2.5. Competition. The EHR market features three dominant firms that cover 65% of the market: Epic, Meditech, and Cerner (Off. Natl. Coord. Health Inf. Technol. 2019). Many have argued that this lack of robust competition raises prices and thereby slows adoption. Further, dominant EHR suppliers have incentives to make their systems hard to mix with others, since this enables them to increase switching costs and reduce competition. This strategy of raising rival costs by limiting interoperability is known as information blocking, and it reduces the benefits of adoption because of reduced connectivity.[7] The 21st Century Cures Act of 2016 set interoperability requirements for all EHR vendors to attempt to limit this practice.

On the hospital provider side, competition is often weak (Cooper et al. 2019). As a result, incentives to improve efficiency through the adoption of technology and other best practices may be blunted (e.g., Bloom et al. 2015). Cutler (2011) points out that health care is exceptionally inefficient in generating incentives for innovation. Despite recent payment reforms, most providers continue to operate on a fee-for-service basis whereby greater provision of care results in greater profits, which means that there is little incentive to seek lower costs through HICT adoption and use.

Overall, the effects of competition are theoretically ambiguous. Greater competition could provide incentives to invest in HICT to improve quality and attract more patients (Chandra et al. 2016). At the same time, competition may provide incentives to avoid seamless information exchange to increase patient switching costs.

2.2.6. Summary. There are many reasons explaining why adoption of HICT may be inefficient. Resistance on the part of the workforce appears particularly relevant in health care due to the high adjustment costs and potential risks to patients in an environment with privacy concerns. The competitive landscape for HICT suppliers and among providers who constitute the demand for HICT provides its own hurdles. Greater understanding of the relative importance of these factors would be useful in understanding the market for HICT and in suggesting useful variation to study its effects.

3. EFFECTS OF HICT ON PRODUCTIVITY

3.1. Methodology

Supplemental Material >

For our literature review, we focused on reviews from the medical literature and on economics papers related to the effects of HICT adoption. More details can be found in the **Supplemental**

implementation of new technologies. Bloom et al. (2020b) provide econometric evidence on the importance of management in hospitals.

[7]Limiting interoperability to strengthen a dominant position is used in many other digital industries (for software examples, see Kuhn & Van Reenen 2008).

Appendix. In brief, we reviewed 975 papers and we summarized 65 in detail. The increase in published papers on HICT over time has been remarkable. There were 118 publications with "Health Information Technology" in the title or abstract in 1990 and 3,556 in 2018. Moreover, the number of papers with "Electronic Health Records" in the title or abstract grew from 3 in 1990 to 3,989 in 2018. The growth after the HITECH Act was passed is particularly impressive, with only 568 papers published in 2008 before the passing of the Act.

3.2. Impact of HICT on Health Outcomes

We now turn to examining the impact of HICT on health outcomes, surveying the medical literature and then the economics literature.

3.2.1. Medical literature. There is a large medical literature focusing on the impact of HICT on patient outcomes, and we focus here on four reviews covering a total of 627 papers written between 1995 and 2017. The most recent review is by Kruse & Beane (2018), which covers 37 papers published between 2011 and 2017; the next one is by Buntin et al. (2011), covering 154 papers in 2007–2010; then comes the review by Goldzweig et al. (2009), covering 179 papers in 2004–2007; and the earliest one is by Chaudhry et al. (2006), examining 257 studies in 1995–2004.

The typical study is cross-sectional across units (e.g., hospitals or physician offices) or within health care providers (across departments or health care staff), and it relates the use of a particular form of HICT to a particular patient outcome. More rarely, longitudinal data allow time series or difference-in-differences designs with great attention to measurement.

Our summary reading of the medical literature is as follows.

1. Overall, there is an average positive effect of HICT on patient outcomes and health care productivity.
2. There is much heterogeneity between individual studies in magnitudes (and, to a lesser extent, signs). There are a nontrivial fraction of inconclusive studies and some studies even finding negative effects.
3. Later papers and reviews have tended to find more positive effects than earlier ones.

In the most recent review, Kruse & Beane (2018) found significantly positive effects of HICT in 30 cases, insignificant effects in 7, and no negative results. The previous survey by Buntin et al. (2011) found positive and significant effects in 60% of papers; 30% of the effects were insignificant, and only 10% were significantly negative. Although the mean findings were also positive in Chaudhry et al. (2006), this earliest review was the most mixed.

The tendency to find larger benefits of HICT in more recent studies may reflect a learning curve both at the hospital level and system-wide. At the health care provider level, it can take many years before a hospital learns how to use HICT effectively due to adjustment costs, which generates a long and variable lag between adoption and outcomes. Later studies usually have longer data series to track such changes. Learning also operates between hospitals, as systems learn from the EHR successes and failures of others. Because later studies focus on later years, they are further along this economy-wide learning curve.

Indeed, the current state of HICT subsidies in the United States provides incentives for the use of the technology through the sharing of information within and across providers. Menachemi et al. (2018) reviewed 24 articles to assess the effect of such health information exchange. Health information exchange systems are known to vary widely in their levels of success, and this review found that they tend to reduce costs by reducing duplicate procedures and imaging.

3.2.2. Economics literature.

Work in the economics literature pays more attention to potentially exogenous sources of variation in the use of HICT. Taken as a whole, this literature tends to find less positive effects compared to the medical literature.

McCullough coauthored a series of papers carefully examining the impact of HICT on health care quality; overall, the findings suggest that HICT improves patient safety, increases guideline adherence, and reduces the likelihood of death. McCullough et al. (2016) consider a large range of technologies using IT adoption surveys from the Healthcare Information and Management Systems Society (HIMSS) and Medicare claims data from 1998 to 2007. They focus on four common diagnoses: acute myocardial infarction, congestive heart failure, coronary atherosclerosis, and pneumonia. In a difference-in-differences analysis studying the staggered adoption of HICT across hospitals, they find beneficial effects of adoption along illness severity, a key indicator. For pneumonia and heart failure patients, the benefits are visible for the top three to four deciles of illness severity. For other heart conditions, such as heart attacks, the results are more mixed. Across the technologies studied, they attribute the benefits to improved information management and coordination across providers rather than to clinical decision support.

Parente & McCullough (2009) examine three technologies: EHRs, picture archiving and communication systems (PACs), and nurse charts. Using a similar difference-in-differences strategy, they find that only EHRs have a clear, statistically significant (but small) effect on improving patient safety. Similarly, McCullough et al. (2010) combine data from the American Hospital Association (AHA) annual survey, which captures hospital characteristics; HIMSS, which captures HICT adoption; and the Centers for Medicare and Medicaid Hospital Compare database, which captures hospital quality measurements. They conclude that EHRs and CPOE have a small positive effect on only one of the six quality measures they studied: the proportion of correct medications provided. Moreover, they find that the effect is larger for teaching hospitals. However, both Parente & McCullough's (2009) and McCullough et al.'s (2010) papers rely on relatively short panels (4 years), which limits their ability to test whether hospitals that adopt HICT are on different trajectories compared to those that do not.

Using Medicare claims data from 1998 to 2005, Agha (2014) uses event studies and fixed-effects regression models that control for hospital and state-year fixed effects, along with separate linear trends for eventual adopters and hospital characteristics, including hospital size, technological investment, and patient characteristics. Like McCullough et al. (2016), she finds no effect on patient mortality or readmission on average.[8]

By contrast, Lin et al. (2018) study Medicare claims from 2008 to 2013, use the 30-day mortality rate by year for 15 common conditions in each hospital as a dependent variable, and find, with a similar flexible strategy, that adopting additional EHR features reduced mortality, but only after a number of years. This suggests that HICT applications may be improving and that there may be important learning effects: In the short run there are little or no effects, but after several years (presumably when learning has happened) the effects do show some positive results.

McKenna et al. (2018) find reductions in mortality after the introduction of HICT in New York State. They use a difference-in-differences approach but look specifically before and after the HITECH Act, which plausibly increased incentives to adopt IT. However, the assumption that all of the differential adoptions across hospitals before and after 2011 are solely due to HITECH incentives is a strong one.

[8]Agha (2014) does not look at whether there is a positive effect of EHRs on more complex cases, as McCullough et al. (2016) find. She also finds increases in costs over 5 years, like Hitt & Tambe (2016) do.

All the papers discussed in this subsection so far use some form of difference-in-differences approach to look at the change in performance following the change in HICT adoption across hospitals. This approach controls for permanent unobserved heterogeneity through the hospital fixed effects, which is an advantage over cross-sectional studies. If adoption rates respond to shocks affecting hospital performance that are not controlled for by other hospital-specific variables and time effects, however, the coefficient on HICT may still be biased.

Miller & Tucker (2011) employ a particularly novel set of empirical strategies to estimate the causal effects of HICT. They focus on all births in US hospitals from 1995 to 2006 and identify technology adoption using HIMSS data from 2007. They find that 38% of their 3,764 hospitals have EHRs by the end of the period, in 2006. Their main approach uses county fixed effects and finds that a 10% increase in the adoption of EHRs results in a substantial 3% reduction in neonatal deaths. To address endogeneity concerns, they use changes in privacy laws to generate quasi-exogenous variation in adoption and show that the results are robust. The instrumental-variable estimates grow in magnitude, although they are less statistically precise.

Chan et al. (2020) use an identification strategy that exploits plausibly exogenous variation in ambulance-company assignment during an emergency health condition. Like Doyle et al. (2015), they find that this assignment affects hospital choice in a quasi-exogenous way, which provides a way to compare similar patients who happen to be treated in different hospitals. They find that marginal patients transported to VA hospitals have a substantial survival benefit compared to patients transported to non-VA hospitals. One potential explanation is that VA hospitals are known to have more advanced HICT. To investigate this mechanism, they restrict the sample to patients treated at non-VA hospitals and find that patients who are transported to their usual hospital (i.e., a hospital where they have been treated in the past) have a substantially larger survival benefit compared to patients treated in a new environment; importantly, this effect is only apparent during the time period following the HITECH Act, when presumably HICT had been widely adopted by hospitals. Their results imply that HICT carries substantial gains for emergency patients, but the authors acknowledge that this is only suggestive evidence, as they do not have direct measures of technology.

3.2.3. Summary of studies of the impact of HICT on health outcomes. Overall, the economics literature, just like its medical counterpart, suggests improvements in health care quality following HICT adoption; however, these results are more modest than those found by medical researchers, and there is plenty of heterogeneity across studies. Again, these effects are not immediately evident but take time to manifest, likely due to the learning that needs to take place. Finally, the results differ across patient groups, with evidence suggesting that more complex patients (i.e., with greater comorbidities) receive the greater benefits from the new technologies.

3.3. Impact of HICT on Productivity

In addition to patient health outcomes, the economics literature typically reports results on productivity measured as value added, defined as revenue minus intermediate inputs (supplies, linens, clothing, etc.). Lee et al. (2013) estimate a production function using data on 309 hospitals in California combined with HIMSS data over the period 1998–2007. To estimate the effects of HICT adoption on value added, they use proxy-based methods (e.g., Olley & Pakes 1996, Ackerberg et al. 2015) as well as dynamic panel data models (e.g., Arellano & Bond 1991). They find very high returns to IT (for both labor and capital), which suggests that there may be barriers to investment (hence the high marginal returns).

Hitt & Tambe (2016) examine the impact of EHRs in 304 New York State nursing homes. Using a difference-in-differences approach that relies on variation in implementation dates, similar to the ones described above, they study efficiency (i.e., distance from the production possibility frontier given their inputs) and productivity (i.e., improvements in value). They find 1% higher productivity and 3% greater efficiency following EHR system implementation. A limitation of the analysis is that nursing homes that adopt HICT may be on a different productivity trajectory compared to those that do not. One of the most interesting findings is that facilities that are one standard deviation higher on a work-organization scale—measuring practices that encourage employee collaboration, decision making, suggestions, and problem solving—are associated with a productivity increase of 1.5% or more when HICT is adopted. This is consistent with the findings of many studies from other industries that suggest an important role for investments complementary to IT, such as investments in managerial skills (e.g., MacDuffie 1995, Bresnahan et al. 2002, Bloom et al. 2012).

3.4. Impact of HICT on Health Care Costs

Health care costs are typically measured in two ways: (*a*) health care expenses paid by payers such as insurance companies and government programs such as Medicare and Medicaid, or (*b*) input costs incurred by providers, including labor and capital expenses. The former is also the revenue received by health care providers, and a concern is that the main effect of HICT has been to enable hospitals to increase the amount they bill insurers. HICT can change the ability to code diagnoses and procedures in ways that increase bills for tasks that previously went uncompensated or undercompensated. In hospital billing, insurers pay based on the complexity of diagnoses, the patient's history and the presentation of the medical condition (e.g. cough or belly pain,), and organs examined. EHRs can maximize the billing by taking into account this billing structure. This clearly creates more profits for providers and might produce more accurate and systematic records than before. However, if the main effect were to "upcode" patients' health, HICT would inflate health care spending. In addition, HICT may 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.

3.4.1. Health care expenses paid by providers. Many of the papers already discussed (particularly those in the economics literature) look at costs as well as quality. Agha (2014) finds an increase in billing following HICT adoption. She finds that medical expenditures over the year following a hospitalization were flat until HICT adoption, when they started growing, eventually becoming 4% higher over the following 4 years. No effect was found for labor demand, however. Combined with the little effect on health outcomes, these results are consistent with concerns that modern HICT could be a means to improve the efficiency of billing rather than of treating patients.

Related, Ganju et al. (2021) analyze through a flexible fixed-effects model whether the introduction of CPOE leads to upcoding. They use data from the Healthcare Cost and Utilization Project's State Inpatient Database between 2004 and 2013 for four US states (Florida, Arizona, Maryland, and Kentucky), and they create severity indexes based on complication and comorbidity codes. They find that there was an increase in the severity index of patients after the introduction of CPOE but only in hospitals that were not subject to Medicare's Recovery Audit Program, which aims to reduce inflated billing.[9] Understanding whether the adoption of new technology leads to

[9]Adler-Milstein & Jha (2014) employ a difference-in-differences strategy and do not find a significant effect on either severity or spending from adopters when compared to controls. With only 4 years of data, however, it is difficult to check whether adopters were on a different trajectory compared to control hospitals.

an increase in severity coding, and whether that effect is due to improved accuracy in diagnosis or to upcoding, remains an important area of research.

3.4.2. Operating costs. Although comparing similar hospitals that adopt IT at different times can yield causal estimates of the effects of the new technology, the usual identification concern remains that hospitals may adopt depending on changing market conditions that can also affect health care productivity. 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 use three empirical strategies to focus on variation in adoption that can yield plausibly causal estimates. These strategies are: (*a*) focusing on hospital systems and adoption of IT by hospitals within the system in other markets [similar to what Miller & Tucker (2009, 2011) do]; (*b*) focusing on adoption by competitors to hospitals within the same system; and (*c*) using the fact that hospitals based farther away from major EHR vendors (like Epic) are slower to adopt. These sources of variation in HICT 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.

3.4.3. Summary on health care costs. As discussed above, the potential for HICT to lower health care spending is immense (Hillestad et al. 2005). The literature yields evidence on health care spending that is more mixed compared to the literature that considers clinical outcomes. Overall, HICT adoption tends to be associated with an increase in costs, at least in the initial years, and the barriers for successful adoption described in Section 2 provide some guidance on the frictions that can impede progress. However, certain applications like health information exchange could lead to a reduction in costs. Given the variation in effects found over time, findings about more recent time periods and specific applications would be valuable evidence on longer-run effects.

4. IMPACT OF HICT ON THE HEALTH CARE WORKFORCE

There is considerable concern that technology will displace workers, which depends on whether the new tools are net complements of or substitutes with labor, and there is still much to learn about how technology interacts with heterogeneous workers (Acemoglu & Autor 2011). The health care sector is very large and heterogeneous in terms of skills and tasks. This section provides background on the health care workforce and reviews the (very sparse) literature on the topic.

4.1. Background Facts on the Health Care Workforce

The growth in US health care spending was accompanied by growth in health care employment. **Figure 2** shows growth in the workforce since 1990. Health care workers are those employed in three main sectors: hospitals, ambulatory health care facilities (e.g., physicians' offices and dentists), and nursing/residential care facilities.[10] The number of health care workers has doubled

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

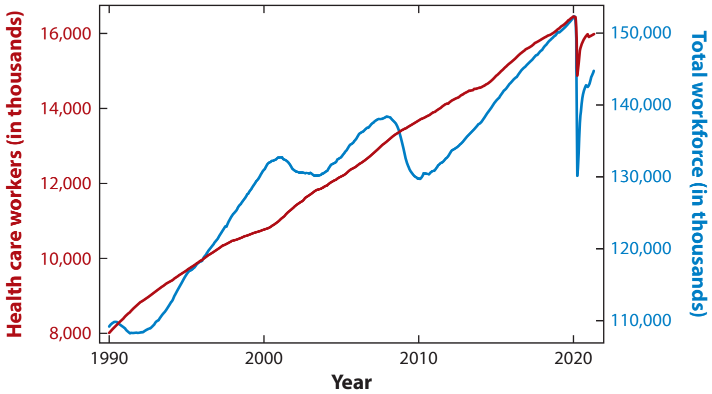

Figure 2

Health care workers and total workforce. This figure presents total nonfarm employees and health care employees (in thousands). Data from US Bureau of Labor Statistics, All Employees, Health Care [CES6562000101], retrieved from FRED, Federal Reserve Bank of St. Louis, on June 30, 2021 (**https://fred.stlouisfed.org/series/CES6562000101**), and from US Bureau of Labor Statistics, All Employees, Total Nonfarm [PAYEMS], retrieved from FRED, Federal Reserve Bank of St. Louis, on June 30, 2021 (**https://fred.stlouisfed.org/series/PAYEMS**).

from about 8 million to 16 million over this period, rising from just over 7% to almost 11% of all US workers. In addition, health care jobs appear to be largely recession proof, rising year after year even though the total number of workers fell during the recessions of the early 1990s, early 2000s, and 2008–2009. The only time there has been a big fall was during the COVID-19 pandemic of 2020, but even this fall in health care jobs has been much lower than the reduction in the workforce in general. The resilience of the health care workforce is not surprising, as the demand for health care rises steadily, even in bad economic times. Finally, the impact of the 2009 HITECH Act is not clearly discernible in **Figure 2**. To the extent that the Act, or HICT more broadly, did influence employment, its effect is not easily detectable in the headline numbers.

The effects of HICT on tasks and employment will vary across the different types of workers. We compiled data from the US Census of Population (CPS) and the American Community Survey (ACS) from 1980 to 2015 in order to describe the major occupations. **Table 1** categorizes the health care workforce into eight occupational groups. We show some examples of suboccupations within the broader groups to clarify the classification, and we include information on employment, education, and wages. In 2015 the largest group was health care assistants, who accounted for around one-quarter of the health care workforce. Nurses were the second largest group (17%), followed by clerical workers (13%). Physicians, health care managers, and professionals associated with medicine (PAMs) were smaller groups, accounting for 5.8%, 7.7%, and 5.4%, respectively.

This employment distribution across health care occupations is rather 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 (Goos & Manning 2007). The fastest growing health care industry is ambulatory health care facilities, which is consistent with the global shift toward delivering health care through the primary sector rather than through inpatient care.

The CPS/ACS samples are too small to look in detail at changes in health care occupations before and after the HITECH Act, so we turn to the Occupational Employment Statistics from the Bureau of Labor Statistics, which offer consistent, detailed breakdowns since 2000. **Figure 3**

Table 1 Some characteristics of the health care workforce

Broad occupation	Examples of suboccupations (2015 definitions)	Share of occupation with college or more, 1980	Employment share in health care workforce, 1980	Median hourly real wage, 1980	Share of occupation with college or more, 2015	Employment share in health care workforce, 2015	Median hourly real wage, 2015
Physicians	Physicians 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
PAMs	Chiropractors Dieticians	59.1%	3.8%	$18.50	82.6%	5.4%	$31.77
Health care assistants	Dental hygienists Licensed vocational nurses	5.2%	27.7%	$11.06	12.1%	23.6%	$14.79
Health care 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

Data constructed from US Census Bureau data for 1980 and “2015” (2014, 2015, and 2016 pooled), sourced from IPUMS (**https://www.ipums.org/**). Health care workers are those employed in hospitals, ambulatory health care facilities, and nursing/residential care facilities. The chain-weighted (implicit) price deflator for personal consumption expenditures deflates real wages to 2015 dollars. Abbreviation: PAM, professional associated with medicine.

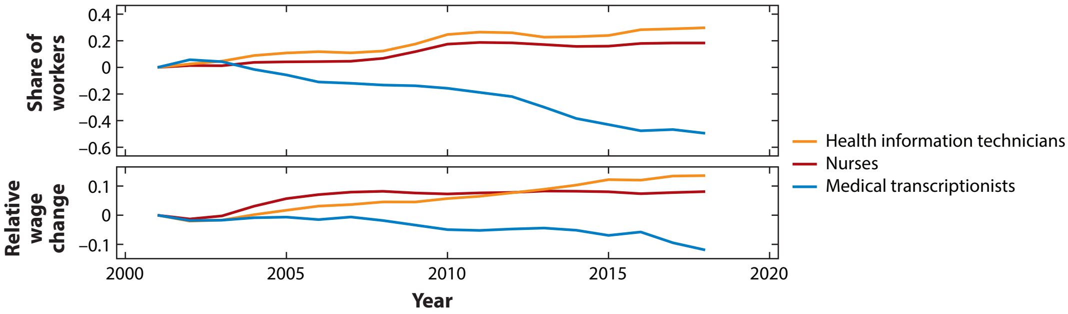

Figure 3

Workforce evolution. Relative employment and wages of health information technicians, nurses, and medical transcriptionists. This figure presents the change in the share of these workers in the total workforce and the change in their average wage relative to the average in the population. Data based on Occupational Employment Statistics provided by the Bureau of Labor Statistics (**https://www.bls.gov/oes/tables.htm**).

shows the evolution of employment (*top*) and wages (*bottom*) relative to employment and wages in the United States as a whole for three groups: nurses, health information technicians, and medical transcriptionists. Both graphs are built to report percentage differences relative to the baseline in 2000.

In terms of trends, perhaps unsurprisingly, information technicians have experienced employment growth (as a share of the health care workforce) as well as wage growth. Meanwhile, medical transcriptionists appear to have been displaced, with both employment share and wages falling. As a comparison, the large category of nurses experienced wage growth until 2005, when the information technicians continued to experience growing wages. To the extent that these trends were driven by HICT, they are consistent with the plausible idea that HICT technicians are a complement to IT, medical transcriptionists are a substitute, and nurses are broadly neutral. Looking at the wage ranking in 1980, nurses are the best paid, technicians are the worst paid, and transcriptionists are in the middle. This is consistent with broader concerns that IT innovation displaces workers in the middle of the skill distribution, a topic we describe more fully below.

4.2. Studies of the Impact of HICT on the Health Care Workforce

There have been relatively few studies of the effects of HICT on the health care workforce, with most publications describing qualitative concerns rather than providing quantitative support (e.g., Masys 2002, Zeng 2016, McFarlane et al. 2019).

There have been some microstudies analyzing the effects of HICT implementation on workers and staffing decisions. Bhargava & Mishra (2014) point out that the effects of HICT are 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 HICT 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 into the system, perform worse with HICT. Meanwhile internists, who use a lot of information, benefit from HICT implementation. For example, they show that after the implementation phase, 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. The finding that the effects will vary by the type of worker—even within a single class, like physicians—is one that we believe will be particularly salient as we track these effects going forward.

In the related setting of nursing homes, Lu et al. (2018) employ an instrumental variable strategy based on the rate of adoption in nearby hospitals to assess the effect of adopting CPOE on a hospital's staffing decisions (assuming there are not unobserved spatially correlated shocks to adoption). They argue that most facilities are at capacity and that they achieve higher revenue by attracting higher-paying customers through quality (vertical) differentiation. They develop a model with technology adoption and vertical differentiation that predicts that HICT will affect nurse demand differently for high-quality versus lower-quality institutions, with IT displacing nurses in the higher-quality segment and the opposite happening in the lower-quality segment. That is, the substitution effect between IT and workers dominates among the more financially successful nursing homes, whereas the complementarity channel dominates in the decisions of firms that have more room for improvement. Their findings show that lower-quality nursing homes increased their staff by 7.6%, while higher-quality nursing homes decreased it by 5.8%, following IT implementation. Meanwhile, Hitt & Tambe (2016), discussed above, find little effect of HICT adoption on labor demand.

The event studies by Agha (2014) described above, examining EHR adoption across hospitals between 1998 and 2004, also consider the impact on employment. These estimates suggest that adoption leads to just over 1% increases in nurse employment and total employment, but this effect is statistically insignificant.

Some studies look at the impact of HICT on training, including the availability of online courses that potentially lower the cost of education and allow for personalized programs. Whereas this is a general trend in all fields, with Global Markets Insights forecasting a growth in digital learning expenditures from $250 billion in 2020 to over $1 trillion by 2027,[11] health care is especially sensitive to it, as lower quality in education could lead to deadly mistakes. Car et al. (2019) conduct a systematic review of randomized controlled trials (RCTs) on the effectiveness of digital versus traditional learning in this sector. Based on a pooled analysis of nine RCTs involving 890 health care professionals, they find no difference in the gain of knowledge after digital education compared to traditional strategies.

4.3. Summary

Micro evidence on the effect of HICT on the workforce is scarce, and in the few existing studies it is not clear whether adoption is driving workforce changes or whether other characteristics might be driving both. Overall, the general findings suggest that there are no negative effects on jobs or wages but some differential impacts on specific groups. This is an area where much more research is needed.

5. LESSONS FROM OTHER SECTORS

There is a vast literature on the impact of ICT on economic outcomes outside of health care, and this in turn is a subset of the vast field of the impact of technological change on the economy. A broad motivation in macroeconomic studies 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.

The original Solow paradox was that this productivity slowdown coincided with the ICT revolution (see Solow 1987). Many explanations have been put forward for the paradox, such as

[11]This estimate can be found at **https://www.gminsights.com/industry-analysis/elearning-market-size**.

mismeasurement and the greater difficulty of innovating as ideas become harder to find (Bloom et al. 2020a). 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 the moment it feeds through to greater productivity (David 1990). This was the case for the invention of electricity in the nineteenth 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. In addition, and by extension, the most recent waves of radical technological innovations such as artificial intelligence may take some time before they show up in productivity improvements (Brynjolfsson et al. 2021).

Microeconomic evidence is more compelling than evidence based on macroeconomic data. Much of this is summarized by Draca et al. (2009). In short, the studies of firms suggest the following.

1. There is a positive and significant association between organizational productivity and the use of ICT.
2. Although this correlation is on average quite large, it is extremely heterogeneous between studies; and even within studies, the effects are generally quite variable across firms.
3. By looking at data over many years, it becomes clear that the positive effects do not take place immediately but are typically revealed after several years.

These findings are consistent with our summary of the health care literature and suggest that something broader than factors specific to health care might be at play. These findings also lend credence to the organizational complementarity account. According to this notion, firms take time to learn the most effective way to use ICT, and there is much ex-ante uncertainty about the optimal way to implement it, which is why the returns are so variable and slow to happen. Many other types of investment must be made, not least of which is a change in the structure of organizations, such as changing the power structure within firms.

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.[12] 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.[13]

The literature on the effects of technology on the labor market is also vast, and a focus 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, and the supply of education that pulls 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 education premium. More recent work suggests that ICT has a more nuanced effect, with computers replacing routine work. For example, tasks traditionally undertaken by low-skilled manual workers on car assembly lines have been largely automated and taken away by robots. However,

[12] Readers are referred to, for example, Bresnahan et al. (2002) for the United States, Caroli & Van Reenen (2001) for the United Kingdom and France, and Bloom et al. (2012) for seven OECD countries.
[13] For a review of the case study evidence, readers may consult Kochan (2020). Examples include the studies by Batt (1999), Cutcher-Gershenfeld (1991), Cutcher-Gershenfeld et al. (2007), and MacDuffie (1995).

routine tasks usually performed by middle-educated workers doing clerical work have also been automated (e.g., automated teller machines), whereas low-skilled workers doing nonroutine 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. We have shown that this might be the case in health care and should be an area of future work.

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

6. CONCLUSIONS

We have surveyed evidence of the impact of HICT on clinical quality, productivity, and the health care workforce. The literature points in a broadly optimistic direction: The more recent cohort of studies suggests a positive effect on patient outcomes but a more modest impact on productivity. As in the broader ICT literature, this positive mean impact obscures large differences in the impact of ICT in different contexts and also the long time lags between adoption and outcomes, which are consistent with the need for management to experiment and learn the most effective ways to use new technology. Costs tend to rise, however, especially in the early adoption phase. The evidence on workforce outcomes is very slim, but what there is suggests little average effects, with a hint of heterogeneous effects by occupational skill.

An important caveat to all these conclusions is that there are few well-designed studies to investigate the causal impact of HICT. Better identification using modern techniques that exploit policy variation, natural experiments, and RCTs should be one focus of the field. Another one should be to look more systematically at the role of the workforce. The relatively recent and enormous growth in the adoption of HICT provides a valuable opportunity to isolate the exogenous sources of variation to estimate these effects in order to guide policy and improve health. Another opportunity is the ongoing introduction of new elements of HICT, where strategic rollouts of the technology across providers, clinics, or patients can yield causal estimates of impact. This is especially feasible with digital interventions that incorporate A/B testing, but such efforts should aim to understand both whether a new technology improves outcomes and why an intervention works in order to develop new interventions that build on these insights. This will also enable the research community to better identify barriers to the successful adoption and use of HICT and ultimately offer solutions to policy makers and practitioners.

Given the potential of HICT to improve health and lower costs, our review suggests that there are many research questions in need of more attention. First, there is great interest in the role of HICT capabilities among providers and public health agencies in combating infectious diseases including Coronavirus and influenza. Second, the industrial organization of EHR providers should have substantial effects on the effectiveness of HICT, as geographic concentration may lead to higher prices but also greater ability to share data and coordinate care. Results in this area would inform policy responses that allow more data portability across systems.

At the provider level, an understanding of what drives success in the use of new tools would provide valuable lessons, given the heterogeneity we observe. Two understudied areas of interest are the potential distraction of EHR interactions, including alert fatigue, and the possibility to facilitate provider data entry to improve patient care, such as through greater use of voice recognition and scribes. Another opportunity is the incorporation of principles from behavioral economics into order-entry systems in order to facilitate best practices determined by leaders in the health care system and professional societies. Examples include default ordering of the most appropriate tests and preventive care and the framing of information in dashboards and digital charts reviewed by the providers. Similar interventions can be studied for the patients as well, including digital tools to improve adherence and other healthy behaviors, potentially with remote monitoring and other feedback to providers to coordinate care. The experience of the COVID-19 pandemic teaches us that even marginal improvements on some of these dimensions could have first-order impacts on patients and health care employees.

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