Hospital Market Consolidation's Effects on Advanced Electronic Health Records Adoption

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Abstract: The adoption of Electronic Health Records (EHR) by hospitals over the past two decades has been widespread. We examine how hospital market consolidation affects the adoption of advanced EHRs in U.S. hospitals. In concentrated hospital markets, hospitals might face weakened competitive pressure to improve hospital quality through adopting more advanced EHRs. But larger multi-hospital systems might be better able to adopt more advanced EHRs through economies of scale. Using a panel of 24,235 hospital-year observations from the 2008-2019 American Hospital Association Annual Survey and its IT Supplement, we estimate regression models with two-way fixed effects for Health Service Areas and years to identify the effects of within-market changes in the Herfindahl-Hirschman Index (HHI) and the size of the multihospital system on the degree of advanced EHR adoption. One set of adoption measures uses the Office of the National Coordinator for Health Information Technology (ONC)'s broad classification of basic versus comprehensive EHR systems, and another set of adoption measures uses the percentage of 26 specific EHR functionalities implemented, both overall and across four categories: results viewing, clinical documentation, decision support, and order entry. Our results are consistent with the two opposing channels through which hospital market consolidation might affect EHR adoption. Regarding the potential for reduced competitive pressure, we find that changes in hospital market concentration are negatively associated with adopting comprehensive EHRs and certain functionalities. Regarding the potential for economies of scale and shared infrastructure, we find that the number of hospitals in a system is positively associated with both the EHR adoption level and percent of functionalities. The magnitudes of these two opposing channels appear to be comparable in size. We also examine differences for nonprofit vs. for-profit hospitals. Our findings contribute to a more complete understanding of the effects of hospital market consolidation on costs and quality and highlight the importance of market structure, multihospital system size, and ownership type when considering efforts to promote EHR adoption across U.S. hospitals.

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1. Introduction

The adoption of Electronic Health Records (EHR) represents a significant advancement in healthcare, aiming to improve patient care, streamline hospital operations, and enhance physician decision-making. EHRs are digitized medical charts (i.e., the digital versions of patients' paper charts) designed to store comprehensive medical information, including medical histories, diagnoses, medications, treatment plans, immunization dates, and test results. These systems can provide a holistic view of patient histories and thus facilitate better tracking of medical trends and optimizing care delivery. For patients, this can translate to better health outcomes, increased satisfaction, and reduced mortality rates, particularly among those with chronic conditions. Physicians can benefit from enhanced decision support, quicker access to patient information, and improved coordination with care teams. Hospitals may gain competitive advantages by attracting skilled physicians and patients, while also potentially reducing staffing requirements, especially for nursing.

The adoption of EHRs has been a central focus in health policy, particularly following the 2009 passage of the American Recovery and Reinvestment Act's Health Information Technology for Economic and Clinical Health (HITECH) provisions.[1] Despite financial incentives and regulatory mandates aimed at increasing EHR adoption, hospitals exhibit substantial variation in their levels of adoption, with some progressing rapidly to comprehensive systems and others remaining at basic levels; EHR adoption is not a simple binary process but rather an ongoing trajectory of usage and upgrading influenced by financial, competitive, and regulatory forces (Wang, 2022). Understanding the factors behind the variation across hospitals in the degree of adoption is valuable. While previous research has analyzed the financial, regulatory, and technological determinants of EHR adoption, relatively little attention has been given to how hospital consolidation has affected these adoption decisions, with important potential implications for the quality of care and interoperability across the healthcare system.

Moreover, hospital adoption of advanced EHRs is an interesting case study for considering the varied effects of hospital market consolidation. On one hand, hospital market consolidation can weaken the competitive pressure for offering lower prices and higher quality to attract more patients. But on the other hand, hospital market consolidation might improve the hospital sector's ability to reduce underlying costs and improve quality through greater financial resources and economies of scale. In the context of advanced EHR adoption, the reduced competitive pressure from consolidation on achieving high-quality care might weaken incentives to strategically invest more heavily in advanced functionalities to attract patients and physicians, while hospitals in more concentrated environments may adopt only what is required by regulatory mandates. However, the large expense of advanced EHRs and the complexity of successfully implementing them may suggest that relatively larger multi-hospital systems (resulting from overall hospital market consolidation) might be more capable of making these costly investments. Additionally, the relationship between market structure and EHR adoption may differ systematically across for nonprofit versus for-profit hospitals facing different objectives and governance structures. We

[1] The HITECH Act aimed at accelerating EHR adoption by introducing financial incentives for hospitals across the U.S. that adopted EHR systems and met specific criteria outlined in the Meaningful Use Program. The Centers for Medicare & Medicaid Services (CMS) established three stages of Meaningful Use (now referred to as the Promoting Interoperability Program) to guide hospitals through progressive levels of EHR adoption: Stage 1 (2011-2013) focused on basic EHR adoption, data capturing and structured data entry, Stage 2 (2014-2016) emphasized interoperability, care coordination, and health information exchange (HIE), and Stage 3 (2017 onwards) aimed at improving patient access to electronic health data and the use of EHRs for clinical decision-making and health outcomes improvement.

use data for 2008-2019 from the American Hospital Association's (AHA) Annual Survey and associated IT Supplement to disentangle these two potential opposing effects of hospital market consolidation. We find evidence consistent with both of these expectations; that is, we find that increases in hospital market concentration, as measured by the Herfindahl-Hirschman Index (HHI), are often associated with decreases in the probability of hospitals adopting more advanced EHR systems, while a larger size of the multihospital system consistently increases the probability of adopting more advanced EHRs. Overall, the magnitudes of these two relationships are comparable in size, suggesting that the net effect of consolidation on advanced EHR adoption might be negligible for many transactions.

2. Related Literature

Our study draws on and contributes to three broad strands of literature: (a) the impact of market dynamics on technology adoption across industries, (b) the broad literature on hospital market concentration, and (c) research on EHR adoption's determinants and health outcomes. We briefly summarize each in the next three subsections.

2.A. Market Dynamics and Technology Adoption

The impact of market dynamics on technology adoption has been studied across various industries, including ATMs (Knittel and Stango, 2009), electric vehicles (Li et al., 2017), the video game industry (Lee, 2013), VCRs (Ohashi, 2003), payment cards (Rochet and Tirole, 2002), social media platforms (Li and Agarwal, 2017), and the Internet of Things (Basaure et al., 2020). A common theme across these studies is that network effects, switching costs, and competitive pressures interact in complex ways to shape the timing and depth of technology adoption. More recent work has examined network effects and strategic adoption in healthcare settings, including nursing homes (Lin, 2015) and the spillover effects of health IT investments on regional adoption and costs (Atasoy et al., 2018).[2] Other recent work has focused on mergers and acquisitions in the context of power plants (Demirer and Karaduman, 2025) and pharmaceuticals (Bokhari et al., 2025).[3,4] Our analysis extends this cross-industry literature to the hospital EHR sector, examining the role of market concentration in shaping EHR adoption patterns.

2.B. Hospital Market Concentration

A second strand of literature related to our paper is the broad literature on hospital market concentration. Several studies focus on the role of hospital concentration on costs, pricing, and economies of scale (Kessler and McClellan, 2000; Dranove and Lindrooth, 2003; Zwanziger and Mooney, 2005; Harrison, 2011; Cutler and Morton, 2013; Tsai and Jha, 2014; Dauda, 2018; Douven et al., 2020; Lu and Pan, 2021; Han et al., 2022; Desai et al., 2023; Du and Tanriverdi, 2023). Additionally, some focus on how the

[2] Atasoy et al. (2018) find that while EHR adoption increases costs at the adopting hospital, it generates significant spillover effects that reduce costs at neighboring hospitals, with these spillovers being stronger in areas with higher hospital density and participation in health information exchange networks.

[3] Demirer and Karaduman (2025) provide evidence from the power plant sector showing that acquisitions improve efficiency by approximately 2 percent on average, with gains driven primarily by better operational practices rather than capital investment. Their finding that high-productivity acquirers improve underperforming targets is instructive for the hospital consolidation context, where system acquisitions similarly promise operational efficiencies and technology standardization. However, efficiency gains from mergers are not guaranteed and may be accompanied by anticompetitive pricing effects.

[4] Bokhari et al. (2025) study the GSK/Pfizer consumer health merger in the Philippines using a structural demand model and find that while the merger generated efficiency gains for one merging party, these were asymmetric, and the merger also facilitated coordinated pricing behavior with a close competitor, suggesting that consolidation can produce both efficiency gains and anticompetitive conduct simultaneously.

bargaining dynamics between hospitals and insurers influence pricing and service availability (Trish and Herring, 2015; Dauda, 2018; Boozary et al., 2019; Maas, 2020). A comprehensive survey of the industrial organization of healthcare markets, covering models of oligopolistic competition between insurers and providers, price negotiations, and market design, is provided by Gaynor, Ho, and Town (2021).

Other studies have explored how hospital market concentration influences healthcare quality and outcomes (Kessler and McClellan, 2000; Gowrisankaran and Town, 2003; Propper et al., 2004; Gaynor et al., 2013; Feng et al., 2015; Colla et al., 2016; Han et al., 2017; Hanson et al., 2019; Lisi et al., 2020; Brekke et al., 2021; Moscelli et al., 2021; Guccio et al., 2024). Recent work has examined this relationship with greater nuance.[5,6,7,8] Several studies also highlight important heterogeneity by ownership type, with for-profit hospitals often responding more strongly to financial and competitive incentives than nonprofits (e.g., Horwitz and Nichols, 2009; Owsley and Lindrooth, 2022; Kunz et al., 2024).

2.C. EHR Adoption

A third strand of literature related to our paper is the extensive body of research on the determinants of EHR adoption. Prior studies have analyzed the technological, financial, and regulatory influences on EHR adoption (Adler-Milstein and Pfeifer, 2017; Lin, 2023a; Lin, 2023b), barriers and accelerators to adoption (Baron et al., 2005; Hikmet et al., 2008; Lin et al., 2018; Savage et al., 2019), and the differential adoption patterns between nonprofit and for-profit hospitals (Lammers, 2013; Freedman and Lin, 2018). More recent work documents important trends in EHR adoption in the post-HITECH era. Jiang et al. (2023) use the AHA Annual Survey to assess a decade of EHR adoption from 2009 to 2019, documenting that basic EHR adoption surged from 6.6 percent to 81.2 percent and comprehensive adoption from 3.6 percent to 63.2 percent, but persistent disparities remain across hospital types, sizes, and locations.[9] Moreover, Adler-Milstein et al. (2017) document that advanced functionalities are disproportionately adopted by larger, system-affiliated hospitals, with for-profits showing slower progress toward meaningful use standards; they also document the emergence of a digital "advanced use" divide, finding that while basic EHR adoption has become widespread, the depth of implementation, particularly

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[5] Patel and Seegert (2020) exploit an investment tax shock and data on the universe of U.S. hospitals to test whether market power encourages or discourages investment. They find that hospitals in concentrated markets increased investment by 5.1 percent ($2.5 million) more than hospitals in competitive markets in response to tax incentives, with investment responses monotonically increasing with market concentration.

[6] Kunz et al. (2024) assess hospital quality using CMS penalty-based measures and find a robust negative for-profit quality gap that is substantially reduced in more competitive markets, suggesting that competitive pressure disciplines for-profit hospitals toward higher quality.

[7] Andreyeva et al. (2024) study over 100 independent hospitals acquired by hospital systems between 2012 and 2018 and find that while acquired hospitals obtain higher prices, operating cost reductions, primarily from reducing employees in support functions and financing costs, are far greater, with operating profit rising approximately $60,000 per bed per year; however, readmission rates rose post-acquisition.

[8] Setzler (2025) develops a unified framework integrating oligopoly and oligopsony power to evaluate hospital mergers using data on all U.S. hospitals from 1996 to 2022. He finds that mergers significantly reduce patient volume, increase prices, reduce employment, lower wages, and deteriorate quality of care, with merger-induced labor market power incentivizing firms to reduce product quality.

[9] Richards, Shi, and Whaley (2025) exploit the heterogeneous economic impacts of the Great Recession and the 2014 Medicaid expansions to study hospitals' capital investment behavior, finding that health IT investment is highly elastic to market fluctuations, economic downturns restrain investment while insurance expansions promote it. Their finding that the IT investment margin is more responsive than other spending categories highlights the sensitivity of hospital technology adoption to the economic and competitive environment.

advanced functionalities such as clinical decision support, patient engagement, and data analytics, varies substantially.[10]

Three other sets of papers on EHR adoption are less directly connected to our analysis but still relevant. First, the impact of EHRs on health and operational outcomes has also been widely studied, often finding that EHRs improve quality and reduce mortality only after several years of maturation (Kazley and Ozcan, 2007; Buntin et al., 2011; Dranove et al., 2014; Adler-Milstein et al., 2015; McCullough et al., 2016; Lin et al., 2018; Ding and Peng, 2020; Upadhyay and Opoku-Agyeman, 2021; Upadhyay and Bhandari, 2024). Bronsoler, Doyle, and Van Reenen (2022) provide a comprehensive review of the health IT literature and find positive effects of health IT on clinical quality and, more recently, on productivity, especially when combined with complementary organizational changes. A second set of other papers has focused on the supply side of the EHR vendor market, which has become increasingly concentrated over time.[11] A third set of other papers has focused on interoperability and the role of health information exchanges (HIE) (Lin et al., 2018; Savage et al., 2019; Pylypchuk et al., 2019; Everson and Patel, 2022; Adler-Milstein et al., 2024).[12]

2.D. Hospital Consolidation and EHR Adoption

Few studies have examined the association between hospital market consolidation and EHR adoption. As noted above, competitive pressures may lead hospitals to invest more heavily in EHR systems to attract patients and physicians. However, hospital market competition might hinder the development of EHR systems for sharing clinical data across unaffiliated entities, complicating the broader integration necessary for community-wide data sharing (Grossman and Bodenheimer, 2006). Also as noted above, consolidation might enable the resulting larger multi-hospital systems to more readily adopt more advanced EHR systems due to greater financial resources and economies of scale. We are aware of three papers that are most directly related to ours in that each examines the association of hospital consolidation and EHR adoption (though with notable differences).

First, Freedman et al. (2018) provide a comprehensive analysis of how hospital market competition affects EHR vendor selection. They investigate whether competitive pressures drive hospitals toward

[10] Apathy, Holmgren, and Adler-Milstein (2021) find that while critical access hospitals have adopted basic EHRs at near-universal rates following the HITECH Act, they struggle with advanced functions such as clinical decision support and patient engagement tools, raising concerns about an emerging and potentially widening digital divide in the depth of EHR capabilities.

[11] Holmgren and Apathy (2023) document that the vendor market's HHI rose from 1,452 in 2012 (competitive) to above 2,500 after 2018 (highly concentrated), as Epic grew from 20.6 to 46.5 percent of hospital beds and Cerner from 17.7 to 25.3 percent. Vendor choice has meaningful consequences for hospital performance: Holmgren, Adler-Milstein, and McCullough (2018) find that EHR vendor explains between 7 and 34 percent of the variation in hospital meaningful use performance across six key criteria, with significant differences across vendors. This concentration in the vendor market interacts with hospital market concentration, as system-affiliated hospitals typically migrate to their parent system's preferred platform upon acquisition.

[12] A related concern is information blocking, the practice of interfering with electronic health information exchange. Everson, Patel, and Adler-Milstein (2021) provide baseline measures of information blocking prevalence at the start of the 21st Century Cures Act, finding that EHR vendors have the strongest competitive incentives to block information to maintain lock-in, while hospitals in markets with a dominant vendor were less likely to report blocking. Everson and Healy (2025) track trends following regulatory action, documenting that the share of hospitals reporting information blocking by any actor fell from 42 percent in 2021 to 27 percent in 2023, though blocking has not been eliminated. Pylypchuk et al. (2022) provide empirical evidence that switching EHR developers increases patient sharing with hospitals using the same developer by 4 to 19 percent, demonstrating how vendor consolidation directly shapes referral patterns and patient flows. Recent work by Dix, Moran, and Nguyen (2025) quantifies the costs of EHR non-interoperability, showing that technological frictions in data exchange between hospitals with different EHR systems directly affect patient flows and health outcomes, underscoring the welfare consequences of hospital technology adoption decisions.

vendor agglomeration, where hospitals within a market choose the same vendor for interoperability, or dispersion, where hospitals opt for different vendors to create barriers to patient switching. Using a multinomial test for agglomeration and dispersion, they find that hospitals in highly competitive markets tend to converge around dominant vendors, increasing from 58 percent to 74 percent in such markets. Their findings suggest that hospitals prioritize interoperability efficiencies over vendor differentiation, but it also highlights a trade-off: vendor clustering facilitates data-sharing and coordination, but it can lead to higher switching costs and reduced long-term flexibility.

Second, Wang (2022) examines not just initial EHR adoption but also the depth of EHR adoption level in competitive markets. Using a dynamic oligopoly model to analyze strategic adoption behavior among hospitals, she finds that competition intensifies preemptive adoption, where hospitals strategically adopt EHRs earlier than they otherwise would to establish technological dominance and deter rivals from upgrading. Moreover, her model reveals that hospitals at the same EHR adoption level compete more intensely than those at different levels, suggesting that hospitals are not only competing on price and service quality but also on technological sophistication, particularly when upgrading from basic EHR systems to advanced functionalities. In smaller markets, hospitals have less incentive to adopt advanced EHR systems, even with subsidies, leading to differences in adoption across different market sizes.

Third, Lin (2023b) examines how hospital chain membership shapes EHR adoption decisions. Using a discrete-choice model with a national sample of U.S. hospitals from 2005 to 2014, she finds that system-affiliated hospitals benefit from internal economies of scale, cost-sharing, and centralized IT coordination that facilitate EHR adoption. Larger chains exhibit particularly strong incentives for internal integration, leveraging shared infrastructure and bargaining power to support technology investment.

2.E. Our Paper's Contribution

Our paper contributes to both the hospital concentration literature and the EHR adoption literature. Within the hospital concentration literature, most papers focus on prices and quality of care, while our study's focus on EHR adoption examines an alternative outcome related to potential underlying efficiencies, though with important implication for how hospitals' investment in EHRs is strongly tied with subsequent quality. Within the EHR adoption literature, our paper builds on prior studies by incorporating more recent and comprehensive data extending beyond the initial EHR adoption phase studied by most earlier papers. That is, while much of the earlier literature focuses on the extensive margin of EHR adoption (i.e., whether a hospital has adopted an EHR), our analysis examines the intensive margin of the level of advanced adoption. Specifically, we analyze ONC's classification of EHR sophistication (i.e., basic, basic with notes, and comprehensive) and the percentage of specific EHR functionalities implemented, both overall and across four distinct categories: results viewing, clinical documentation, decision support, and order entry.

For the intersection of these two literatures, a central conceptual contribution of our paper is jointly identifying two opposing channels through which hospital market consolidation may affect EHR adoption. To that end, we use the term "consolidation" here to apply broadly to the various effects of mergers and acquisitions and the term "concentration" to apply more narrowly to the effects of competition alone; economies of scale could then be one effect from consolidation that attempts hold the level of competition steady. As noted above, we expect that increases in hospital market concentration, driven by hospital mergers and acquisitions (within a given geographic market), will reduce the competitive pressure faced by hospitals to improve quality to attract patients and, in turn, may disincentivize the costly adoption of more advanced EHR systems. Concurrently, yet working in the opposite direction, that same consolidation (whether within a given geographic market or across different geographic markets) generally increases the system's size, as independent hospitals merge into a new system or an independent hospital is acquired by an existing multihospital system. Larger systems can leverage economies of scale, shared IT infrastructure, centralized procurement, and internal cost-sharing to facilitate advanced EHR adoption. Because these two channels operate in opposite directions, the implications of the net cost/benefit of hospital consolidation will generally be dependent on the type of transaction. Transactions among hospitals within a local geographic market might have no net impact on advanced EHR adoption if the competitive-pressure channel and the economies-of-scale channel largely offset one another. In contrast, transactions among hospitals in separate local geographic markets would presumably only have the positive impact on advanced EHR adoption, i.e., there would be no competitive-pressure channel and only the economies-of-scale channel. An advantage to our empirical approach (described in the next section) is that we can disentangle these two channels.

3. Methods

3.A. Overview:

We use hospital-level data from the 2008-2019 AHA Annual Survey and IT Supplement to examine hospital/year-level regression models with a measure of advanced EHR adoption as the dependent variable and hospital market concentration, measured by the Herfindahl-Hirschman Index (HHI), as one primary explanatory variable and the number of hospitals in the ownership system as a secondary explanatory variable. Our regressions include several hospital characteristics, time-varying county-level characteristics, and two-way fixed effects for the Health Service Area (HSA) and time, so that our identification strategy relies on within-market changes in hospital market concentration over time to identify changes in hospital-level advanced EHR adoption over time. In the next two subsections, we describe these data for EHR adoption and market concentration in more detail. (We then describe the empirical specifications and control characteristics after these two subsections.)

3.B. AHA IT Supplement Data for EHR Adoption:

Our analysis uses data from the American Hospital Association (AHA) Annual Survey of Hospitals and its associated IT Supplement for the years 2008 through 2019. The AHA Annual Survey is one of the most comprehensive sources of information on the universe of U.S. hospitals, and the AHA's IT Supplement, administered alongside the Annual Survey, collects data on a wide range of health information technology metrics, including the implementation of electronic health records, interoperability capabilities, health information exchange participation, and the adoption of advanced health IT tools such as telemedicine and clinical decision support systems.[13,14]

[13] Roughly 86% of private general medical and surgical hospitals in the AHA respond to the IT Supplement; we examine the differences in respondents vs. non-respondents further below.

[14] Much of the existing literature on EHR adoption relies on data from the Healthcare Information and Management Systems Society (HIMSS) Analytics database. The version of these data available to academic researchers only covers the time period through the early 2010s. Specifically, the Dorenfest Institute version of the HIMSS database used to be freely available to academic researchers and included data through approximately 2012. HIMSS Analytics itself continued operating commercially until January 2019, when Definitive Healthcare acquired its data services business; after the acquisition, the data was folded into Definitive Healthcare's proprietary platform. Many of the academic studies using the HIMSS database therefore examined the

Our analysis focuses on the IT Supplement's identification of whether the hospital has adopted 26 specific EHR functionalities, ultimately enabling both a broad classification of the EHR adoption level and a granular examination of the depth and composition of EHR systems. These functionalities are grouped into five broad categories: results viewing functionalities (comprised of laboratory reports, radiology reports, radiology images, diagnostic test results, diagnostic test images, and consultant reports); clinical documentation (comprised of patient demographics, physician notes, nursing notes, problem lists, medication lists, discharge summaries, and advanced directives); decision support (comprised of clinical guidelines, clinical reminders, drug allergy alerts, drug-drug interaction alerts, drug-lab interaction alerts, and drug dosing support); computerized provider order entry (comprised of laboratory tests, radiology tests, medications, consultation requests, and nursing orders); and other functionalities (comprised of bar coding or radio frequency ID for supply chain management and telehealth).[15]

These functionalities in the AHA IT Supplement questionnaire were developed in partnership with the Department of Health and Human Services' Office of the National Coordinator for Health Information Technology (ONC) (Blumenthal et al., 2006; Henry et al., 2016). In particular, ONC relied on a prior consensus expert panel both to identify these specific 26 functionalities and to classify three distinct levels of EHR systems (beyond an initial category not meeting any of the three sets of requirements): (1) basic EHR systems without a clinical note capability, (2) basic EHR systems with a clinical note capability, and (3) comprehensive EHR systems.[16]

Our first set of primary analyses therefore examine separate logistic regressions for the log odds that a hospital's EHR meets a given ONC classification for that level of EHR sophistication. Specifically, we construct three binary indicators for cumulative EHR adoption thresholds: at least a basic EHR system, at least a basic EHR system with notes, and a comprehensive EHR system. Each of these indicators is the dependent variable for a simple logistic regression with the hospital/year as the unit of observation. We also examine a full ordered logit for the four potential ordinal ONC classifications as the dependent variables in regression analysis (though this model relies on the proportional odds assumption that each predictor's effect is consistent across the three potential thresholds of the ordered response).

Our second set of primary analyses examine the depth of EHR adoption by constructing measures of the percentage of individual EHR functionalities adopted by each hospital as a continuous measure. Our primary measure is the percentage of EHR functionalities adopted out of the 26 total identified in the survey. Following the AHA IT Supplement's framework for ONC's broad categories of EHR adoption,

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initial years prior to and immediately after the ARRA's HITECH provisions, before widespread adoption had occurred; as such, many examined hospital-level initial decisions to adopt any EHR (compared to an older paper-based system). By our using the AHA IT Supplement from 2008 through 2019, we can better capture the full trajectory of advanced hospital EHR adoption under the HITECH Act, from initial implementation through the period of near-universal basic adoption.

[15] Remote patient monitoring (included in the "other" functionalities category) was added to the IT Supplement questionnaire in 2015, so we do not include this functionality in our analysis of 2008 through 2019.

[16] In particular, the ONC classification for basic EHR systems (without notes) requires laboratory report viewing, radiology report viewing, diagnostic test report viewing, patient demographics, problem lists, medication lists, discharge summaries, and computerized provider order entry for medications. The ONC classification for comprehensive EHR systems requires all six results viewing functionalities, all seven clinical documentation functionalities, all six decision support functionalities, and all five computerized provider order entry functionalities.

we also measure the percent of EHR functionalities within each category: results viewing (out of six total), clinical documentation (out of seven total), decision support (out of six total), and order entry (out of five total).[18] The percentage adopted overall, or within each category, then serves as the dependent variable in an OLS regression. The latter measures provide the potential for examining where hospitals are investing in health IT capabilities and whether market concentration differentially affects the adoption of different types of EHR functionalities.

In supplementary analysis, we also examine whether the hospital is certified as meeting meaningful use requirements.[19] This variable was added to the AHA IT Supplement in 2011 (though there is little variation across hospitals after 2014 as nearly all became certified for meaningful use).

3.C. HHI Measure of Hospital Market Concentration:

We measure hospital market concentration using the Herfindahl-Hirschman Index (HHI). The HHI is the sum of the squared market shares of each hospital (or hospital ownership system for multihospital systems) in the local market, so that HHI values range from near 0 (representing a large number of relatively smaller competitors) to 10,000 (representing a monopoly where one firm controls the entire market). The U.S. Department of Justice (DOJ) and Federal Trade Commission (FTC)'s updated guidelines view competitive markets as having HHIs less than 1,000; moderately concentrated markets as having HHIs between 1,000 and 1,800; and concentrated markets as having HHIs over 1,800 (U.S. Department of Justice, 2024).[20] For our regression analyses, we express the HHI in thousands to interpret the HHI regression coefficient as measuring the effect of a 1,000-point change.[21]

We construct market shares (for each independent hospital or multihospital system) within the local market based on the distribution of inpatient admissions. We use Health Service Areas (HSA), defined by the National Center for Health Statistics (NCHS), to represent local markets for routine inpatient care. There are 805 HSAs in the U.S., with each HSA being a group of contiguous counties.[22]

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[18] Given the heterogeneity of the functionalities within the "other" category and the fact that only two are consistently measured during the entire 2009-2018 period, we do not examine a "percentage adopted" measure for this category.

[19] In 2009, Congress passed the Health Information Technology for Economic and Clinical Health (HITECH) Act as part of the American Recovery and Reinvestment Act. The HITECH Act established the Medicare and Medicaid EHR Incentive Programs, which provided substantial financial incentives to hospitals and eligible professionals that demonstrated "meaningful use" of certified EHR technology. The program was implemented in stages: Stage 1 (beginning in 2011) set the baseline requirements for electronic data capture and information sharing, Stage 2 (beginning in 2014) expanded requirements to emphasize health information exchange, and Stage 3 (optional in 2017, required in 2018) imposed further requirements around clinical decision support and patient access. Under the Medicare program, eligible hospitals could receive initial incentive payments ranging from $2 million to over $6 million depending on patient volume, while hospitals that failed to demonstrate meaningful use faced Medicare payment reductions beginning in 2015, escalating from 1 percent to as much as 5 percent of their Medicare reimbursements (Blumenthal and Tavenner, 2010). In 2018, CMS renamed the program to "Promoting Interoperability," shifting the emphasis from EHR adoption toward interoperability and data exchange.

[20] The U.S. DOJ and FTC's 2023 merger guidelines indicate that "transactions that increase the HHI by more than 100 points in highly concentrated markets are presumed likely to enhance market power." Previously, the FTC/DOJ's 2010 guidelines defined competitive markets as having HHIs less than 1,500; moderately concentrated markets as having HHIs between 1,500 and 2,500; concentrated markets as having HHIs over 2,500; and transactions increasing the HHI by 200 or more points in highly concentrated markets as likely enhancing market power.

[21] A 1,000-point change is therefore somewhat close in magnitude to the 800-point increase in the HHI from a hypothetical "five to four" merger of two equally sized firms into one with 40% market share; this HHI would increase from 2,000 to 2,800.

[22] The Dartmouth Atlas' Hospital Referral Regions (HRR) represent the market for specialty/tertiary hospitalizations; there are 306 HRRs in the U.S. compared to the 805 NCHS HSAs in the U.S. we use. Incidentally, the NCHS HSAs we use for our analysis should not be confused with the Dartmouth Atlas' 3,436 "Hospital Service Area" designation for the geographic area surrounding (mostly) single hospitals.

For our primary measure of HHIs for hospital market concentration, we calculate market shares based on a measure of each individual hospital's admissions over the entire period rather than individual hospital's admissions from that particular year; we refer to the HHI measure as one using "static" admissions (i.e., a fixed distribution of patient origin flows across hospitals computed over the study period). We do this to address potential endogeneity concerns about a given hospital's market share periodically changing in response to patients observing short-term changes in individual hospital prices and/or quality and thus affecting their choice of that individual hospital (and, in turn, affecting its market share and resulting HHI). Using the static measure of admissions rather than annual measure of admissions therefore isolates variation in market concentration arising only from hospital mergers, system acquisitions, new hospital openings, or old hospital closures, rather than from year-to-year fluctuations in patient sorting. We also incorporate a one-year lagged HHI to mitigate any concerns about simultaneity between current market structure and hospital technology adoption decisions. As a sensitivity analysis, we also estimate models using the lagged HHI based on annual admissions.

3.D. Empirical Specification:

The primary model specification is as follows:

$$Y_{it} = \beta_0 + \beta_1 HHI_{mt-1} + \gamma_{it} + \eta_{ct} + \nu_m + \mu_t + \varepsilon_{it}$$

where *i* indexes hospitals, *t* indexes years, *m* indexes HSA markets, and *c* indexes counties. Observations are therefore at the hospital-year level. The term Y_{it} represents an advanced EHR adoption outcome of interest for hospital *i* in year *t*. The term $HHI_{m,t-1}$ represents the one-year-lagged Herfindahl-Hirschman Index measuring hospital market concentration in HSA *m* (based on static market shares for individual hospitals but potentially changing system-level market shares based on mergers, acquisitions, openings, and closures). The term γ_{it} represents a vector of hospital characteristics, and the term η_{ct} represents a vector of county characteristics; these specific measures are described in a subsection below. The term ν_m represents Health Service Area fixed effects, which absorb all time-invariant differences across hospital markets (i.e., local demographic and institutional factors that are stable over the sample period). The term μ_t represents year fixed effects that capture common time trends in EHR adoption (such as the effects of implementing the HITECH Act and the CMS meaningful use incentive program). Finally, ε_{it} represents the error term.

We estimate several variants of this regression model for advanced EHR adoption with different dependent variables and estimation methods applicable to the functional form of that dependent variable. For binary EHR adoption outcomes, the function is a logit; these include whether the hospital has at least a basic EHR, whether the hospital has at least a basic EHR with notes, and whether the hospital has a comprehensive EHR. We report average marginal effects (AME) from these logit models to facilitate interpretation of the coefficients as changes in the probability of adoption. For this ordinal ONC classification of EHR systems (four levels: 0, 1, 2, 3), we estimate an ordered logit model and report odds ratios, which indicate how a one-unit change in the independent variable multiplies the odds of being in a relatively higher EHR adoption category. As noted above, this model relies on the proportional odds assumption holding in that each predictor's effect is consistent across the three potential thresholds of the ordered response. For the continuous EHR functionality measures (i.e., the percentage of functionalities adopted, overall and by category), we estimate OLS regressions.

As our primary interest is in the HHI measure of market concentration, the standard errors account for clustering at the HSA level in all specifications due to the potential for within-market correlation of the error term. The two-way fixed effects approach with both HSA fixed effects and year fixed effects ensures that the identification strategy relies on within-market variation of the HHI measure for market concentration over time (rather than on cross-sectional differences across markets). This approach addresses concerns about unobserved market-level confounders that are time-invariant, though it does not rule out time-varying unobserved confounders (thus not included as control variables) that may simultaneously affect both market structure and EHR adoption.

3.E. Hospital/Year Sample:

We restrict our analytical sample to general medical and surgical hospitals and do not consider smaller specialty hospitals. Similarly, we restrict our analytical sample to private hospitals (i.e., nonprofit hospitals and for-profit, investor-owned hospitals) and exclude federal and local public hospitals as they are likely to face different underlying constraints for EHR adoption and would not be influenced by market concentration in the private sector. In addition, not all hospitals in the AHA Annual Survey respond to the IT Supplement. To assess whether selective non-response might bias our estimates, we compare the characteristics of hospitals that responded to the IT Supplement with those that did not by estimating a logit model for the odds of responding. Besides dropping hospital/year observations that have missing values for any of our primary outcomes or any of our hospital and county-level controls, we also drop additional observations that are dropped from any of the regression models due to perfect prediction or collinearity with fixed effects in order to ensure that all nine outcomes are estimated on the same sample of hospital/year observations.[23] Finally, we perform additional analyses stratifying by ownership status to test whether nonprofit hospitals respond differently than for-profits to market consolidation.

3.F. Control Characteristics:

An important hospital-level characteristic related to market consolidation is the number of hospitals in the health system to which the hospital belongs (which equals one if the hospital is independent). Hospitals that are part of larger systems may have greater financial resources and economies of scale that facilitate EHR adoption. Given the skewness of this number, we include a logged value in our regression model and interpret as the percentage increase in the overall system. The additional vector of hospital-level control variables includes several indicators for bed size category, an indicator for for-profit (investor-owned) status, an indicator for teaching hospital status (i.e., Accreditation Council for Graduate Medical Education [ACGME]), and an indicator for whether the hospital is a certified trauma center. Like hospitals that are part of a system, individual hospitals that are larger may have greater financial resources and economies of scale that facilitate EHR adoption. Teaching hospitals and trauma centers may face different EHR needs due to the complexity of their clinical operations.

[23] To do so, we employ the following iterative convergence procedure. Different model specifications (e.g., logit vs. ordered logit vs. OLS) may drop different observations due to perfect prediction or collinearity with fixed effects. We therefore iteratively estimate all specifications for each set of models, identify the intersection of their estimation samples, and re-estimate until no additional observations are lost. This guarantees that any differences across our nine outcomes reflect differences in the underlying relationship rather than differences in sample composition.

County-level controls account for the socioeconomic and healthcare environment in which each hospital operates. These include the percentage of the population aged 65 and over, the percentage of the population that is non-white non-Hispanic, the percentage with four or more years of college education, per capita income (in $1,000s), the poverty rate, the uninsured rate, the number of physicians per 1,000 population, and an indicator for the presence of a Federally Qualified Health Center (FQHC). These variables capture local demand characteristics, resource availability, and the broader healthcare infrastructure that may influence hospital IT investment decisions.

4. Results

Table 1 presents summary statistics for the analytical sample of 24,235 hospital/years. The sample is composed of 85.1 percent nonprofit and 14.9 percent for-profit hospitals. Regarding the average EHR adoption levels during this 2008-2019 time period, 46.9 percent of hospital-years are not classified as having a basic EHR by ONC standards, while 6.4 percent have a basic EHR, 10.7 percent have a basic EHR with clinical notes, and 35.9 percent have a comprehensive EHR. The mean percentage of the 26 EHR functionalities adopted is 70.0 percent, with results viewing functionalities having the highest mean adoption rate (84.3 percent) and order entry functionalities the lowest (63.2 percent). The mean lagged static HHI is 3,683, indicating, on average, highly concentrated markets, according to the U.S. DOJ and FTC's 2023 merger guidelines, and the mean number of hospitals in system is 25.7, reflecting the prevalence of large multihospital systems in the period of study. Appendix Table 1 presents our analysis comparing respondents to the AHA IT supplement to non-respondents. The response rate among private general medical and surgical hospitals is 86%. The odds of responding were not statistically different between respondents and non-respondents for our key explanatory variables, the HHI measure of market concentration and the log number of hospitals in the system, so that selective non-response seems unlikely to bias our key findings. However, response rates were systematically higher for larger hospitals (as measured by bed size) and nonprofit hospitals.

Figures 1 through 3 present additional descriptive information about our EHR outcomes. Specifically, Figure 1 presents the distribution of the ONC EHR adoption classification levels over time. The figure shows dramatic growth in EHR adoption: in 2008, fewer than 5 percent of hospitals met even the basic EHR threshold, but by 2019, over 95 percent of hospitals had at least a basic EHR and approximately 80 percent had achieved a comprehensive EHR classification. The same overall pattern of adoption is observed for both nonprofit and for-profit hospitals, though for-profit hospitals consistently lagged nonprofit hospitals in reaching each successive adoption level throughout the period.

Figure 2 presents the mean percentage of the potential 26 EHR functionalities adopted over time. Overall adoption increased from approximately 39 percent of functionalities in 2008 to over 95 percent by 2019. Throughout the period, for-profit hospitals adopted a lower share of functionalities than nonprofit hospitals, with a gap of roughly 6 percentage points in 2008 that widened to approximately 15 percentage points by 2011. Beginning around 2011, coinciding with the start of the CMS meaningful use incentive program, for-profit hospitals' adoption accelerated markedly, narrowing the gap with nonprofit hospitals throughout the 2011–2015 period. By 2018–2019, the three lines had nearly converged, with all hospital types approaching 95 percent adoption. Figure 3 disaggregates the increasing adoption trend observed in Figure 2 by functionality type, revealing that results viewing functionalities started at the highest baseline and maintained the highest adoption rates throughout, while order entry functionalities started lowest but experienced the most rapid growth, particularly after 2011 when the HITECH Act's meaningful use incentives took effect.

Additionally, Appendix Figure 1 presents the percent of hospitals with an EHR that is certified as meeting Meaningful Use over time. This variable was first available in the AHA IT Supplement in 2011, corresponding to the first year of the CMS meaningful use incentive program. By 2015 and onward, over 90 percent of hospitals in our sample had achieved meaningful use certification, leaving little remaining variation to analyze. Accordingly, we restrict our supplementary analysis of meaningful use certification to the 2011-2014 period.

Figures 4 through 6 present additional descriptive information about our primary explanatory variables. Specifically, Figure 4 is a set of two U.S. maps with hospital market HHIs for HSAs, using our "static" measure of admissions; one is for the beginning of our study period, 2008, and one is for the end, 2019. HSA borders are shown as the medium width line, while county borders are shown as the thinner line and state borders are shown as the thicker line. Lighter shades indicate more competitive markets (i.e., lower HHIs), while darker shades indicate more concentrated markets (i.e., higher HHI). Figure 5 maps the change in hospital market HHIs for HSAs from 2008 to 2019 using this static market share measure. Red shading indicates HSAs that experienced increases in market concentration (due solely to mergers, acquisitions, or closures), green shading indicates decreases in market concentration, and white indicates HSAs with no change in market structure over the period. (Appendix Figures 2 and 3 show versions of these maps with HHIs using the annual admissions to determine market shares rather than the static market shares.)

Figure 6 shows the mean number of hospitals in the system (if applicable) over time; this equals one for independent hospitals. For-profit hospitals belong to substantially larger systems than nonprofit hospitals throughout the period, with a mean system size of approximately 81 hospitals in 2008 compared to approximately 12 for nonprofits.[25] Nonprofit hospitals, by contrast, show a gradual and steady increase from about 12 to 19 hospitals per system, reflecting the growth of regional nonprofit systems. These trends reflect the increasing prevalence and scale of multihospital systems, particularly in the for-profit sector, and help motivate the inclusion of system size as a primary measure in our models.

Table 2 presents the full regression results from the specification for the probability of the hospital/year's advanced EHR adoption. It includes three logit models (each reporting average marginal effects) and one ordered logit model (reporting odds ratios). Our primary variable of interest, the lagged static HHI, has a marginally significant negative relationship for the advanced EHR threshold (AME = -0.016, $p < 0.10$), indicating that a 1,000-point increase in HHI is associated with a 1.6 percentage point decrease in the probability of having an advanced EHR. Relative to the sample's mean adoption rate of 35.9 percent, this effect represents a 4.5 percent decline in the prevalence of advanced EHRs.[26] The HHI coefficients for the

[25] This reflects the dominance of a small number of national for-profit chains, such as HCA Healthcare, Community Health Systems, and Tenet Healthcare, that each operate dozens to over 200 hospitals nationwide. The for-profit line exhibits high volatility, including a dip around 2012 followed by a sharp increase to nearly 100 by 2014, consistent with the timing of major for-profit chain mergers, most notably Community Health systems' acquisition of Health Management Associates (71 hospitals) in January 2014.

[26] That is, the 4.5 percent figure is calculated as the average marginal effect (0.016) divided by the sample mean of advanced EHR adoption (0.359).

other two logit models are negative but not statistically significant at conventional levels; this helps explain why the ordered logit is also insignificant when the three level thresholds are combined in a single model. That said, the consistently negative sign across all four specifications generally supports a negative relationship between hospital market concentration and EHR adoption.

The log number of hospitals in the system is positive and highly significant across all four models (e.g., AME = 0.028, $p < 0.01$ for comprehensive EHR), indicating that hospitals belonging to larger systems are more likely to adopt advanced EHRs. Because system size enters the model in logarithmic form, each coefficient should be interpreted as the change in the outcome resulting from an $e \approx 2.71$ times increase in the number of hospitals in the system; scaling these down to instead represent a doubling of the number of hospitals in a system implies a 0.9 percentage point increase in the probability of at least basic EHR adoption, a 1.1 percentage point increase for a basic-with-notes EHR, and a 1.9 percentage point increase for a comprehensive EHR.[27] Additionally, nonprofit ownership, larger hospitals with more beds, and certified trauma centers are each associated with advanced EHR adoption. The year indicators show a pronounced upward trajectory in adoption over time, consistent with the combined effects of technological maturation and the HITECH Act incentive programs.

Table 3 presents the OLS results for the percentage of EHR functionalities adopted, both overall and by the four functionality categories. The lagged static HHI coefficient has a negative and marginally significant relationship for the results viewing functionalities ($B = -0.012$, $p < 0.10$) and the clinical documentation functionalities ($B = -0.011$, $p < 0.10$); the sign for the other three outcomes is negative. These estimates suggest that a 1,000-point increase in HHI is associated with approximately a 1.2 percentage point reduction in results viewing functionalities and a 1.1 percentage point reduction in clinical documentation functionalities. These effects each represent approximately 1.4 percent of the underlying percentage of adopted functionalities (84.3 percent results viewing and 74.1 percent clinical documentation, respectively), indicating that market concentration exerts a small but detectable influence on the depth of EHR implementation.

The log number of hospitals in the system is positive and highly significant across all five models, reinforcing the finding that system membership facilitates the adoption of more advanced EHRs. Applying the same scaling factor to the coefficient described above, doubling the system's size is associated with a 0.9 percentage point increase in overall functionality adoption, with the largest effect for decision support functionalities (1.2 percentage points) and smaller effects for clinical documentation and order entry (0.6 percentage points each). Nonprofit ownership and larger hospitals with more beds are again associated with significantly higher adoption of EHR functionalities.

Appendix Table 2 presents results for the logit model for Certified Meaningful Use (CMU) during the 2011–2014 period. As noted above, this variable was added to the AHA IT Supplement in 2011. We focus on the period when the CMS meaningful use incentive program was most active and the CMU variable exhibited meaningful variation. After 2015, the CMU measure in the AHA IT Supplement exhibits little variation as most hospitals had achieved certification by that point. The lagged static HHI

[27] In particular, a one-unit increase in the natural log corresponds to multiplying system size by $e \approx 2.718$. Doubling system size therefore corresponds to a $\ln(2) \approx 0.693$ portion of that increase. As such, the doubling effect is calculated as the estimated average marginal effect multiplied by 0.693 (e.g., $0.028 \times 0.693 \approx 0.019$ for an advanced EHR).

coefficient is essentially zero and statistically insignificant, providing no evidence that market concentration affected whether hospitals achieved meaningful use certification during this period. Interestingly, the log number of hospitals in the system has a negative and significant coefficient (AME = −0.012, $p < 0.01$), suggesting that (in contrast to our findings for comprehensive systems with more functionalities) hospitals in larger systems were somewhat slower to achieve initial meaningful use certification, perhaps reflecting the organizational complexity of coordinating certification across a large system. The year indicators' effects emphasize rapid growth in CMU from 2011 to 2014.

Tables 4 and 5 examine potential heterogeneity by hospital ownership type, separately estimating the adoption and functionality models for nonprofit and for-profit hospitals using the lagged static HHI. The first row of each table repeats the full-sample results from Tables 2 and 3, respectively.[28] In Table 4, the negative finding for hospital market concentration on advanced EHR adoption is more pronounced among nonprofit hospitals (AME = −0.021, $p < 0.05$), while for-profit hospitals show a positive but insignificant coefficient. In Table 5, the HHI measure's coefficients for nonprofit hospitals are uniformly negative across all five functionality categories; none reaches conventional levels of statistical significance, though the magnitudes are comparable to the full sample. For for-profit hospitals, the coefficients are statistically insignificant across all specifications, possibly due to the substantially smaller sample size limiting statistical power, but the magnitudes of these coefficients are close to zero.

Tables 6 and 7 replicate the ownership subgroup analysis presented in Tables 4 and 5 using the lagged HHI measure using annual admissions for market shares instead of the static measure for market shares. This is essentially a sensitivity check on the potential endogeneity of the latter (i.e., advanced EHR adoption might lead to short-term changes in individual hospitals' market shares). While the results are qualitatively consistent with the primary specification (in that they are negatively signed), they are all smaller in magnitude and statistically insignificant; for example, the advanced EHR adoption's AME for nonprofit hospitals is -0.012 (SE = 0.009) in Table 6 compared to -0.021 (SE = 0.010, $p < 0.05$) in Table 2. Our interpretation is that, as one might expect, the HHIs incorporating annual market shares may exhibit a positive bias due to endogeneity, so that the HHIs incorporating static market shares (and thus solely reflecting mergers, acquisitions, and closures) are better able to detect the negative relationship.

5. Discussion

This study examines the relationship between hospital market consolidation and the adoption of advanced electronic health records using the AHA's hospital-level panel data from 2008 through 2019.[29] Our findings provide evidence that hospitals in more concentrated hospital markets adopt advanced EHR technology at somewhat lower rates, though the estimated effects are generally modest in magnitude and frequently do not reach conventional levels of statistical significance.

[28] The nonprofit and for-profit subsamples' number of observations do not sum to the full sample's number of observations because the iterative convergence procedure, which ensures a common sample across all columns within each panel, is applied separately within each subgroup, and a small number of additional observations are dropped due to perfect prediction within the smaller subsamples.

[29] The rapid growth in advanced EHR adoption captured by the year indicators (across all nine regression models) underscores the dominant role that federal policy, particularly the HITECH Act and the CMS meaningful use incentive program, played in driving adoption during this period.

Across our primary specifications, the lagged static HHI measure of market concentration carries a consistently negative coefficient in both the adoption-level models (Table 2) and the functionality-depth models (Table 3). The strongest result is for the probability of comprehensive EHR adoption among nonprofit hospitals (AME = −0.021, $p < 0.05$ in Table 4), representing approximately 5.8 percent of the sample's mean adoption rate of 35.9 percent. For EHR functionalities, the estimated effects from a 1,000-point increase in the HHI represent between 1.3 and 1.5 percent of the respective sample means for results viewing and clinical documentation, which we interpret as relatively small in magnitudes. Taken together, we interpret these results as a relatively modest channel of competitive pressure on adopting quality-enhancing technology.

Our finding that relatively larger multihospital systems are positively and robustly associated with EHR adoption across all specifications is consistent with prior literature suggesting that health systems facilitate technology diffusion through shared resources, centralized IT infrastructure, and economies of scale in implementation. In practical terms, doubling the number of hospitals in a system is associated with a 1.9 percentage point increase in the probability of comprehensive EHR adoption and a 0.9 percentage point increase in overall functionality adoption.

Overall, these magnitudes are relatively similar. That is, consolidation leading to a 1,000-point increase in the HHI would have a 2.1 percentage-point decrease in the probability of adopting a comprehensive EHR system, while consolidation leading to a doubling of the hospital system's size would have a 1.9 percentage-point increase in the probability of adopting a comprehensive EHR system. For within-market mergers, these two opposing effects (of decreased competitive pressure to adopt versus increasing capacity to adopt) will partially offset each other. In particular, the canonical "five-to-four" merger of equally sized hospitals (with its 800-unit increase in the HHI) would see a partial 1.7 percentage-point decrease nearly offset by the partial 1.9 percentage-point increase (with its doubling in system size). In contrast, an acquisition of a hospital in an HSA outside a given system's current reach might enable only the upside of economies of scale (and not any downside from weakened competition).

The consistently large negative coefficients on for-profit ownership status across all specifications suggest that ownership is an important predictor of advanced EHR adoption. For-profit ownership is associated with a 12.8 percentage point decrease in comprehensive EHR adoption (relative to a sample mean of 35.9 percent) and 9.1 percentage points fewer functionalities adopted (representing 13.0 percent of the sample mean of 70.0 percent). This finding aligns with prior research documenting that for-profit hospitals have historically lagged behind nonprofits in health IT investment, potentially reflecting different organizational incentives and investment horizons. The ownership-stratified results in Tables 4 and 5 further suggest that any effect of market concentration on EHR adoption is more pronounced among nonprofit hospitals. The large difference in system size between for-profit and nonprofit hospitals, illustrated in Figure 6, provides important context for interpreting the ownership-stratified results. For-profit hospitals belong to systems averaging about 83 hospitals, roughly five times the size of the typical nonprofit system. These large national chains maintain centralized IT infrastructure, dedicated EHR implementation teams, and the bargaining power to negotiate favorable contracts with EHR vendors, resources that should, in principle, be sufficient to drive EHR adoption regardless of competitive conditions in any individual local market. This interpretation is consistent with our finding that the HHI coefficient is statistically insignificant for for-profit hospitals (Tables 4 and 6) while reaching significance for nonprofits: for-profit hospitals' adoption decisions may be driven primarily by system-level directives and resources rather than local market dynamics, while nonprofit hospitals, operating in smaller, more regionally oriented systems, may be more responsive to competitive pressure in their local markets.

5.A. Limitations

Several limitations of this study should be acknowledged. First, despite the inclusion of HSA fixed effects and year fixed effects, our identification strategy relies on within-market variation in our static HHI measure over time, which is driven by mergers, acquisitions, hospital openings, and closures. These events are not random and may be correlated with unobserved time-varying factors that also affect EHR adoption, such as changes in local economic conditions or shifts in hospital leadership priorities. While we control for a rich set of hospital and county characteristics (and the static measure of market share should largely purge the HHI measure of short-term reverse causality), we cannot fully rule out omitted variable bias from time-varying confounders.

Second, the HHI can be an imprecise measure of overall hospital market concentration. Defining the appropriate local market for each hospital is complicated. While NCHS's Health Service Areas are a well-established approximation for local hospital markets, the true geographic boundaries of competition may differ for different service lines and for urban versus rural hospitals. Misspecification of market boundaries could attenuate the estimated relationship between concentration and outcomes. Similarly, our HHI measure is based on inpatient admissions and does not account for outpatient competition or competition from non-hospital providers (e.g., ambulatory surgery centers, urgent care clinics). To the extent that hospitals face competitive pressure from these alternative providers, our HHI may understate the true level of competition faced by some hospitals.

Third, the AHA IT Supplement relies on self-reported data from hospital administrators, which may be subject to measurement error or social desirability bias, particularly as EHR adoption became a policy priority. Additionally, the binary EHR functionality variables indicate whether a functionality is present but do not capture the depth of implementation, the extent of clinician utilization, or the quality of the system. A hospital reporting that it has adopted a given functionality may range from one that has fully integrated the tool into clinical workflows to one that has merely installed but rarely uses the software.[30]

Fourth, the AHA IT Supplement does not achieve universal response among hospitals in the AHA Annual Survey. Although our response bias analysis (Appendix Table 1) shows no significant difference in our key explanatory variables between respondents and non-respondents, the differential response by hospital size and for-profit status implies our results may be most representative of larger nonprofit hospitals.

Fifth, our study period (2008-2019) coincides with massive federal investment in EHR adoption through the HITECH Act, which may have attenuated competitive effects by reducing the financial barriers to adoption for all hospitals regardless of market structure. The strong effects for the year indicators in our models are consistent with policy forces dominating market forces during this period, and it is possible that competitive effects were more pronounced before HITECH or may become more relevant as the focus of policy shifts from adoption to interoperability and advanced use.

[30] As EHR adoption approaches saturation, future research might examine whether market concentration affects the quality and depth of EHR use, interoperability, and patient outcomes associated with more advanced measures of EHR adoption.

5.B. Conclusion

Our study provides a comprehensive examination of the relationship between hospital market concentration and advanced EHR adoption across the 2008-2019 period, capturing the full trajectory of the HITECH Act era from initial implementation through near-universal basic adoption. Using hospital-level panel data from the AHA Annual Survey and IT Supplement with two-way fixed effects for Health Service Area and year, we find suggestive evidence that hospitals in more concentrated markets adopt EHR technology at modestly lower rates, though not all of the individual estimates reach conventional levels of statistical significance. The strongest result is for the probability of comprehensive EHR adoption among nonprofit hospitals, where a 1,000-point increase in the HHI is associated with a 2.1 percentage point reduction, or roughly 5.8 percent of the sample mean. The size of the hospital system is, in contrast, robustly positive; doubling system size is associated with a 1.9 percentage point increase in the probability of comprehensive adoption. Taken together, our results indicate that the organizational structure through which consolidation occurs may facilitate technological diffusion even as the resulting market concentration discourages it.

Our results carry implications for both antitrust policy and health IT regulation. While the direct effect of market concentration on EHR adoption appears modest, estimated at approximately 2 to 5 percent of sample mean adoption rates, and potentially dampened because the substantial federal incentives under the HITECH Act likely dominated market forces during this period, the finding that competitive pressure is associated with greater technology investment reinforces concerns about the potential long-term consequences of hospital consolidation for quality of care and innovation. As the policy landscape shifts from EHR adoption incentives toward interoperability mandates and advanced use requirements, the competitive dynamics of technology investment may become more salient.

6. References

Adler-Milstein, J., Everson, J., & Lee, S. Y. D. (2015). EHR adoption and hospital performance: Time-related effects. Health Services Research, 50(6), 1751–1771.

Adler-Milstein, J., Holmgren, A. J., Kralovec, P., Worzala, C., Searcy, T., & Patel, V. (2017). Electronic health record adoption in US hospitals: The emergence of a digital “advanced use” divide. Journal of the American Medical Informatics Association, 24(6), 1142–1148.

Adler-Milstein, J., Linden, A., Hsia, R. Y., & Everson, J. (2024). Electronic connectivity between hospital pairs: Impact on emergency department-related utilization. Journal of the American Medical Informatics Association, 31(1), 15–23.

Adler-Milstein, J., & Pfeifer, E. (2017). Information blocking: Is it occurring and what policy strategies can address it? The Milbank Quarterly, 95(1), 117–135.

Andreyeva, E., Gupta, A., Ishitani, C. E., Sylwestrzak, M., & Ukert, B. (2024). The corporatization of independent hospitals. Journal of Political Economy Microeconomics, 2(3), 602-663.

Apathy, N. C., Holmgren, A. J., & Adler-Milstein, J. (2021). A decade post-HITECH: Critical access hospitals have electronic health records but struggle to keep up with other advanced functions. Journal of the American Medical Informatics Association, 28(9), 1947-1954.

Atasoy, H., Chen, P., & Ganju, K. (2018). The Spillover Effects of Health IT Investments on Regional Healthcare Costs. Management Science, 64(6), 2515–2534.

Baron, R. J., Fabens, E. L., Schiffman, M., & Wolf, E. (2005). Electronic health records: Just around the corner? Or over the cliff? Annals of Internal Medicine, 143(3), 222–226.

Basaure, A., Vesselkov, A., & Töyli, J. (2020). Internet of things (IoT) platform competition: Consumer switching versus provider multihoming. Technovation, 90–91.

Blumenthal D, DesRoches CM, Donelan K, Ferris TG, Jha AK, Kaushal R, et al. Health Information Technology in the United States: The Information Base for Progress. Princeton, NJ: Robert Wood Johnson Foundation; 2006.

Blumenthal, D., & Tavenner, M. (2010). The "meaningful use" regulation for electronic health records. New England Journal of Medicine, 363(6), 501–504.

Bokhari, F. A. S., Ennis, S., Vega, C., & Yan, W. (2025). Merger efficiency and coordinated effects: Nothing to sneeze at? Evidence from cough and cold medicines in the Philippines. Working Paper.

Boozary, A. S., Feyman, Y., Reinhardt, U. E., & Jha, A. K. (2019). The association between hospital concentration and insurance premiums in ACA marketplaces. Health Affairs, 38(4), 668–674.

Brekke, K. R., Canta, C., Siciliani, L., & Straume, O. R. (2021). Hospital competition in a national health service: Evidence from a patient choice reform. Journal of Health Economics, 79, 102509.

Bronsoler, A., Doyle, J. J., & Van Reenen, J. (2022). The impact of health information and communication technology on clinical quality, productivity, and workers. Annual Review of Economics, 14, 23-46.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal, D. (2011). The benefits of health information technology: A review of the recent literature shows predominantly positive results. Health Affairs, 30(3), 464–471.

Centers for Medicare & Medicaid Services (CMS). (n.d.). Medicare and Medicaid EHR incentive programs: Stage 1 requirements.

Colla, C., Bynum, J., Austin, A., & Skinner, J. (2016). Hospital competition, quality, and expenditures in the US Medicare population. National Bureau of Economic Research (No. W22826).

Cutler, D. M., & Scott Morton, F. (2013). Hospitals, market share, and consolidation. JAMA, 310(18), 1964–1970.

Dauda, S. (2018). Hospital and health insurance markets concentration and inpatient hospital transaction prices in the U.S. health care market. Health Services Research, 53(2), 1203–1226.

Demirer, M., & Karaduman, O. (2025). Do mergers and acquisitions improve efficiency? Evidence from power plants. Journal of Political Economy, forthcoming. (NBER Working Paper No. 32727.)

Desai, S. M., Padmanabhan, P., Chen, A. Z., Lewis, A., & Glied, S. A. (2023). Hospital concentration and low-income populations: Evidence from New York State Medicaid. Journal of Health Economics, 90, 102770.

Dinesh, R. P., Rajan, B., & Chakraborty, S. (2022). Do EHR and HIE deliver on their promise? Analysis of Pennsylvania acute care hospitals. International Journal of Production Economics, 245.

Ding, X., & Peng, X. (2020). The impact of electronic medical records on the process of care: Alignment with complexity and clinical focus. Decision Sciences, 53, 348–389.

Dix, R., Moran, K., & Nguyen, T. (2025). Costs of technological frictions: Evidence from EHR (Non-)Interoperability. Working Paper.

Douven, R., Burger, M., & Schut, F. (2020). Does managed competition constrain hospitals' contract prices? Evidence from the Netherlands. Health Economics, Policy and Law, 15(3), 341–354.

Dranove, D., & Lindrooth, R. (2003). Hospital consolidation and costs: Another look at the evidence. Journal of Health Economics, 22(6), 983–997.

Dranove, D., Garthwaite, C., Ody, C., & Starc, A. (2014). The trillion-dollar conundrum: Complementarities and health information technology. American Economic Journal: Economic Policy, 6(4), 239–270.

Du, K., & Tanriverdi, H. (2023). Does IT enable collusion or competition? Examining the effects of IT on service pricing in multimarket multihospital systems. MIS Quarterly, 47(4), 1425–1453.

Everson, J., & Adler-Milstein, J. (2016). Engagement in hospital health information exchange is associated with vendor marketplace dominance. Health Affairs, 35(7), 1286–1293.

Everson, J., & Healy, D. (2025). Information-blocking trends following regulatory action. Journal of the American Medical Informatics Association, 32(4), 665-674.

Everson, J., & Patel, V. (2022). Hospital's adoption of multiple methods of obtaining outside information and use of that information. Journal of the American Medical Informatics Association, 29(9), 1489–1496.

Everson, J., Patel, V., & Adler-Milstein, J. (2021). Information blocking remains prevalent at the start of 21st Century Cures Act: Results from a survey of health information exchange organizations. Journal of the American Medical Informatics Association, 28(4), 727-732.

Feng, Y., Pistollato, M., Charlesworth, A., Devlin, N., Propper, C., & Sussex, J. (2015). Association between market concentration of hospitals and patient health gain following hip replacement surgery. Journal of Health Services Research & Policy, 20(1), 11–17.

Freedman, S., & Lin, H. (2018). Hospital ownership type and innovation: The case of electronic medical records adoption. Nonprofit and Voluntary Sector Quarterly, 47(4), 711–732.

Freedman, S., Lin, H., & Prince, J. (2018). Does competition lead to agglomeration or dispersion in EMR vendor decisions? Review of Industrial Organization, 53(1), 57–79.

Gaynor, M., Ho, K., & Town, R. J. (2021). The industrial organization of health care markets. In K. Ho, A. Hortacsu, & A. Lizzeri (Eds.), Handbook of Industrial Organization (Vol. 4, Issue 1). Elsevier.

Gaynor, M., Moreno-Serra, R., & Propper, C. (2013). Death by market power: Reform, competition, and patient outcomes in the National Health Service. American Economic Journal: Economic Policy, 5(4), 134–166.

Gowrisankaran, G., & Town, R. J. (2003). Competition, payers, and hospital quality. Health Services Research, 38(6p1), 1403–1422.

Grossman, J. M., Bodenheimer, T. S., & McKenzie, K. (2006). Marketwatch: Hospital-physician portals: The role of competition in driving clinical data exchange. Health Affairs, 25(6), 1629–1636.

Guccio, C., Lisi, D., Martorana, M. F., & Pignataro, G. (2024). Is local competition effective in improving quality and efficiency of hospitals? Insights from an asymmetric spatial competition model. Research in Economics, 78(3), 100962.

Han, A., Lee, K.-H., & Park, J. (2022). The impact of price transparency and competition on hospital costs: A research on all-payer claims databases. BMC Health Services Research, 22(1).

Han, J., Kairies, S. N., Vomhof, M., & Kairies-Schwarz, N. (2017). Quality competition and hospital mergers—An experiment. Health Economics, 26, 36–51.

Hanson, C., Herring, B., & Trish, E. (2019). Do health insurance and hospital market concentration influence hospital patients' experience of care? Health Services Research, 54(4), 805-815.
Harrison, T. D. (2011). Do mergers really reduce costs? Evidence from hospitals. Economic Inquiry, 49(4), 1054–1069.
Henry, J., Pylypchuk, Y., Searcy T. & Patel V. (May 2016) Adoption of Electronic Health Record Systems among U.S. Non-Federal Acute Care Hospitals: 2008-2015. ONC Data Brief, no.35. Office of the National Coordinator for Health Information Technology: Washington DC.
Hikmet, N., Bhattacherjee, A., & Menachemi, N. (2008). The role of organizational factors in the adoption of healthcare information technology in Florida hospitals. Health Care Management Science, 11, 1–9.
Holmgren, A. J., & Apathy, N. C. (2023). Trends in US hospital electronic health record vendor market concentration, 2012-2021. Journal of General Internal Medicine, 38(7), 1765-1767.
Holmgren, A. J., Adler-Milstein, J., & McCullough, J. (2018). Are all certified EHRs created equal? Assessing the relationship between EHR vendor and hospital meaningful use performance. Journal of the American Medical Informatics Association, 25(6), 654–660.
Horwitz, J. R., & Nichols, A. (2009). Hospital ownership and medical services: Market mix, spillover effects, and nonprofit objectives. Journal of Health Economics, 28(5), 924–937.
Jiang, J. X., Qi, K., Bai, G., & Schulman, K. (2023). Pre-pandemic assessment: A decade of progress in electronic health record adoption among U.S. hospitals. Health Affairs Scholar, 1(5), qxad056.
Kazley, A. S., & Ozcan, Y. A. (2007). Organizational and environmental determinants of hospital EMR adoption: A national study. Journal of Medical Systems, 31, 375–384.
Kessler, D. P., & McClellan, M. B. (2000). Is hospital competition socially wasteful? The Quarterly Journal of Economics, 115(2), 577–615.
Knittel, C., & Stango, V. (2009). How does incompatibility affect prices?: Evidence from ATM's. The Journal of industrial economics, 57(3), 557–582.
Kunz, J. S., Propper, C., Staub, K. E., & Winkelmann, R. (2024). Assessing the quality of public services: For-profits, chains, and concentration in the hospital market. Health Economics, 33(9), 2162–2181.
Lammers, E. (2013). The effect of hospital-physician integration on health information technology adoption. Health Economics, 22(10), 1215–1229.
Lee, R. S. (2013). Vertical Integration and Exclusivity in Platform and Two-Sided Markets. The American Economic Review, 103(7), 2960–3000.
Li, S., Tong, L., Xing, J., & Zhou, Y. (2017). The Market for Electric Vehicles: Indirect Network Effects and Policy Design. Journal of the Association of Environmental and Resource Economists, 4(1), 89–133.
Li, Z., & Agarwal, A. (2017). Platform Integration and Demand Spillovers in Complementary Markets: Evidence from Facebook's Integration of Instagram. Management Science, 63(10), 3438–3458.
Lin, H. (2015). Quality choice and market structure: a dynamic analysis of nursing home oligopolies. International Economic Review, 56(4), 1261–1290.
Lin, J. (2023a). Strategic complements or substitutes? The case of adopting health information technology by US hospitals. Review of Economics and Statistics, 105(5), 1237–1254.
Lin, J. (2023b). To follow the market or the parent system: Evidence from health IT adoption by hospital chains. Economic Inquiry, 61(4), 891–910.
Lin, S. C., Everson, J., & Adler-Milstein, J. (2018). Technology, incentives, or both? Factors related to level of hospital health information exchange. Health Services Research, 53(5), 3285–3308.
Lisi, D., Siciliani, L., & Straume, O. R. (2020). Hospital competition under pay-for-performance: Quality, mortality, and readmissions. Journal of Economics & Management Strategy, 29(2), 289–314.
Lu, L., & Pan, J. (2021). Does hospital competition lead to medical equipment expansion? Evidence on the medical arms race. Health Care Management Science, 24(3), 582–596.
Maas, S. (2020, July). Concentration and pricing power: Hospitals versus insurers. The NBER Digest, 4. Gale Business: Insights.

McCullough, J. S., Parente, S. T., & Town, R. (2016). Health information technology and patient outcomes: The role of information and labor coordination. The RAND Journal of Economics, 47(1), 207–236.
Moscelli, G., Gravelle, H., & Siciliani, L. (2021). Hospital competition and quality for non-emergency patients in the English NHS. RAND Journal of Economics, 52(2), 382–414.
Office of the National Coordinator for Health Information Technology (ONC). (n.d.). National trends in hospital and physician adoption of electronic health records.
Ohashi, H. (2003). The Role of Network Effects in the US VCR Market, 1978-1986. Journal of Economics & Management Strategy, 12(4), 447–494.
Owsley, K. M., & Lindrooth, R. C. (2022). Understanding the relationship between nonprofit hospital community benefit spending and system membership: An analysis of independent hospital acquisitions. Journal of Health Economics, 86, Article 102696.
Patel, E., & Seegert, N. (2020). Does market power encourage or discourage investment? Evidence from the hospital market. Journal of Law and Economics, 63(4), 667-698.
Propper, C., Burgess, S., & Green, K. (2004). Does competition between hospitals improve the quality of care?: Hospital death rates and the NHS internal market. Journal of Public Economics, 88(7), 1247–1272.
Pylypchuk, Y., Alvarado, C. S., Patel, V., & Searcy, T. (2019). Uncovering differences in interoperability across hospital size. Healthcare: The Journal of Delivery Science and Innovation, 7(4).
Pylypchuk, Y., Meyerhoefer, C. D., Encinosa, W., & Searcy, T. (2022). The role of electronic health record developers in hospital patient sharing. Journal of the American Medical Informatics Association, 29(3), 435–442.
Richards, M., Shi, M., & Whaley, C. (2025). Economic shocks and healthcare capital investments. (NBER Working Paper No. 33487.)
Rochet, J.-C., & Tirole, J. (2002). Cooperation among Competitors: Some Economics of Payment Card Associations. The Rand Journal of Economics, 33(4), 549–570.
Savage, L., Gaynor, M., & Adler-Milstein, J. (2019). Digital health data and information sharing: A new frontier for health care competition? Antitrust Law Journal, 82(2), 593–622.
Setzler, B. (2025). Labor and product market power, endogenous quality, and the consolidation of the US hospital industry. (NBER Working Paper No. 34180.)
Trish, E. E., & Herring, B. J. (2015). How do health insurer market concentration and bargaining power with hospitals affect health insurance premiums? Journal of Health Economics, 42, 104–114.
Tsai, T. C., & Jha, A. K. (2014). Hospital consolidation, competition, and quality: Is bigger necessarily better? JAMA, 312(1), 29–30.
U.S. Department of Justice. (2024, January 17). Herfindahl-Hirschman Index (link).
Upadhyay, S., & Bhandari, N. (2024). Patient engagement functionalities' influence on quality outcomes: The road via EHR presence. Journal of Healthcare Management, 69(2), 118–131.
Upadhyay, S., & Opoku-Agyeman, W. (2021). Factors that determine comprehensive categorical classification of EHR implementation levels. Health Services Insights, 14.
Wang, Y. (2022). Competition and multilevel technology adoption: A dynamic analysis of electronic medical records adoption in U.S. hospitals. International Economic Review, 63(3), 1357–1395.
Zwanziger, J., & Mooney, C. (2005). Has competition lowered hospital prices? Inquiry: The Journal of Health Care Organization, Provision, and Financing, 42(1), 73–85.

Table 1: Summary Statistics for the Analytical Sample of Hospital/Years

Primary Measures:	**Mean**	**SD**	**Min**	**Max**
EHR Not Classified by ONC as Basic	0.469	0.499	0	1
EHR Classified by ONC as Basic	0.064	0.245	0	1
EHR Classified by ONC as Basic with Clinical Notes	0.107	0.309	0	1
EHR Classified by ONC as Comprehensive	0.359	0.480	0	1
EHR's Percent of All 26 Functionalities	0.700	0.308	0	1
EHR's Percent of Results Viewing Functionalities	0.843	0.279	0	1
EHR's Percent of Clinical Documentation Functionalities	0.741	0.333	0	1
EHR's Percent of Decision Support Functionalities	0.694	0.393	0	1
EHR's Percent of Order Entry Functionalities	0.632	0.466	0	1
Hospital HHI (1000s): Lagged Static Admissions	3.683	2.112	0.4	10
Hospital HHI (1000s): Lagged Annual Admissions	3.730	2.162	0.4	10
Number of Hospitals in System	25.713	42.208	1	200
Hospital-level Controls:				
Ownership: For-Profit Investor-Owned	0.149	0.356	0	1
Ownership: Nonprofit	0.851	0.356	0	1
Size: 6-24 Beds	0.078	0.269	0	1
Size: 25-49 Beds	0.169	0.375	0	1
Size: 50-99 Beds	0.151	0.358	0	1
Size: 100-199 Beds	0.227	0.419	0	1
Size: 200-299 Beds	0.147	0.354	0	1
Size: 300-399 Beds	0.094	0.292	0	1
Size: 400-499 Beds	0.051	0.219	0	1
Size: 500 or More Beds	0.082	0.275	0	1
Teaching Hospital (ACGME)	0.315	0.464	0	1
Certified Trauma Center	0.491	0.500	0	1
County-level Controls:				
County's Percent Age 65+	15.734	4.209	4.26	51.6
County's Percent Not White Non-Hispanic	28.380	21.499	0.97	97.31
County's Percent with 4+ Years College	27.198	10.668	5.6	75.3
County's Per Capita Income ($1000s)	43.748	13.296	17.23	173.2
County's Percent in Poverty	14.743	5.304	2.60	48.10
County's Percent Uninsured	13.402	5.997	2.1	42.30
County's Physicians Per 1000 Capita	2.201	1.832	0	34.67
County Has a Federally Qualified Health Center	0.740	0.438	0	1

Notes: N = 24,235. Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. SD = standard deviation. EHR = Electronic Health Record. ONC = Office of the National Coordinator for Health Information Technology. HHI = Herfindahl-Hirschman Index. ACGME = Accreditation Council for Graduate Medical Education.

Table 2: Probability of Hospital/Year's Advanced EHR Adoption

	Logit for At Least Basic EHR	Logit for At Least Basic+ EHR	Logit for Comprehensive EHR	Ordered Logit for Level
	AME / SE	AME / SE	AME / SE	OR / SE
Hospital HHI (1000s): Lagged Static Admissions	-0.003	-0.006	-0.016*	0.901
	(0.010)	(0.011)	(0.009)	(0.061)
Log of Number of Hospitals in System	0.013***	0.016***	0.028***	1.185***
	(0.003)	(0.004)	(0.004)	(0.034)
Ownership: For-Profit Investor-Owned	-0.100***	-0.117***	-0.128***	0.376***
	(0.015)	(0.018)	(0.020)	(0.053)
Size: 25-49 Beds	0.016	0.003	0.004	1.075
	(0.015)	(0.016)	(0.017)	(0.124)
Size: 50-99 Beds	0.036**	0.016	0.021	1.244*
	(0.017)	(0.017)	(0.017)	(0.151)
Size: 100-199 Beds	0.044***	0.013	0.029*	1.287**
	(0.016)	(0.016)	(0.017)	(0.157)
Size: 200-299 Beds	0.069***	0.036**	0.045**	1.544***
	(0.017)	(0.017)	(0.019)	(0.203)
Size: 300-399 Beds	0.068***	0.030	0.042**	1.509***
	(0.019)	(0.019)	(0.020)	(0.217)
Size: 400-499 Beds	0.108***	0.052**	0.044*	1.822***
	(0.022)	(0.024)	(0.024)	(0.303)
Size: 500 or More Beds	0.116***	0.074***	0.085***	2.216***
	(0.022)	(0.022)	(0.023)	(0.364)
Teaching Hospital (ACGME)	0.019**	0.003	0.004	1.084
	(0.010)	(0.010)	(0.010)	(0.076)
Certified Trauma Center	0.016*	0.013	0.021**	1.157**
	(0.009)	(0.010)	(0.010)	(0.085)
County's Percent Age 65+	-0.004**	-0.004**	-0.004*	0.971**
	(0.002)	(0.002)	(0.002)	(0.013)
County's Percent Not White Non-Hispanic	-0.001***	-0.002***	-0.001	0.990**
	(0.001)	(0.001)	(0.001)	(0.004)
County's Percent with 4+ Years College	0.001	0.002*	0.003***	1.017**
	(0.001)	(0.001)	(0.001)	(0.007)
County's Per Capita Income ($1000s)	-0.001**	-0.001	-0.001**	0.989***
	(0.001)	(0.001)	(0.001)	(0.004)
County's Percent in Poverty	-0.001	-0.001	-0.002	0.983
	(0.002)	(0.002)	(0.002)	(0.013)
County's Percent Uninsured	0.003	0.004	0.002	1.020
	(0.002)	(0.002)	(0.002)	(0.016)
County's Physicians Per 1000 Capita	0.010**	0.007	0.003	1.060*
	(0.004)	(0.005)	(0.004)	(0.036)
County Has a Federally Qualified Health Center	0.009	0.021*	0.006	1.077
	(0.011)	(0.012)	(0.013)	(0.092)
Year 2009	0.029***	0.019***	0.015***	1.707***
	(0.007)	(0.006)	(0.004)	(0.215)
Year 2010	0.047***	0.031***	0.028***	2.259***
	(0.008)	(0.006)	(0.006)	(0.298)
Year 2011	0.149***	0.111***	0.093***	6.175***
	(0.012)	(0.011)	(0.009)	(0.890)
Year 2012	0.336***	0.243***	0.180***	18.498***
	(0.014)	(0.013)	(0.010)	(2.663)
Year 2013	0.478***	0.362***	0.280***	37.174***
	(0.015)	(0.015)	(0.012)	(5.581)
Year 2014	0.614***	0.494***	0.381***	68.767***
	(0.013)	(0.012)	(0.011)	(10.878)
Year 2015	0.740***	0.608***	0.453***	114.071***
	(0.013)	(0.016)	(0.017)	(20.198)
Year 2016	0.786***	0.742***	0.601***	223.907***
	(0.013)	(0.015)	(0.017)	(41.814)
Year 2017	0.817***	0.797***	0.629***	281.863***
	(0.011)	(0.013)	(0.016)	(52.901)
Year 2018	0.896***	0.899***	0.732***	557.956***
	(0.010)	(0.010)	(0.015)	(110.788)
Year 2019	0.913***	0.923***	0.802***	881.990***
	(0.009)	(0.008)	(0.013)	(175.819)
Observations	24,235	24,235	24,235	24,235

Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. AME = average marginal effects from a logit regression for the EHR classification. SE = standard errors (accounting for clustering at the Health Service Area). OR = odds ratio from an ordered logit regression. Each regression includes Health Service Area (HSA) fixed effects. The base year for the time indicators is 2008. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Percent of Hospital/Year's Potential EHR Functionalities

	All 26 Functionalities	Results Viewing	Clinical Documentation	Decision Support	Order Entry
	B / SE	B / SE	B / SE	B / SE	B / SE
Hospital HHI (1000s): Lagged Static Adm.	-0.009	-0.012*	-0.011*	-0.008	-0.006
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Log of Number of Hospitals in System	0.013***	0.014***	0.008***	0.018***	0.008**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Ownership: For-Profit Investor-Owned	-0.091***	-0.098***	-0.084***	-0.097***	-0.073***
	(0.010)	(0.012)	(0.011)	(0.015)	(0.014)
Size: 25-49 Beds	0.027**	0.041***	0.024**	0.027*	0.025*
	(0.010)	(0.013)	(0.012)	(0.014)	(0.015)
Size: 50-99 Beds	0.052***	0.080***	0.058***	0.054***	0.035**
	(0.011)	(0.015)	(0.012)	(0.014)	(0.015)
Size: 100-199 Beds	0.079***	0.125***	0.089***	0.086***	0.028*
	(0.011)	(0.016)	(0.012)	(0.014)	(0.015)
Size: 200-299 Beds	0.111***	0.170***	0.114***	0.131***	0.054***
	(0.012)	(0.016)	(0.013)	(0.014)	(0.016)
Size: 300-399 Beds	0.111***	0.169***	0.119***	0.128***	0.049***
	(0.012)	(0.015)	(0.013)	(0.016)	(0.018)
Size: 400-499 Beds	0.127***	0.179***	0.129***	0.142***	0.088***
	(0.014)	(0.017)	(0.016)	(0.017)	(0.022)
Size: 500 or More Beds	0.135***	0.170***	0.134***	0.160***	0.106***
	(0.013)	(0.017)	(0.014)	(0.017)	(0.021)
Teaching Hospital (ACGME)	-0.003	-0.013**	-0.007	-0.009	0.018*
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Certified Trauma Center	0.028***	0.033***	0.023***	0.035***	0.016*
	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)
County's Percent Age 65+	-0.004***	-0.007***	-0.004**	-0.005***	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
County's Percent Not White Non-Hispanic	-0.001**	-0.001***	-0.001*	-0.001**	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
County's Percent with 4+ Years College	0.001**	0.001*	0.001*	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
County's Per Capita Income ($1000s)	-0.000	-0.001	-0.000	-0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County's Percent in Poverty	-0.000	-0.001	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
County's Percent Uninsured	-0.001	-0.003**	-0.002	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
County's Physicians Per 1000 Capita	0.004**	0.002	0.002	0.004*	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
County Has a FQHC	0.014*	0.020**	0.019**	0.005	0.017*
	(0.007)	(0.009)	(0.009)	(0.010)	(0.010)
Year 2009	0.021***	0.032***	0.027***	0.021**	0.009
	(0.006)	(0.008)	(0.008)	(0.010)	(0.009)
Year 2010	0.050***	0.071***	0.056***	0.055***	0.033***
	(0.007)	(0.009)	(0.009)	(0.011)	(0.010)
Year 2011	0.133***	0.130***	0.143***	0.150***	0.147***
	(0.008)	(0.010)	(0.011)	(0.013)	(0.012)
Year 2012	0.258***	0.189***	0.264***	0.291***	0.339***
	(0.009)	(0.010)	(0.011)	(0.013)	(0.015)
Year 2013	0.350***	0.230***	0.353***	0.389***	0.506***
	(0.009)	(0.010)	(0.011)	(0.013)	(0.015)
Year 2014	0.424***	0.252***	0.413***	0.482***	0.661***
	(0.009)	(0.011)	(0.012)	(0.014)	(0.014)
Year 2015	0.456***	0.264***	0.448***	0.501***	0.727***
	(0.011)	(0.013)	(0.013)	(0.016)	(0.017)
Year 2016	0.480***	0.285***	0.479***	0.524***	0.740***
	(0.012)	(0.014)	(0.014)	(0.017)	(0.018)
Year 2017	0.500***	0.293***	0.502***	0.549***	0.764***
	(0.011)	(0.014)	(0.014)	(0.017)	(0.018)
Year 2018	0.564***	0.326***	0.540***	0.594***	0.806***
	(0.012)	(0.014)	(0.014)	(0.017)	(0.018)
Year 2019	0.584***	0.341***	0.552***	0.619***	0.819***
	(0.012)	(0.014)	(0.015)	(0.017)	(0.018)
Constant	0.382***	0.714***	0.441***	0.321***	0.115**
	(0.036)	(0.044)	(0.044)	(0.047)	(0.054)
Observations	24,235	24,235	24,235	24,235	24,235

Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. B = Coefficient from OLS regression for the percentage of a given set of functionalities adopted in the EHR system. SE = standard errors (accounting for clustering at the Health Service Area). Each regression model includes Health Service Area (HSA) fixed effects. The base year for the time indicators is 2008. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Probability of Hospital/Year's Advanced EHR Adoption by Ownership Type

	Logit for At Least Basic EHR	Logit for At Least Basic+ EHR	Logit for Comprehensive EHR	Ordered Logit for Level
	AME / SE	AME / SE	AME / SE	OR / SE
All Hospitals (N=24,235)				
Hospital HHI (1000s): Lagged Static Admissions	-0.003	-0.006	-0.016*	0.901
	(0.010)	(0.011)	(0.009)	(0.061)
Nonprofit Hospitals (N=20,516)				
Hospital HHI (1000s): Lagged Static Admissions	-0.001	-0.005	-0.021**	0.898
	(0.011)	(0.012)	(0.010)	(0.068)
For-Profit Hospitals (N=3,110)				
Hospital HHI (1000s): Lagged Static Admissions	0.015	0.006	0.058	1.130
	(0.026)	(0.026)	(0.037)	(0.269)

Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. AME = average marginal effects from a logit regression for the EHR classification. SE = standard errors (accounting for clustering at the Health Service Area). OR = odds ratio from an ordered logit regression. Each regression model includes all the hospital and county characteristics shown in Table 2, Health Service Area (HSA) fixed effects, and year fixed effects. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Percent of Hospital/Year's Potential EHR Functionalities by Ownership Type

	All 26 Functionalities	Results Viewing	Clinical Documentation	Decision Support	Order Entry
	B / SE	B / SE	B / SE	B / SE	B / SE
All Hospitals (N=24,235)					
Hospital HHI (1000s): Lagged Static Adm.	-0.009	-0.012*	-0.011*	-0.008	-0.006
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Nonprofit Hospitals (N=20,516)					
Hospital HHI (1000s): Lagged Static Adm.	-0.007	-0.008	-0.010	-0.009	-0.005
	(0.006)	(0.006)	(0.007)	(0.009)	(0.011)
For-Profit Hospitals (N=3,110)					
Hospital HHI (1000s): Lagged Static Adm.	0.000	0.001	-0.000	0.002	-0.005
	(0.020)	(0.025)	(0.025)	(0.027)	(0.020)

Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. B = Coefficient from OLS regression for the percentage of a given set of functionalities adopted in the EHR system. SE = standard errors (accounting for clustering at the Health Service Area). Each regression model includes all the hospital and county characteristics shown in Table 3, Health Service Area (HSA) fixed effects, and year fixed effects. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Advanced EHR Adoption by Ownership Type: Alternative Annual HHI Measure

	Logit for At Least Basic EHR	Logit for At Least Basic+ EHR	Logit for Comprehensive EHR	Ordered Logit for Level
	AME / SE	**AME / SE**	**AME / SE**	**OR / SE**
All Hospitals (N=24,235)				
Hospital HHI (1000s): Lagged Annual Admissions	0.000	-0.004	-0.012	0.941
	(0.009)	(0.009)	(0.008)	(0.056)
Nonprofit Hospitals (N=20,516)				
Hospital HHI (1000s): Lagged Annual Admissions	0.004	0.001	-0.012	0.958
	(0.009)	(0.009)	(0.009)	(0.064)
For-Profit Hospitals (N=3,110)				
Hospital HHI (1000s): Lagged Annual Admissions	-0.017	-0.031	0.011	0.908
	(0.025)	(0.025)	(0.034)	(0.187)

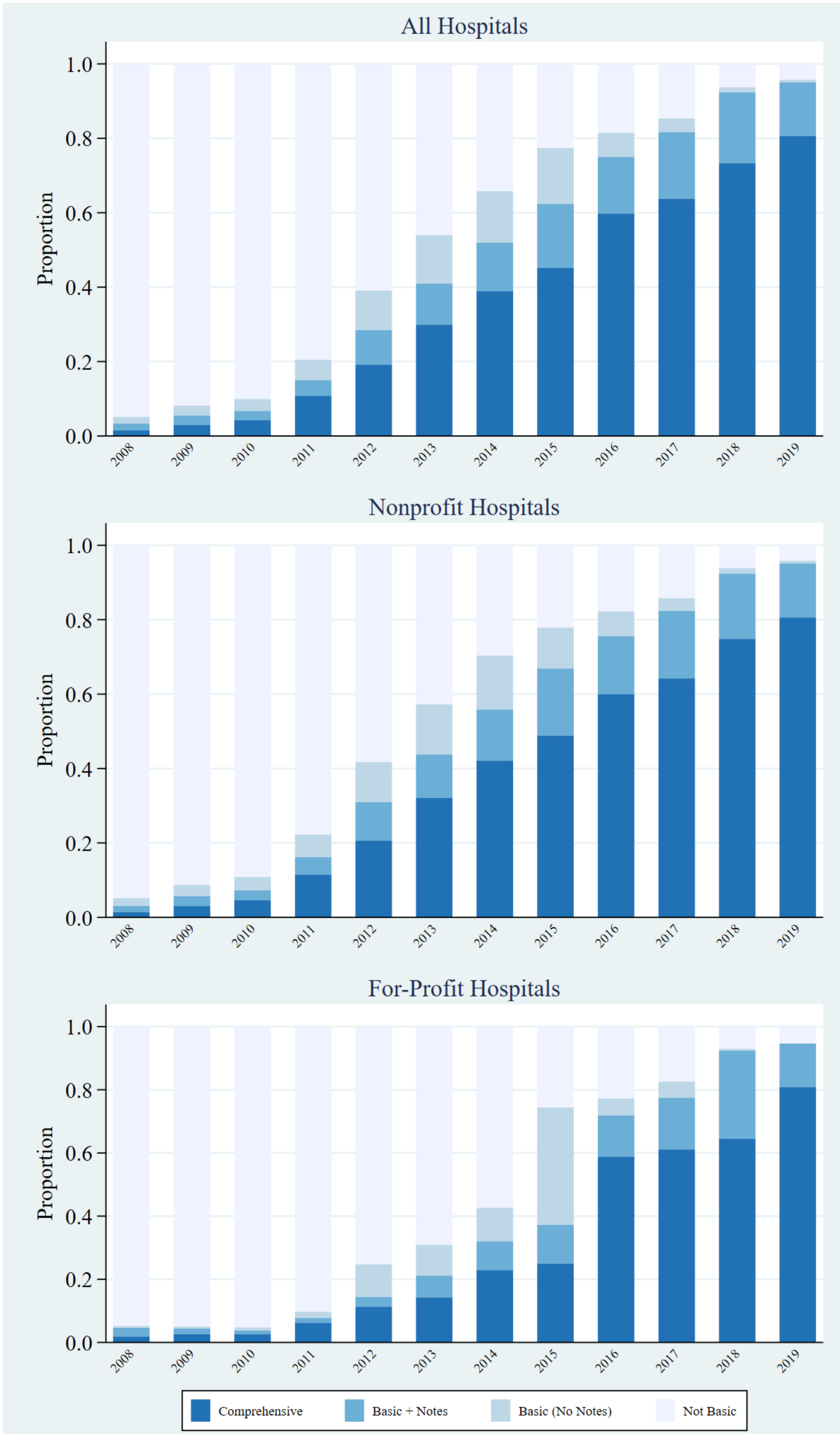
Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. AME = average marginal effects from a logit regression for the EHR classification. SE = standard errors (accounting for clustering at the Health Service Area). OR = odds ratio from an ordered logit regression. Each regression model includes all the hospital and county characteristics shown in Table 2, Health Service Area (HSA) fixed effects, and year fixed effects. Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01

Table 7: Percent of EHR Functionalities by Ownership Type: Alternative Annual HHI Measure

	All 26 Functionalities	Results Viewing	Clinical Documentation	Decision Support	Order Entry
	B / SE	**B / SE**	**B / SE**	**B / SE**	**B / SE**
All Hospitals (N=24,235)					
Hospital HHI (1000s): Lagged Annual Adm.	-0.003	-0.003	-0.004	-0.003	-0.002
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)
Nonprofit Hospitals (N=20,516)					
Hospital HHI (1000s): Lagged Annual Adm.	-0.002	-0.002	-0.004	-0.002	-0.003
	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
For-Profit Hospitals (N=3,110)					
Hospital HHI (1000s): Lagged Annual Adm.	-0.001	0.010	0.005	-0.018	-0.013
	(0.018)	(0.023)	(0.022)	(0.024)	(0.017)

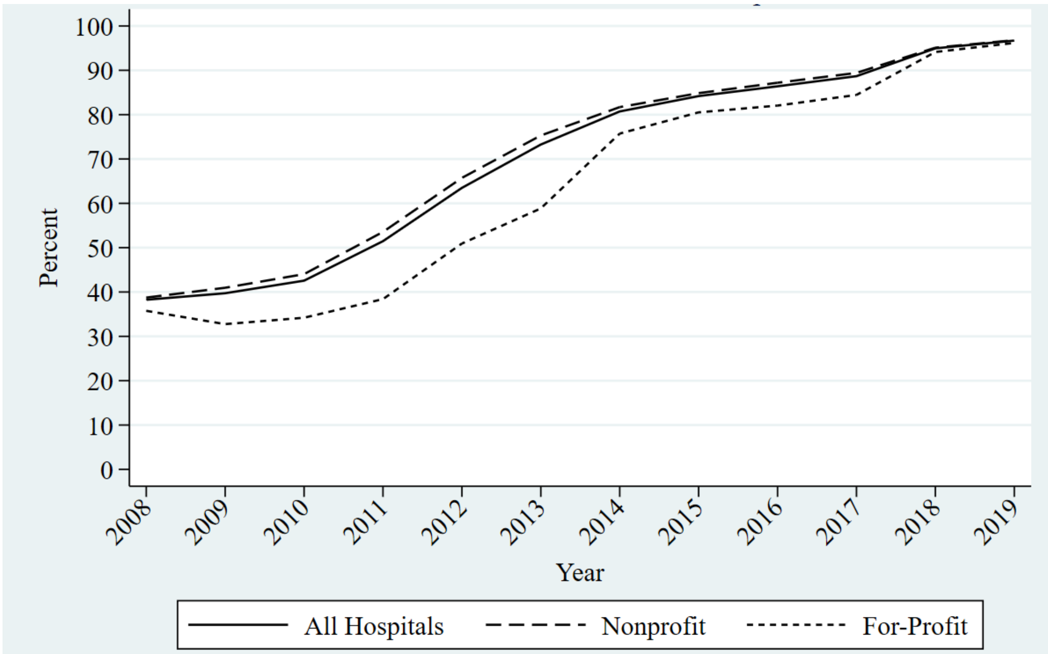
Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. B = Coefficient from OLS regression for the percentage of a given set of functionalities adopted in the EHR system. SE = standard errors (accounting for clustering at the Health Service Area). Each regression model includes all the hospital and county characteristics shown in Table 3, Health Service Area (HSA) fixed effects, and year fixed effects. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Distribution of ONC EHR Adoption Classification Levels Over Time



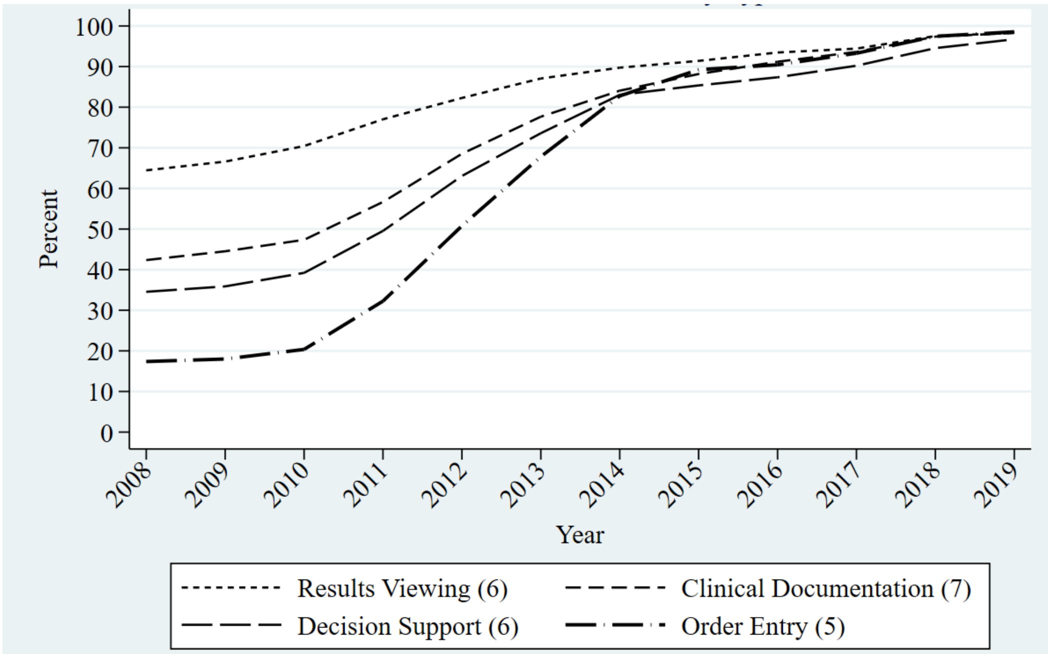
Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. ONC = Office of the National Coordinator for Health Information Technology. EHR = Electronic Health Record.

Figure 2: Percent of Potential 26 EHR Functionalities Adopted Over Time



Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. EHR = Electronic Health Record.

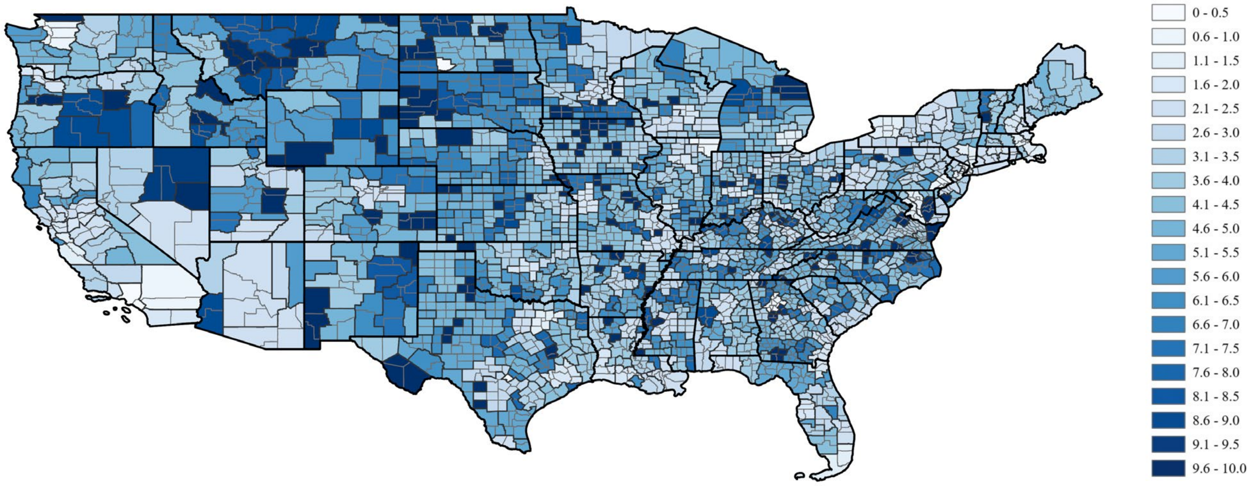
Figure 3: Percent of Potential EHR Functionalities Adopted by Type Over Time



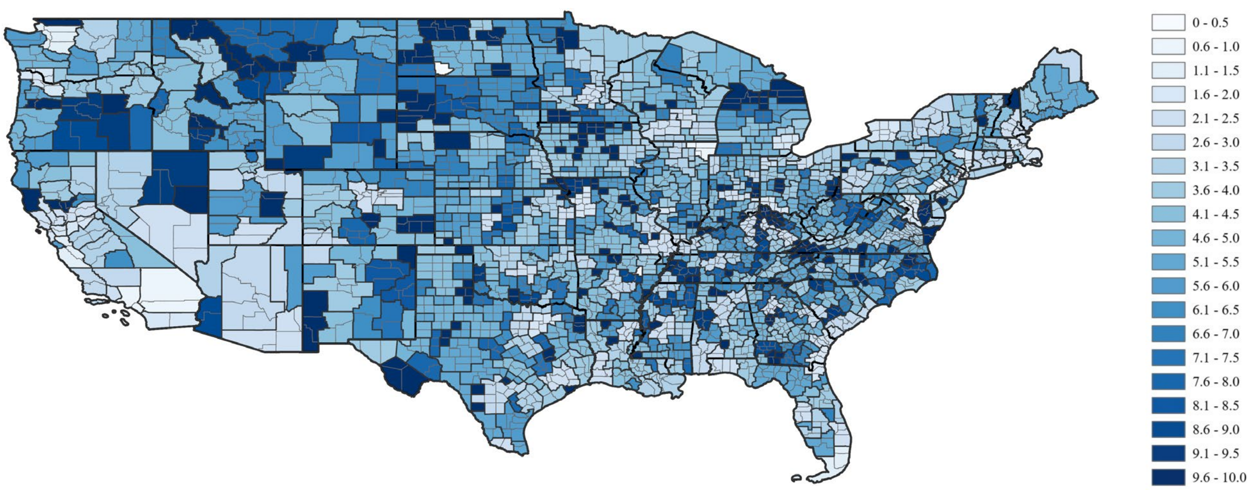
Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. EHR = Electronic Health Record.

Figure 4: Hospital Market HHIs for HSAs in the U.S.

2008:

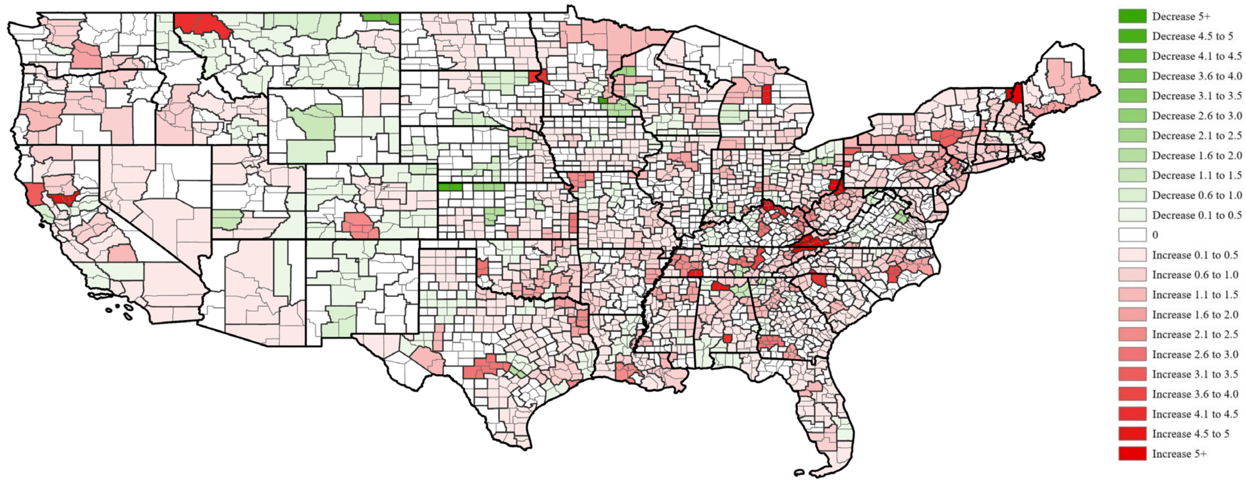


2019:



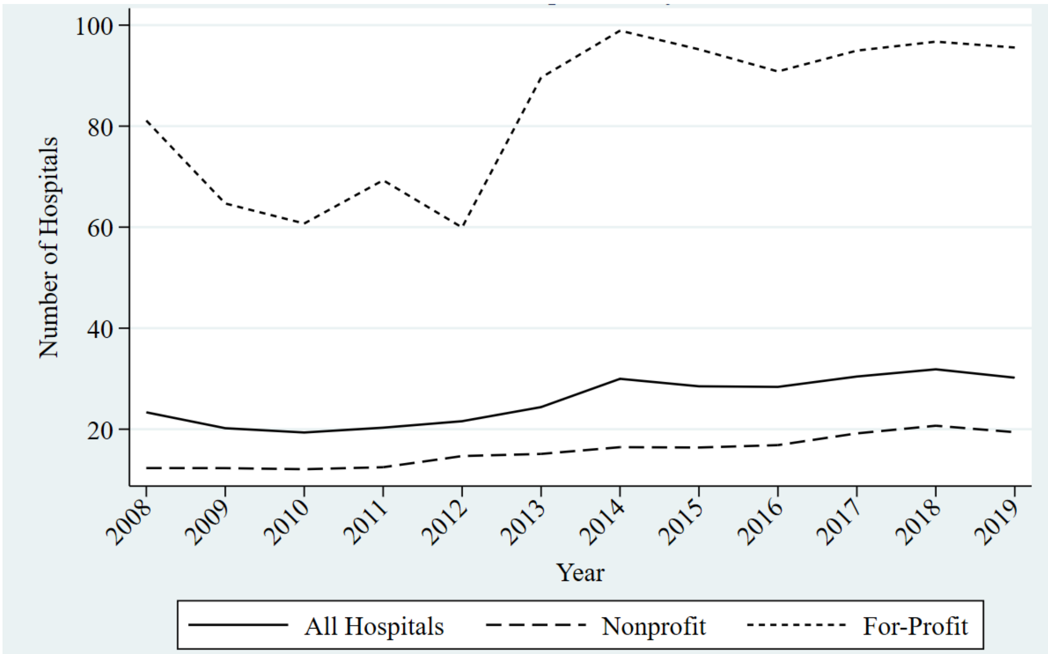
Notes: HHI = Herfindahl-Hirschman Index. HSA = Health Service Area. Market shares to calculate the HHIs incorporate each hospital ownership system's static number of admissions in the HSA over the entire period (rather than the specific year). County borders are shown as the thinner line, HSA borders are shown as the medium width line, and state borders are shown as the thicker line.

Figure 5: Change in Hospital Market HHIs for HSAs in the U.S. from 2008 to 2019



Notes: HHI = Herfindahl-Hirschman Index. HSA = Health Service Area. Market shares to calculate the HHIs incorporate each hospital ownership system's static number of admissions in the HSA over the entire period (rather than the specific year). County borders are shown as the thinner line, HSA borders are shown as the medium width line, and state borders are shown as the thicker line.

Figure 6: Mean Number of Hospitals in System Over Time



Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement.

Appendix Table 1: Analysis of Respondents to the AHA IT Supplement

	Respondents to the IT Supplement		Non-Respondents to the IT Supplement		Logit Model for Odds of Responding	
	Mean	**SD**	**Mean**	**SD**	**AME**	**SE**
Hospital HHI (1000s): Lagged Static Adm.	3.683	2.110	3.726	2.187	-0.003	(0.003)
Log of Number of Hospitals in System	1.965	1.684	2.162	1.766	-0.005	(0.003)
Ownership: For-Profit, Investor-Owned	0.152	0.359	0.305	0.461	-0.137***	(0.014)
Size: 25-49 Beds	0.170	0.375	0.206	0.404	0.017	(0.017)
Size: 50-99 Beds	0.151	0.358	0.178	0.382	0.032**	(0.018)
Size: 100-199 Beds	0.228	0.420	0.247	0.431	0.067***	(0.018)
Size: 200-299 Beds	0.146	0.353	0.124	0.330	0.109***	(0.020)
Size: 300-399 Beds	0.094	0.292	0.067	0.250	0.134***	(0.023)
Size: 400-499 Beds	0.050	0.219	0.031	0.173	0.162***	(0.026)
Size: 500 or More Beds	0.082	0.274	0.041	0.198	0.180***	(0.027)
Teaching Hospital (ACGME)	0.313	0.464	0.214	0.410	0.029***	(0.012)
Certified Trauma Center	0.490	0.500	0.343	0.475	0.085***	(0.010)
County's Percent Age 65+	15.734	4.213	15.729	4.432	-0.001	(0.002)
County's Percent Not White Non-Hispanic	28.410	21.516	31.631	22.294	-0.002***	(0.000)
County's Percent with 4+ Years College	27.165	10.654	25.554	10.599	0.001	(0.001)
County's Per Capita Income ($1000s)	43.720	13.280	42.413	12.985	-0.001*	(0.001)
County's Percent in Poverty	14.758	5.308	15.774	5.605	-0.003***	(0.001)
County's Percent Uninsured	13.422	6.005	14.794	6.279	0.000	(0.001)
County's Physicians Per 1,000 Capita	2.198	1.830	1.940	1.565	0.007	(0.005)
County Has a Federally Qualified Health Center	0.740	0.439	0.760	0.427	-0.039***	(0.012)
Year 2009	0.091	0.288	0.070	0.256	0.075*	(0.012)
Year 2010	0.085	0.279	0.082	0.275	0.030**	(0.012)
Year 2011	0.076	0.265	0.099	0.298	-0.032***	(0.015)
Year 2012	0.084	0.27	0.086	0.280	0.026*	(0.013)
Year 2013	0.079	0.270	0.093	0.291	-0.006	(0.015)
Year 2014	0.080	0.271	0.089	0.285	0.004	(0.016)
Year 2015	0.083	0.276	0.081	0.274	0.035*	(0.019)
Year 2016	0.087	0.281	0.077	0.267	0.057***	(0.019)
Year 2017	0.085	0.280	0.079	0.269	0.048**	(0.020)
Year 2018	0.086	0.280	0.076	0.265	0.058***	(0.019)
Year 2019	0.082	0.274	0.080	0.272	0.034	(0.021)
Observations	25,312		15,019		40,331	

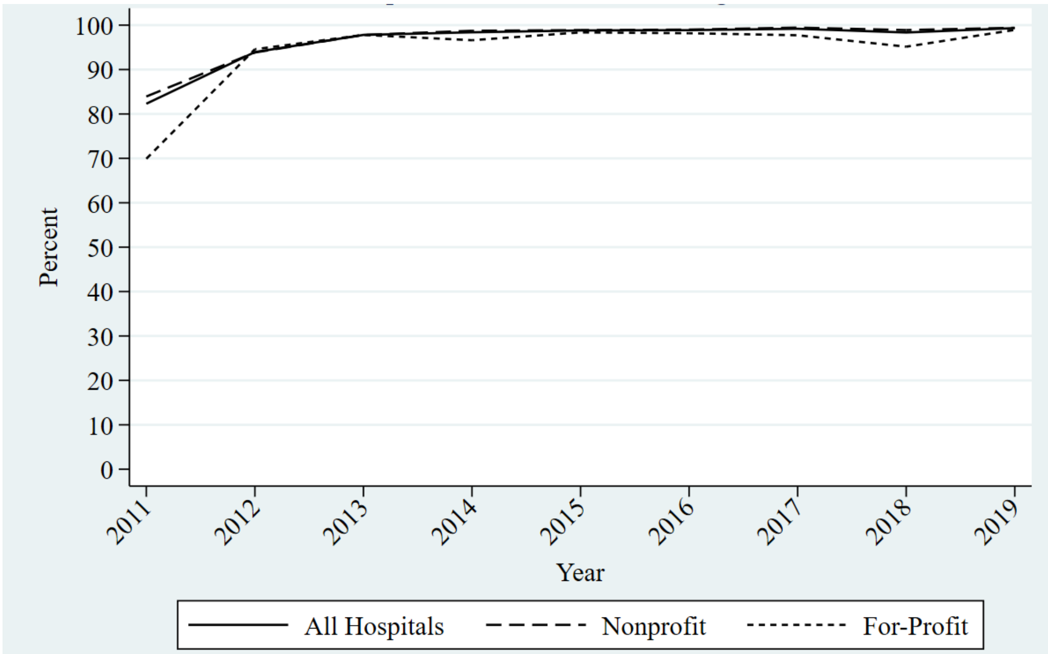
Notes: Sample is the 2008-2019 American Hospital Association (AHA) Annual Survey (not restricted to IT Supplement respondents or to the common estimation sample presented in the other tables). SD = standard deviation. AME = average marginal effects from a logit regression for hospital response to the IT Supplement questionnaire. SE = standard errors. (These models do not include HSA fixed effects.) The base year for the time indicators is 2008.

Appendix Table 2: Likelihood that Hospital/Year's EHR is Certified as Meeting Meaningful Use

	AME / SE
Hospital HHI (1000s): Lagged Static Admissions	-0.003
	(0.045)
Log of Number of Hospitals in System	-0.012***
	(0.004)
Ownership: For-Profit Investor-Owned	-0.030
	(0.021)
Size: 25-49 Beds	0.022
	(0.022)
Size: 50-99 Beds	0.041*
	(0.023)
Size: 100-199 Beds	0.053**
	(0.021)
Size: 200-299 Beds	0.057**
	(0.025)
Size: 300-399 Beds	0.072**
	(0.028)
Size: 400-499 Beds	0.133***
	(0.039)
Size: 500 or More Beds	0.075**
	(0.035)
Teaching Hospital (ACGME)	0.009
	(0.022)
Certified Trauma Center	-0.001
	(0.014)
County's Percent Age 65+	-0.006**
	(0.003)
County's Percent Not White Non-Hispanic	-0.000
	(0.001)
County's Percent with 4+ Years College	0.001
	(0.001)
County's Per Capita Income ($1000s)	0.001
	(0.001)
County's Percent in Poverty	0.000
	(0.002)
County's Percent Uninsured	0.002
	(0.004)
County's Physicians Per 1000 Capita	-0.007*
	(0.004)
County Has a Federally Qualified Health Center	-0.027
	(0.017)
Year 2012	0.211***
	(0.021)
Year 2013	0.286***
	(0.019)
Year 2014	0.300***
	(0.021)
Observations	4,328

Notes: Sample is the 2011-2014 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. AME = average marginal effects from a logit regression for certified meaningful use. (This variable was added to the AHA IT Supplement in 2011 but has little variation after 2014.) SE = standard errors (accounting for clustering at the Health Service Area). The regression model includes Health Service Area (HSA) fixed effects. The base year for the time indicators is 2011. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

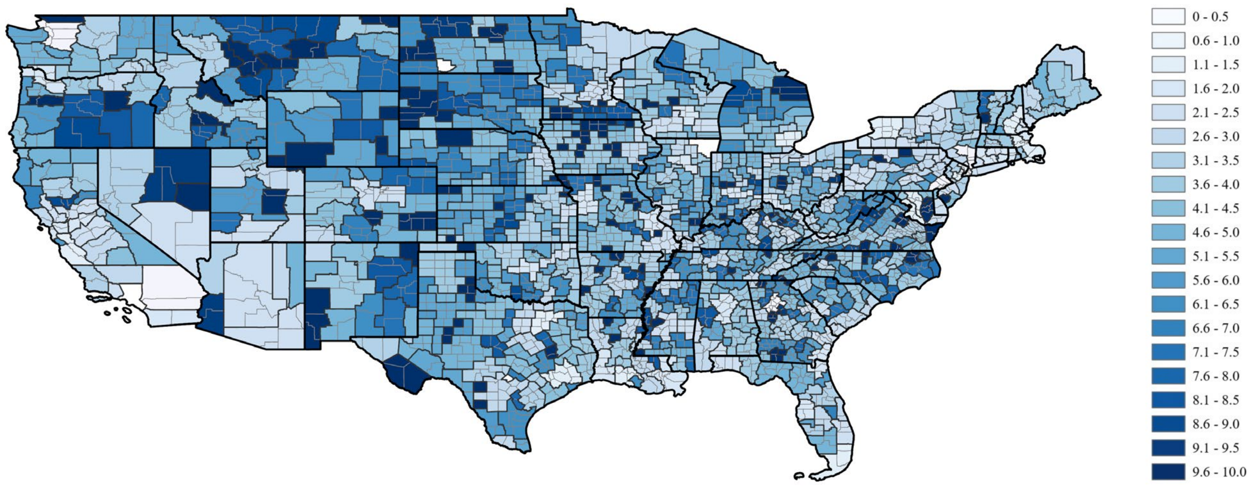
Appendix Figure 1: Hospital's EHR is Certified as Meeting Meaningful Use Over Time



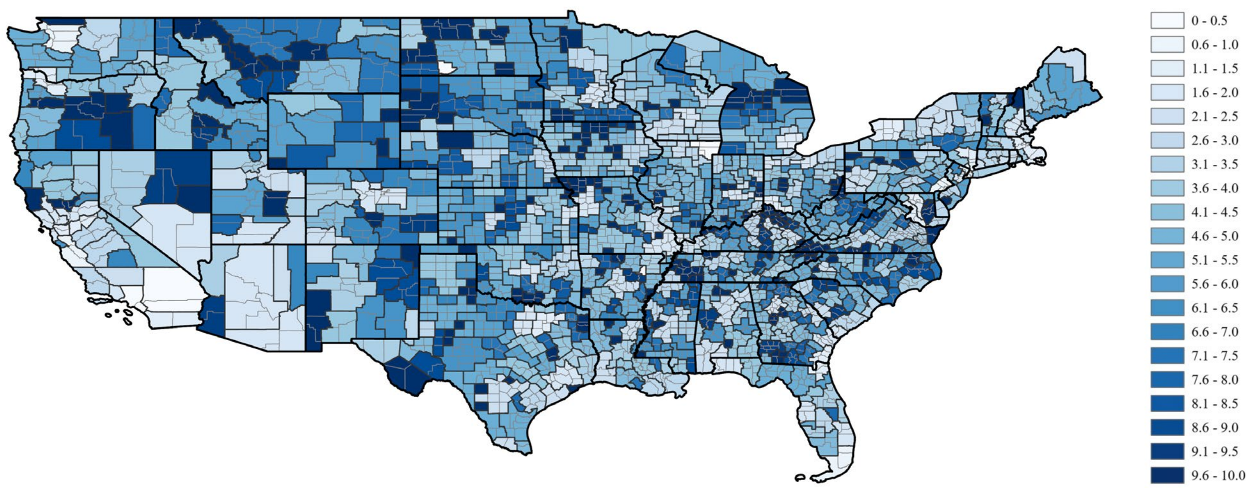
Notes: Sample is the 2011-2019 American Hospital Association (AHA) Annual Survey and the AHA's IT Supplement. (This variable for certified meaningful use was added to the AHA IT Supplement in 2011.) EHR = Electronic Health Record.

Appendix Figure 2: Hospital Market HHIs for HSAs in the U.S.: Annual Admissions Measures

2008:

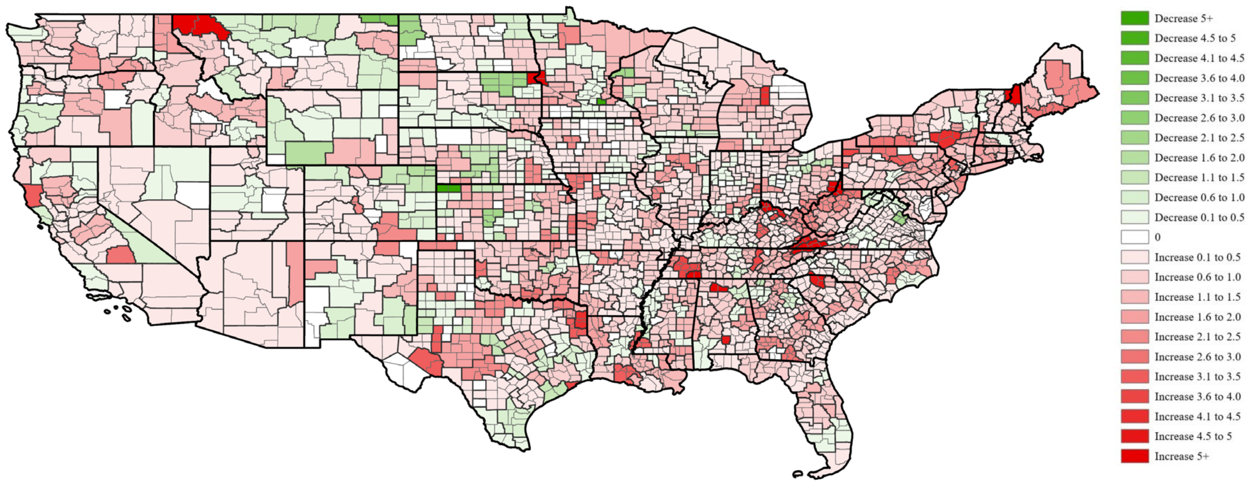


2019:



Notes: HHI = Herfindahl-Hirschman Index. HSA = Health Service Area. Market shares to calculate the HHIs incorporate each hospital ownership system's number of admissions in the HSA in the specific year (rather than over the entire period). County borders are shown as the thinner line, HSA borders are shown as the medium width line, and state borders are shown as the thicker line.

Appendix Figure 3: Change in Hospital HHIs for HSAs from 2008 to 2019: Annual Measures



Notes: HHI = Herfindahl-Hirschman Index. HSA = Health Service Area. Market shares to calculate the HHIs incorporate each hospital ownership system's number of admissions in the HSA in the specific year (rather than over the entire period). County borders are shown as the thinner line, HSA borders are shown as the medium width line, and state borders are shown as the thicker line.