Health IT Diffusion and Physician Density

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Abstract

This paper examines how the diffusion of advanced health information technology (HIT) affects the density of hospital-based (HB) physicians. Leveraging sharp county-level increases in HIT adoption driven by federal incentives, we compare physician density per 100k population in counties with rapid diffusion (treatment group) to those with slower or no uptake during our sample period (control group). Using an event-study framework, we find that HIT diffusion led to a 11.1% increase in the HB physician rate in treated counties relative to control counties, and medical and surgical specialties account for most of the increase. Moreover, the growth in HB physician density is evident, absent major consolidation activities, and contributes to overall growth in total physicians. This growth is concentrated among early-career physicians and in physician shortage areas. Mechanism tests suggest that physicians benefit financially from practicing in treated counties, with higher Medicare reimbursement and hospital profits. Outpatient surgeries rise most in counties with moderate pre-period care utilization. Various robustness checks support our results. Our findings suggest that strategic HIT investments can attract physicians, expand care capacity, and reduce geographic disparities in health care access.

Keywords: health information technology, hospital-based physicians, aggregate physician density, financial incentives, health care utilization

JEL Codes: I11, J44, O33

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1 Introduction

The rapid advancement of digital technologies has significantly reshaped industries across the economy. Health Information Technology (HIT), in particular, has emerged as a critical lever for improving the practice of medicine. The federal government has invested over $20 billions in promoting HIT adoption, mainly through the Health Information Technology for Economic and Clinical Health (HITECH) Act (CMS, 2018a). While much research has examined how HIT impacts the quality and cost of care, its effect on the density of working physicians—the key players in care provision and primary users of the new technology—remains far less understood. As hospitals and healthcare providers increasingly invest in HIT infrastructure, partly in response to competitive pressures and the "medical arms race" to modernize care environments, understanding these labor market dynamics becomes crucial. This paper aims to fill this gap by examining how the diffusion of hospital HIT affects the density of local physicians at the county level.

We focus on HIT diffusion in hospital care, particularly the adoption of Computerized Provider Order Entry (CPOE), an advanced HIT system that enables physicians to electronically enter treatment orders, integrate patient data and clinical guidelines, and communicate with pharmacy, laboratory, and other departments (Dranove et al., 2014). In contrast, basic HIT systems, such as clinical data repositories or clinical decision systems, store patient data in computerized databases and provide clinical treatment recommendations or alerts based on patient data and clinical guidelines (Agha, 2014), but lack CPOE's deeper automation and integration capabilities (Lu et al., 2018). Industry analyses typically consider advanced HIT as representing the final stage of HIT adoption (HIMSS, 2011). While CPOE may affect physicians' decisions on care volume and practice location, the latter remains understudied despite its direct relevance to persistent physician shortages.

We examine how the density of hospital-based (HB) physicians—those employed under contract with hospitals to provide direct patient care—is affected by the diffusion of hospital CPOE at the county level. Physicians may be drawn to areas with high HIT adoption or from non-hospital settings with expanded firm boundary (McCullough et al., 2010), particularly as HIT appears to be most beneficial to more complex patients whose diagnoses require cross-specialty care coordination (McCullough et al., 2016). However, the learning costs and workflow changes associated with HIT adoption, especially during the transitioning phase, could also pose deterrents for some physicians. The net effect of HIT diffusion on the density of physicians, particularly across specialties, settings, physician career stages, and geographic locations, is ex-ante *ambiguous*.

We base our main analysis on an event-study approach à la East et al. (2023), leveraging the sharp increase in adoption rates to separate the sample into treatment and control groups. Our key outcome measure is physician density, defined as HB physician counts per 100k population at the county level. We analyze the change in HB physicians over time in counties with rapid HIT diffusion relative to that in the comparison group. The event-study design allows us to test for the presence of pre-existing, confounding factors that might affect HB physician density or the timing and level of HIT adoption. To mitigate potential bias from the standard difference-in-differences (DiD) model with two-way fixed effects (TWFE), we use the staggered DiD estimator à la De Chaisemartin and d'Haultfoeuille (2024) as our main estimator, and we demonstrate robustness using other recent DiD estimators (à la Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

Using a novel dataset we constructed from multiple sources, we find that counties with rapid HIT diffusion experienced an average 11.1% increase in HB physicians per 100k population relative to control counties during 2005-2017. Medical and surgical specialties account for most of this growth, likely benefiting from HIT-enabled access to complex diagnostic data, coordinated care, and efficient scheduling. This growth is further concentrated among early-career physicians and in Health Professional Shortage Areas (HPSAs). These results suggest that, given the same increase in HIT adoption, physicians (especially younger ones) may be more likely to consider practicing in underserved areas where greater opportunities and benefits exist. Additional analyses reveal that HB physicians in treated counties receive higher Medicare-allowed payments and perform more Medicare services compared to those in control counties after HIT adoption, potentially due to quicker service provision and more convenient ordering processes. Furthermore, we find that hospitals in areas with rapid HIT diffusion exhibit higher average profits, indicating greater financial stability that may allow more future HB physician hires.

A potential threat to identification would arise if HIT diffusion is correlated with unobservable county characteristics that also affect aggregate HB physician location choices. For instance, hospitals in counties with better IT infrastructure may adopt HIT more rapidly due to complementarities with the local IT environment (Dranove et al., 2014) and attract more physicians, especially those who prefer and have experience using digital technologies. To address this concern, we control for an extensive set of county characteristics and various fixed effects. Importantly, the absence of differential pre-trends in HB physician density between treated and control counties supports our

identifying assumption. In addition, the rapid diffusion of HIT was likely driven by the HITECH Act and several HIT-relevant indirect incentives under the Affordable Care Act (ACA), both of which tie payments to hospitals for HIT adoption. These large regulatory programs provide policy-driven incentives that help mitigate concerns about endogenous HIT diffusion.

Another potential concern is that our findings may simply reflect employment reclassification of previously non-HB physicians due to consolidation activities. Large health systems that often adopt HIT early (Agha, 2014) may simultaneously expand the physician workforce through mergers and acquisitions (M&As) or vertical integrations (VIs) to attract more patients (Baker et al., 2016). In this case, the increasing HB physicians would be mainly driven by "expanding firm boundaries" (McCullough and Snir, 2010) rather than a true expansion of HB physician workforce. To address this concern, we first estimate the effect of HIT diffusion on total physicians and compare it with that on HB physicians. The finding of greater increase in total physicians suggests evidence of a net increase in HB physicians as a result of HIT diffusion. Additionally, we re-estimate our models excluding counties with substantial M&A or VI activities, and the results remain robust, suggesting that our results are not mainly driven by firm boundaries changes.

We then explore heterogeneity by prior utilization level and examine the HIT implications for subsequent downstream patient care, measured by inpatient and outpatient surgery volumes. Splitting the sample into tertiles by pre-period utilization levels, we find that treated counties in the middle tertile exhibit notable increases in outpatient surgical services after the rapid HIT diffusion. Those outpatient surgeries, particularly elective ones such as cosmetic surgeries and most joint replacements, significantly contribute to hospital net income,[1] which aligns with our findings of higher hospital profits in treated counties. These results suggest that higher HIT adoption allows hospitals to streamline care delivery and expand outpatient surgical capacity, boosting revenues through improved coordination and patient throughput.

We conduct extensive robustness checks and placebo tests. Placebo tests show no significant changes in physician density among groups less likely to be influenced by HIT adoption, such as physicians primarily engaged in research or teaching, those in specialties less HIT-relevant (e.g., dermatology and occupational medicine), and physicians employed by federal agencies. Our results remain robust across multiple subsamples, including counties with limited adoption variability, counties with continuous physician presence, counties without extremely large/small populations

[1] Source: https://www.hfma.org/finance-and-business-strategy/strategic-planning/hospitals-see-a-margin-advantage-as-care-migrates-to-the-outpatient-department/.

(excluding the top/bottom 10%), and balanced event studies. In addition, alternative model specifications, such as excluding state-specific time trends or county-level controls, and recent staggered DiD estimators yield consistent results. Furthermore, our results are robust to alternative definitions of HIT adoption when combining CPOE with physician documentation, another advanced HIT component. All these tests support our main results.

Our paper contributes to two strands of literature. First, our paper contributes to the literature on the impact of HIT with new evidence on the aggregate density of HB physicians and how the effects vary by specialty, career stage, shortage area status, and pre-existing health care utilization level. The impacts of HIT on care quality and financial performance have been extensively investigated. For instance, prior studies find that HIT positively affects patient health by reducing infant mortality or morbidity, mortality for most complex patients, adverse safety events, and morbidity for those with opioid-related conditions (Miller and Tucker, 2011; McCullough et al., 2016; Freedman et al., 2018; Wang, 2021). Meanwhile, HIT adoption increases the costs for Medicare patients (Agha, 2014) and initial costs to hospitals, which may decrease after 3-6 years depending on local IT intensity (Dranove et al., 2014). These mixed cost results may partly stem from large variations in HIT vendor performance (Lin and Olson, 2024).

Recent work finds that hospital HIT adoption can increase exit rates (via retirement) or shifts to office-based practice among hospitalists, particularly older physicians (Glenn, 2024).[2] Like other enterprise information systems, HIT adoption entails major changes in hospital operations, so its effects on clinicians' productivity, workflow, and mobility are inherently complex. Greenwood et al. (2019) find that whether HIT complements or disrupts clinicians' work—and thus influences their stay-or-leave decisions—depends on the specific applications, individual characteristics, and organizational context.[3] Related work from nursing homes shows that HIT reduces nurses in high-end facilities but increases them in low-end ones, with little net effect overall (Lu et al., 2018). We extend this literature by examining how advanced HIT diffusion affects local physician density across broader specialties and practice settings, which is directly relevant to patient access to care.

Second, our study complements the broad literature on physician labor supply, most of which

[2]The author defines hospitalists as any general practice physicians (either under full hospital employment or internists that contract services to hospitals) who see 70% or more of their patients within a hospital setting.

[3]Their study, based on Florida hospitals between 2000-2010, predates the rapid nationwide diffusion of advanced HIT. Their finding that basic HIT components improved physician retention may be consistent with our interpretation, since HIT's benefits typically emerge after a learning period (Bronsoler et al., 2022). Our sample period covers the rapid nationwide diffusion of advanced HIT, which parallels their setting when basic HIT became widely adopted.

focuses on how much care physicians provide in response to policy shocks. For instance, a strand of literature examines how physicians adapt to policy interventions—such as new or expanding insurance programs—regarding care provision (Baker and Royalty, 2000; Garthwaite, 2012; Buchmueller et al., 2016; Neprash et al., 2018; Curto and Bhole, 2022). However, the supply of medical services also hinges on the density of working physicians, which has been understudied but is highly relevant to the challenge of medical professional shortage.[4] A growing literature explores this dimension by studying how physicians select practice locations in response to insurance program expansions, student loan forgiveness programs, or physician subsidies for HPSAs (Falcettoni, 2018; Kulka and McWeeny, 2018; Huh, 2021; Huh and Lin, 2024; Khoury et al., 2024). We contribute to work on aggregate physician distribution and density from a technological angle, which combines market-driven incentives and policy-led changes in the past decades. Building on this literature, we exploit plausibly exogenous variation in HIT on physician distribution to understand the effects of digital technologies on physicians, hospitals, and patient care provisions.

Our paper has broad policy implications and relevant insights for managerial practices. As HIT investment continues to grow globally (Wang and Bloch, 2023), our findings show how these investments can improve health care workforce efficiency and expand access to care while sustaining providers' financial health. For hospital administrators, HIT has the potential to ease administrative burdens in cross-department coordination and to serve as a competitive strategy to attract and retain physicians. For policy makers, understanding the dynamics between digital technology and physician density can improve policy design on workforce sustainability and equitable care access. For instance, targeted HIT investments may attract early-career physicians to underserved areas, potentially reducing geographic disparities in health care access and improving local prosperity.

This paper proceeds as follows. Section 2 describes the institutional background. Section 3 discusses the data and summary statistics. Section 4 details the empirical strategy. Section 5 presents the results. Section 6 concludes the paper.

[4] Some related studies classify the volume of care provided as the intensive margin and the number of working physicians as the extensive margin in physician labor supply decisions.

2 Background

2.1 The Diffusion of HIT: Policy Background

Electronic health records (EHRs)—the central component of HIT—were invented in the 1970s but saw limited adoption until the 2000s.[5] EHRs enable health care providers to store, access, retrieve, exchange, and manage patient health information electronically, replacing paper records. Initially, hospitals employed a best-of-breed approach, selecting specialized vendors by each department for specific needs. However, this fragmented IT structure led to increased patient safety risks, inefficiencies, and provider frustration. The growing demand for care coordination prompted a shift towards integrated IT systems, linking internal departments to improve efficiency and safety. We focus on HIT adoption in hospital care, which manages patient records on an episode-of-care basis and involves complex tests and treatments. Hospital HIT functions as an integrated enterprise system, connecting internal departments to enhance operational efficiency through various built-in tools. Although ambulatory care HIT also plays an important role, it differs substantially in design and purpose, usually serving simpler, longitudinal patient records within individual practices.[6]

The widespread adoption of hospital HIT began in the 2010s, driven by federal policy. The 2009 HITECH Act allocated approximately $30 billion to promote HIT adoption. Implemented in three stages (2011, 2014, and 2018), the program provided substantial financial incentives to healthcare providers demonstrating meaningful use (MU) of EHRs (CMS and HHS, 2012). By mid-2018, eligible hospitals received over $21 billion in incentive payments (CMS, 2018a). Since 2015, hospitals failing to adopt HIT and meet MU requirements have faced Medicare reimbursement penalties. Complementing these direct incentives, the Affordable Care Act (ACA), enacted in 2010, reinforced HIT adoption through indirect incentives. The ACA funded comparative effectiveness research using EHR-derived data (Gallego et al., 2013) and introduced initiatives such as care coordination improvements, quality tracking, and outcome-based reimbursements—all dependent on widespread EHR adoption.[7] About 40 ACA provisions are identified that either require or facilitate HIT use (Harvell et al., 2013). Together, strong government commitment and active health care sector engagement drove the rapid diffusion of hospital HIT in recent decades.

[5] See https://www.extractsystems.com/a-brief-history-of-the-emr/.

[6] See https://www.practicefusion.com/blog/emrs-hospital-vs-ambulatory-solutions/.

[7] See https://www.commonwealthfund.org/blog/2020/comparative-effectiveness-research-10-years-after-aca-where-do-we-go-here; https://www.coloradohealthinstitute.org/research/aca-10-years-innovation-data.

2.2 HIT Adoption Measures: CPOE Functionality

We use CPOE to measure advanced HIT adoption as it represents a critical module that enables providers to enter medication, laboratory, and radiology orders electronically, often includes built-in clinical decision support tools, and serves as a core component of the HIT meaningful use requirements.[8] Unlike other HIT components, CPOE directly structures patient data in ways that align with coding and billing requirements, making it particularly relevant when examining health technology adoption in contexts where payment mechanisms are important considerations (Ganju et al., 2022). As a relatively recent technology, CPOE has been studied as an important automation technology (Lu et al., 2018). Figure A1 shows a CPOE interface.

CPOE can enhance efficiency and care quality in several ways. First, by centralizing patient health information, CPOE allows physicians to access critical data when making medical orders. This capability is essential for safe and effective care, given that many non-surgical medical interventions (e.g., diagnostic tests and medication administration) begin with physician orders. Second, CPOE provides pre-programmed, institutionally-approved templates that streamline ordering and promote adherence to clinical protocols. By ensuring orders are standardized, legible, and complete, CPOE reduces the risk of lost orders—a common issue in the paper record era. Third, electronic communication through CPOE accelerates turnaround times by reducing delays in cross-department communications. For instance, CPOE can significantly reduce the time between ordering a knee X-ray and receiving test results, which previously required manual coordination with the radiology department. Fourth, CPOE eases clinicians' documentation burden by reducing redundant data entry. Importantly, when paired with clinical decision support systems, CPOE can detect potential drug–drug interactions and allergies, enhancing patient safety at the ordering stage. Finally, better record-keeping and audit trails may lower malpractice risks.

The advantages of HIT outlined above can ultimately translate into financial gains for physicians via improved efficiency, motivating physicians to seek workplaces equipped with advanced HIT. Moreover, hospitals may benefit financially from HIT adoption, enabling them to hire more physicians and enhance patient care. However, like other enterprise information systems, HIT has a steep learning curve and entails substantial fixed costs. Anecdotal evidence suggests that CPOE implementation can disrupt clinician workflow, especially during the early stages, requiring major adjustments and the re-establishment of routines. Thus, it remains uncertain whether physicians,

[8] See https://www.healthit.gov/faq/what-computerized-provider-order-entry.

across varying levels of IT proficiency and specialties, are willing to practice in and adapt to a highly digitized work environment. The trade-off between potential long-term efficiency gains and short-term adaptation costs may affect which types of physicians are drawn to such environments.

2.3 Aggregate Physician Density: Conceptual Considerations

Local density of physicians is shaped by individual location choices and broader market dynamics. We study how the rapid diffusion of HIT impacts HB physician density at the county level across broad specialties, acknowledging that aggregate changes may reflect new entries or relocation, as well as compositional shifts, including hiring more junior physicians after a senior physician retires or exits. Thus, aggregate physician density may increase even when individual location decisions vary, as hospitals adjust staffing patterns in response to technological adoption, evolving patient needs, and existing workforce composition.

From hospitals' perspective, HIT adoption may influence physician rates through strategic staffing decisions driven by revenue and operational considerations. Hospitals that invest in HIT may try to maximize returns by hiring physicians who can fully leverage the technology, particularly in markets with moderate but growing demand for medical services. In highly saturated areas, additional physician hires may yield diminishing returns, while in low-demand areas, patient volumes may be insufficient to justify staff expansion. HIT may improve care delivery efficiency by increasing patient throughput, boosting revenue, and enabling hospitals to attract and retain high-quality physicians in shortage areas to meet excess care demand.

From physicians' perspectives, responses to local HIT diffusion may vary by specialty, career stage, and comfort with technology. Physician location decisions are often shaped by financial incentives, local amenities, proximity to medical training sites, and policy-driven factors such as tort reforms and Medicaid expansions (Kulka and McWeeny, 2018; Khoury et al., 2024; Kessler et al., 2005; Malani and Reif, 2015; Huh, 2021; Huh and Lin, 2024). HIT may serve as a pull factor for physicians, particularly early-career ones more adaptable to digital environments, by boosting care efficiency and enhancing earnings. In contrast, physicians less comfortable with digital technology may be discouraged by the demands of practicing in HIT-intensive environments.

From the patients' perspective, HIT adoption can influence healthcare utilization by making access to services more convenient and timely. By streamlining scheduling, facilitating faster bookings, and improving care coordination, HIT may encourage patients to seek elective procedures

earlier and more easily, boosting local demand for physician services. While patients may prefer hospitals with advanced HIT capabilities, our county-level aggregation mitigates concerns about patient sorting. Ultimately, these demand-side responses may complement hospital and physician supply adjustments, reinforcing changes in aggregate local physician density.

Collectively, these perspectives suggest that HIT diffusion affects physician density through interconnected channels involving hospital staffing, physician preferences, and patient utilization. In Section 5, we first analyze how HIT affects local HB physician density, then explore potential mechanisms related to providers' financial performance, followed by changes in care utilization.

3 Data and Summary Statistics

3.1 Data Sources and Variable Definitions

Physician Density Data: Our primary dataset is the Area Health Resources Files (AHRF) (AHRF, 2018), which aggregates information from over 50 sources on health professionals, healthcare utilization, facilities, and demographic characteristics at various geographic levels. We focus on hospital-based (HB) physicians, defined as non-federal doctors of medicine (MDs) employed full-time under contract with hospitals, providing direct patient care focused on physical health.[9] Our main outcome is the county-year level HB physicians per 100k population.[10] To isolate physicians likely affected by HIT adoption, we exclude specialties with limited HIT relevance: such as Aerospace Medicine, Dermatology, Forensic Pathology, Medical Genetics, Nuclear Medicine, Occupational Medicine, Pathology (Anatomic/Clinical), Physical Medicine/Rehabilitation, and Public Health/Preventive Medicine.[11] These excluded specialties are grouped and analyzed in a placebo test (Section 5.1).

[9] We focus on physical care, where treatment processes and outcomes are relatively standardized and comparable. Our definition of HB physicians includes hospital residents, defined as physicians "in supervised practice of medicine among patients in a hospital or in its outpatient department with continued instruction in the science and art of medicine by the staff of the facility" (AHRF, 2018). Non-federal physicians are those not employed by federal agencies, such as the Army, Navy, Air Force, Veterans Administration, or the Public Health Service. Given their distinct employment structure, federal physicians are expected not to be influenced by HIT adoption, serving as a falsification test (Section 5.1).

[10] We use physician counts per 100k population à la Chen and Roth (2024), who recommend converting outcomes in per capita units. While Poisson regression could address zero values, the modern DiD estimators are more suitable for models based on linear regressions. As a robustness check, we re-estimate the main specifications excluding counties that ever had zero HB physicians during our sample periods, finding similar results (Section 5.7).

[11] The excluded specialties were selected based on discussions with physicians and medical school faculty. We especially thank Dr. Keith Joiner for his valuable insights.

The AHRF provides data on physician characteristics, including age, self-designated specialty, and professional activity. We categorize physicians into career stages by age: early-career (under 45), mid-career (45–64), and late-career (65+).[12] Specialties fall into four broad categories: medical specialties, surgical specialties, total general practice (GP), and other specialties. Table A1 lists detailed underlying specialties within each category. In addition, physician activities are classified into patient care and non-patient care (e.g., research, teaching, and administration). Since non-patient care roles involve less HIT interaction, these physicians serve as another placebo test.

Finally, the AHRF provides rich county-level demographic and healthcare utilization data, which we use as controls. Demographic variables include the percentage of the population aged 65 and older, poverty rate, income per capita, Medicare Advantage penetration rate, percentage of Medicaid eligibles, and educational attainment (percentage with at least a college degree). We use the 2005 values of these variables and interact them with a linear time trend to capture time variation while mitigating potential endogeneity from HIT diffusion à la Dranove et al. (2014). For utilization, we focus on total inpatient and outpatient surgical operations at hospitals, supplemented by outpatient visits and Medicare inpatient discharges.[13]

HIT Adoption Data: The Healthcare Information and Management Systems Society (HIMSS) Analytics Database provides comprehensive coverage of demographic and automation information for most US hospitals and affiliated non-hospital care facilities, including ambulatory care centers, sub-acute care facilities, and home healthcare providers. A hospital is considered to have adopted HIT when CPOE is live and operational within the organization. We construct the county-year level HIT adoption rate by dividing the total number of beds in adopting hospitals by the total number of hospital beds in the county. This measure represents a weighted average adoption rate, adjusting for hospital bed size across local facilities.[14] Our one-year lagged CPOE data span 2005–2017, a period marked by rapid US HIT adoption, as shown in Figure 1. The left panel of the figure plots the average county-level adoption rate, starting below 0.5% in 2005 and exceeding 85% by 2017. Table A2 provides year-by-year adoption rates, highlighting the magnitude of this nationwide diffusion.

Following the general strategy developed in East et al. (2023), we divide the sample into treat-

[12] AHRF reports physician age groups as: $\leq$35, 35-44, 45-54, 55-64, 65-74, and $\geq$75. We use 45 and 65 as cutoffs to reflect typical physician career stages, with each stage comprising 34.3%, 51.7%, and 14.0% of physicians.

[13] The measures of surgical operations and outpatient visits are aggregated across the entire population, including Medicare and non-Medicare patients.

[14] The data include hospital addresses with zip codes. We assign county-level information using a crosswalk between zip codes and county FIPS codes. See https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

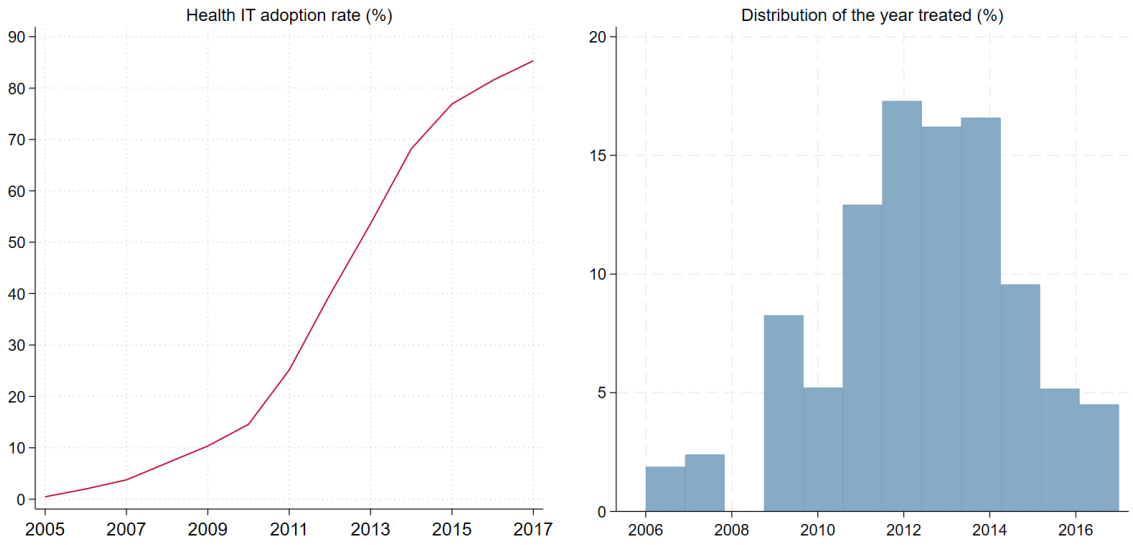


Figure 1: Health IT diffusion pattern

Notes: The figure on the left-hand side shows the average hospital-based health IT adoption rate across counties each year during our sample period. The figure on the right-hand side shows the distribution of treatment years. Outcomes in 2009 are missing in the raw AHRF dataset, so 2008 adoption cases are excluded from the histogram and our analysis, as we assume HIT adoption takes one year to materialize and influence physician supply.

ment and control groups based on sharp increases in HIT adoption rates. A county is considered treated in year τ if it experiences a *sharp jump*—the *largest* year-over-year increase in adoption during the sample period—under one of the following conditions: (i) the adoption rate rises from zero to a strictly positive value at τ; or (ii) the adoption rate, already positive at $\tau - 1$, increases by more than 100% at τ.[15] All counties meeting either criterion are classified as treated. This approach ensures that the identified sharp jump reflects a substantial change in HIT adoption—either transitioning from no adoption to some adoption or undergoing a significant expansion—so that pre- and post-adoption statuses are meaningfully distinct.

Our classification captures substantial changes in HIT adoption status for most counties (Figure 2). The figure groups counties by the number of distinct positive adoption rates observed during the sample period and plots adoption rates against year relative to treatment for each group.[16] Although adoption trajectories vary across groups, a common pattern emerges: adoption rates remain relatively flat before treatment but rise sharply afterward. We exploit both the variation in HIT

[15] As a robustness check, we apply an alternative threshold, requiring the relative increase in (ii) to exceed the sample's median increase (154%) while still representing the county's largest jump. Results remain consistent.

[16] HIT adoption rates in consecutive years are considered indistinguishable if the year-over-year change is less than 2%.

adoption between treatment and control counties and the staggered timing of adoption within the treatment group to identify the impact of HIT diffusion on HB physician density over time.

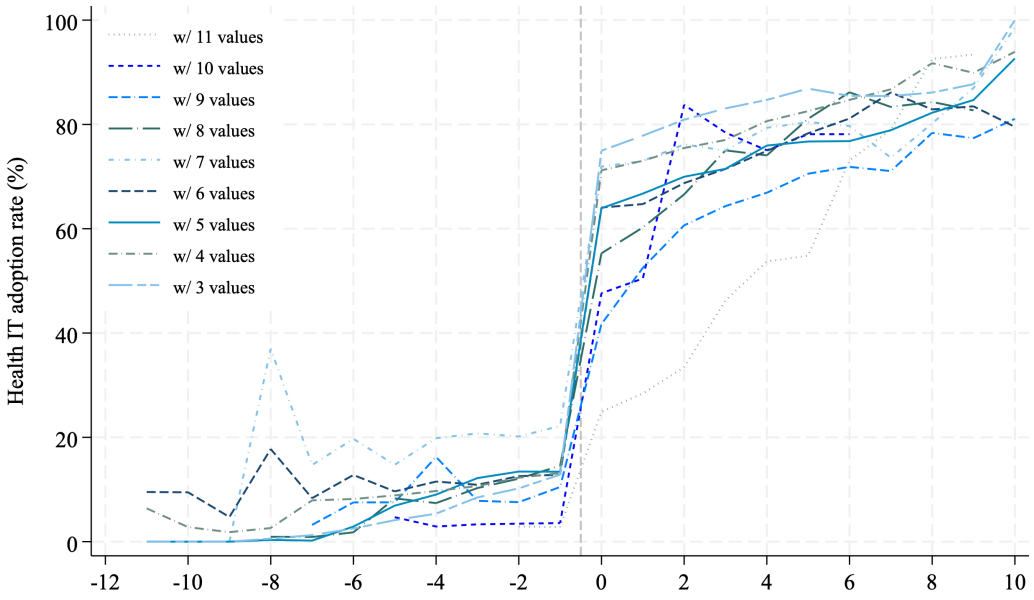


Figure 2: Health IT adoption rate relative to treatment year

Notes: Authors' calculation based on county-level HIT adoption rate over time. Different legends represent subsamples of counties encountering various values in HIT adoption rates. For example, the trend for "w/ 3 values" includes counties that experienced three distinct changes in HIT adoption rate during our sample period; since different counties encountered the three jumps at different times, we observe more than three different values in the aggregate graph. Some fluctuations occur mainly because we aggregate county-years by distinct adoption values; thus, the set of contributing counties may change over time, especially when some counties have shorter pre- or post-treatment periods.

The HIMSS database also contains information on system affiliations for hospitals and non-hospital facilities. We classify a system as having undergone: (1) a merger or acquisition (M&A) if the number of hospitals increased from the previous year, and (2) a vertical integration (VI) if the number of affiliated ambulatory care facilities increased from the previous year. Using these classifications, we identify counties that experienced "substantial" M&A or VI activities and examine whether our findings are linked to broader trends in health care consolidation.

Medicare Provider and Service Data: Our third data source is the Medicare Physician & Other Practitioners by Provider and Service dataset (CMS). From this dataset, we extract two key physician-level measures: the total allowed amounts a physician receives for treating Medicare beneficiaries and the number of Medicare services conducted by each physician. The total allowed amount includes Medicare payments, patient deductibles and coinsurance, and any third-party contributions. These measures assess whether physicians benefit financially from practicing in areas

with higher HIT adoption. Since this dataset starts in 2013, the analysis using these two measures is limited to a shorter time frame. We aggregate each measure to the county level by summing values across all HB physicians within the same county.

Market Structure and Financial Performance Data: We supplement the above datasets with the Healthcare Cost Report Information System (HCRIS), from which we obtain additional county-level controls and alternative outcome measures. The Centers for Medicare & Medicaid Services (CMS) requires Medicare-certified institutional providers to submit annual cost reports detailing provider characteristics, utilization, and financial statements. To measure hospital market concentration at the county level, we construct the Herfindahl-Hirschman Index (HHI), defined as the sum of squared market shares of all local hospitals in the county, where each hospital's market share is calculated based on its proportion of total hospital beds within the county.[17] A higher HHI indicates a more concentrated hospital market. From this dataset, we also obtain hospital-level total revenues, total costs, and profits (i.e., the difference between the two) as measures of hospital financial performance. We then compute county-level averages of these measures by averaging across all hospitals within each county.

Sample Construction. We conduct the main analyses at the county level, as our key outcome measures on physician density are only available at this level. The AHRF includes approximately 3,230 counties. After merging all datasets, our final analytical sample consists of approximately 2,394 counties for 2006-2018, excluding 2009 due to missing AHRF data. When merging datasets, we apply a one-year lag between HIT adoption and physician supply outcomes to account for physician response time, tying 2008 adoption to 2009 outcomes. The reduction in our merged sample size primarily results from missing data from HIMSS. To ensure the validity of the county-level HIT adoption rate derived from HIMSS, we compare the number of hospitals recorded in HIMSS with those in HCRIS. On average, HIMSS covers 95% of the hospitals listed in HCRIS. Given that over 96% of US hospitals participate in Medicare, we believe that the HIT adoption rates derived from the HIMSS data accurately represent the overall HIT adoption status across most counties.[18]

[17] We treat each hospital as a separate "firm." An alternative approach would define market shares at the health system level, but many large systems operate across multiple counties or regions, complicating the measurement.

[18] See https://www.aha.org/fact-sheets/2022-05-25-fact-sheet-majority-hospital-payments-dependent-medicare-or-medicaid.

3.2 Summary Statistics

Figure 3 shows the geographic distribution of HIT adoption (top panel) and HB physician density per 100k population (bottom panel) across the US at the beginning and end of our sample period. The upper panel maps reveal a drastic nationwide expansion in HIT adoption, rising from sparse uptake in 2005 to near-universal adoption of CPOE by 2017. Concurrently, HB physician density increased in several regions, with notable growth in the Northeast, Upper Midwest, and parts of the West, although the rural South and Mountain West continue to exhibit lower densities. Since many rural areas often face limited healthcare resources and provider shortages, understanding whether HIT adoption can support physician capacity is especially relevant. The substantial regional variation in both HIT adoption and physician supply suggests potential associations between these trends, motivating a more systematic analysis to determine the extent to which these patterns reflect causal relationships.

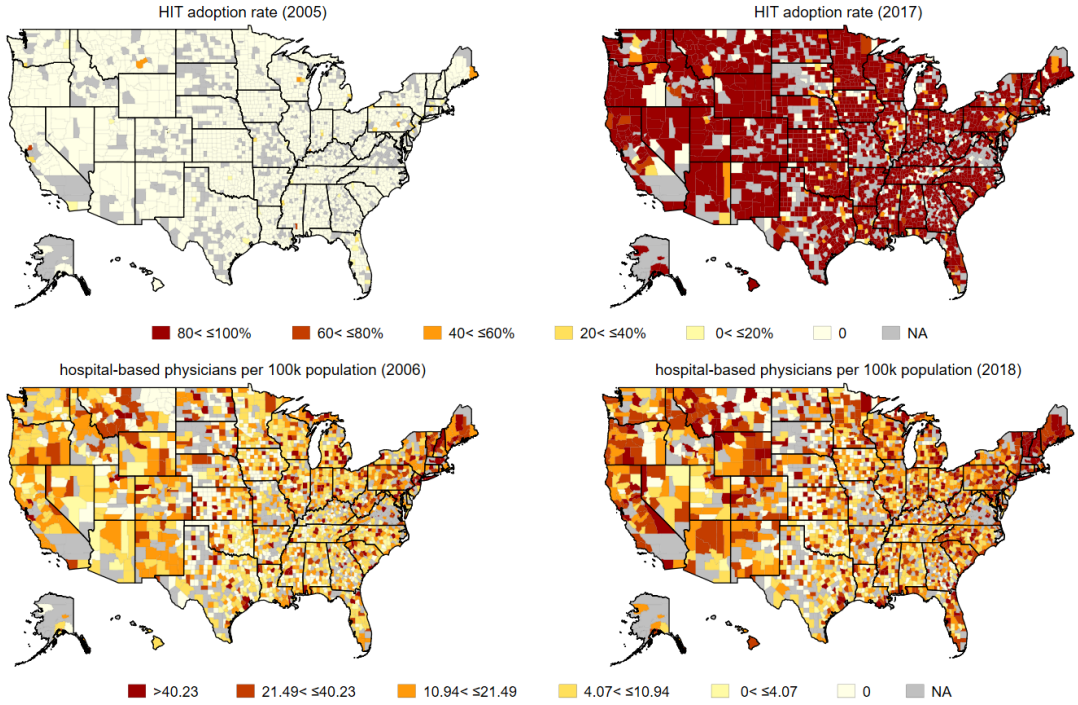


Figure 3: Geographic distribution of HIT adoption and hospital-based physician density

Notes: This figure shows the regional variations in HIT adoption rates and hospital-based physician density across the US. Our outcome data are from 2006-2018, with one-year lagged HIT data from 2005-2017. The top panel shows county-level HIT adoption rates, grouped in 20% increments. The bottom panel presents hospital-based physicians per 100k population, where we use 0 and the values of first quartile, second quartile, third quartile, and top 10% as cutoffs. Each map uses color gradients to represent numerical values, with darker shades representing higher values.

Table 1: Summary statistics for key variables: overall and by treatment status

	Overall	Never-treated	Ever-treated
HB physician counts per 100k population	17.2	13.0	17.7
	(37.8)	(17.0)	(39.6)
Health IT adoption rate (%)	1.46	0	1.64
	(5.39)	(0)	(5.69)
% 65+ population	15.7	17.2	15.5
	(4.07)	(4.35)	(4.00)
Poverty rate (%)	15.9	16.6	15.8
	(5.95)	(6.10)	(5.92)
Income per capita	32,356	34,872	32,046
	(8,325)	(10,304)	(7,996)
Medicare Advantage penetration rate (%)	4.06	2.87	4.21
	(7.73)	(5.58)	(7.95)
% Medicaid eligibles	20.3	21.1	20.2
	(8.35)	(9.10)	(8.25)
% above college degree	12.6	11.4	12.8
	(5.7)	(5.1)	(5.7)
Hospital HHI	0.80	0.92	0.78
	(0.27)	(0.15)	(0.27)
Population density	239	107	256
	(1,722)	(520)	(1,815)
# counties	2,394	265	2,129

Notes: This table reports summary statistics for the dependent, independent, and control variables in the pre-treatment period, for the full sample and by treatment status. Standard deviations are in parentheses. Table A2 provides year-by-year statistics.

Table 1 reports the summary statistics of the main variables for the full sample and separately for the ever-treated (treatment group) and never-treated counties (control group) based on the pre-adoption years. On average, counties had about 17 HB physicians per 100k population. Before treatment, the average HIT adoption rate was below 1.5% across all counties, with only a small subset showing positive pre-treatment adoption rates. The statistics by treatment status reveal that HB physician counts per 100k population were lower in never-treated counties. Both groups were similar across most county-level observable characteristics, except that ever-treated counties were more densely populated, had less concentrated hospital markets, smaller aging populations, and

higher Medicare Advantage penetration rates before HIT adoption. The sample includes 2,394 counties, with 2,129 classified as ever adopters. Among these, over 70% transitioned from 0 to 100% adoption, and 92% exhibited no more than three distinct adoption rate values over time. This distribution supports our approach of defining treatment and control groups based on discrete changes in HIT adoption rates.[19]

4 Empirical Strategy

We investigate how HB physician density—the number of HB physicians per 100k population—changes in response to the rapid diffusion of advanced HIT (i.e., CPOE) at the county level. On the one hand, physicians may prefer working in HIT-intensive environments due to the expected clinical benefits and the enhanced modern appeal that IT brings to the profession. On the other hand, some physicians may choose to practice in less HIT-intensive environments if they perceive significant barriers to adopting new technologies, particularly among those less familiar with IT. Notably, individual responses may not translate directly to aggregate outcomes—for instance, if a senior physician retires in response to HIT adoption, a hospital might replace them with multiple younger, IT-savvy physicians, resulting in a net positive gain in overall physician supply. Consequently, the effect of HIT adoption on HB physician density is ex-ante ambiguous.

We examine the effect of the rapid HIT diffusion on HB physician density at the county level using a staggered DiD design. Specifically, we estimate the following regression equation:

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_{it-1} + \gamma X_{it} + \lambda_{st} + \delta_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the number of HB physicians per 100k population in county i and year t. The main variable of interest, Treat_{it-1}, represents county i's treatment status in the *previous* year, with a one-year lag to account for physicians' response time to HIT diffusion. Following the approach in East et al. (2023), we define county i as treated based on sharp changes in its HIT adoption rate, using the criteria outlined in Section 3.1. Specifically, a county is considered treated if either (i) it transitions from no adoption to adoption with a sharp increase in the adoption rate, or (ii) an already-adopted county experiences a year-over-year adoption rate increase exceeding 100%.

X_{it} includes a rich set of county-year level variables, as described in Section 3.1. λ_{st} represents

[19] Table A2 reports yearly summary statistics for the variables we use in the analyses.

state-specific time trends, where s denotes the state of county i. These trends allow for differential trajectories across states, accounting for time-varying unobservables at the state level, such as state health policies, patient demographics, and medical practice patterns.[20] δ_i denotes county fixed effects, controlling for time-invariant county characteristics that might simultaneously affect local physician workforce and HIT diffusion. Our key coefficient of interest, β_1, measures the effect of HIT adoption on the rate of local HB physicians per 100k at the county level. A positive β_1 would imply that more physicians are willing to practice in areas with greater HIT adoption, whereas a negative β_1 would suggest physician reluctance to work in HIT-intensive environments.

The identification relies on within-county variation in HB physician density over time. Our key identifying assumption is that county-level HIT adoption is exogenous to unobserved factors influencing local physician rates (per 100k), after accounting for county characteristics and fixed effects. One concern is that counties with more resources complementary to IT adoption may adopt HIT faster and attract more physicians due to the rich resources. However, this concern is mitigated by the nationwide push for HIT adoption following federal initiatives, notably the HITECH Act and ACA-related incentives. These policies rewarded meaningful HIT use and penalized non-adoption, prompting widespread adoption across regions. As shown in Figure 1, most adoptions occurred between 2011 and 2014, soon after these Acts were enacted. Another potential threat involves health care consolidation, where large hospital systems acquiring physician practices may adopt HIT simultaneously, confounding the observed physician increases. We address this by exploring heterogeneity across counties with different levels of market concentration (measured by pre-period HHI) and by conducting robustness checks that exclude counties with substantial mergers, acquisitions, or vertical integrations, with results detailed in Section 5.2.

We extend the specification in Equation (1) using an event-study framework to examine whether pre-treatment trends in HB physician density differ between treated and control counties:

$$Y_{it} = \beta_0 + \sum_{\tau=-4,\, \tau\neq 0}^{6} \beta_1^{\tau} \times \mathbb{1}\{t=\tau\}\text{EverTreated}_i + \gamma X_{it} + \lambda_{st} + \delta_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where EverTreated_i indicates whether county i was ever treated during the sample period. This specification is similar to Equation (1) but replaces the key treatment variable with interactions between the ever-treated indicator and a series of time-since-treatment dummies. We omit the

[20] An alternative is to add state-year fixed effects, but this might eliminate too much useful variation for identification.

period right before the treatment (i.e., $\tau = 0$) as the reference period, so each estimated β_1^τ reflects the effect relative to this base period. These interactions capture how the rate of HB physicians shifts following a sharp increase in local HIT adoption. Positive (negative) estimates for β_1^τ when $\tau > 0$ suggest that physicians are more (less) likely to practice in areas with extensive HIT adoption.

We estimate the main specifications in Equations (1) and (2) using a modern DiD estimator that accounts for staggered treatment timing and heterogeneous treatment effects (De Chaisemartin and d'Haultfoeuille, 2024). Recent econometric literature highlights that traditional two-way fixed effects (TWFE) estimators may produce biased estimates in such settings. To ensure robustness, we also present results using alternative estimators from Borusyak et al. (2024), Callaway and Sant'Anna (2021), and Sun and Abraham (2021) (Section 5.7). Standard errors are clustered at the state level to allow for arbitrary autocorrelation among shocks within a state (Drukker, 2003). We weight the regressions by county population size to produce estimates that reflect the population-adjusted average effect. This approach also corrects for heteroskedasticity, as the variance of the outcome is inversely related to county population size (Ruhm, 2000; Miller et al., 2009).

Heterogeneity: We extend our main specifications to examine how the change in physician density as a consequence of HIT diffusion varies by physician and county characteristics. First, we assess heterogeneity by physician specialty, as the extent to which medical physicians respond to HIT adoption may differ from surgeons, given varying levels of exposure to and reliance on HIT across specialties. Second, we explore differences by career stage, hypothesizing that early-career physicians, who are often more IT-savvy and adaptable, are more likely to embrace new technologies and (re)consider location choices in response to changing external environments. To test this hypothesis, we re-estimate our main specifications by physicians' career stage. Third, we examine whether the effects of HIT diffusion vary between physician shortage areas and those without such shortages, given the growing challenge of uneven physician distribution across regions. These analyses provide insights into potential underlying mechanisms through which HIT diffusion affects the geographic distribution of physicians. We expect that physicians with greater incentives or lower opportunity costs to use HIT are the main drivers of observed effects.

Mechanism and Robustness Tests: To further explore factors that may impact physicians' response to HIT diffusion, we examine its effect on provider financial performance. Specifically, we analyze two types of financial metrics described in Section 3.1, assessing whether offering care in HIT-intensive environments yields measurable financial benefits for healthcare providers—

including HB physicians and hospitals. Additionally, we explore heterogeneity across counties with different levels of pre-existing healthcare utilization and assess how HIT diffusion may influence subsequent patient care utilization. Finally, we perform a series of sensitivity checks to evaluate the robustness of our main findings, ensuring that the results are not driven by specific sample compositions or model specifications.

5 Results

5.1 Main Results: HIT and HB Physician Density

We begin by discussing the results from our main specifications. Figure 4 shows the event-study estimates and associated 95% confidence intervals from estimating Equation (2). The figure shows results for four physician categories: HB physicians (circles), federal physicians (diamonds), physicians in other categories (squares), and physicians in placebo specialties (triangles). The horizontal axis shows the number of years relative to the year before treatment (normalized as period zero). We observe a notable increase in the number of HB physicians per 100k population in treated counties relative to the control group, following the sharp rise in HIT adoption. This relative increase grows in magnitude over the post-treatment years and persists for several years afterwards. There is no evidence of differential pre-treatment trends in HB physician supply between the treatment and control groups, supporting the parallel trends assumption of our empirical strategy.

As a falsification test, we re-estimate the main specifications using the following outcome measures: (i) HB federal physicians, (ii) physicians in other categories, and (iii) physicians in placebo specialties—all of which are expected to exhibit limited job mobility in response to HIT diffusion. For example, federal physicians are generally less likely to change jobs or practice locations due to the unique benefits associated with their positions, such as job security, subsidized health insurance, and generous pension plans.[21] Similarly, physicians engaged in research or teaching activities (category ii) and those in specialties with minimal HIT usage, such as Aerospace Medicine and Forensic Pathology (category iii), are less likely to be influenced by HIT adoption. Figure 4 presents the event-study results for each of these physician categories, compared with the main outcome variable. As expected, we find no significant effects of HIT adoption on physician density across these placebo groups, reinforcing the validity of our main findings.

[21] Federal employment offers certain advantages that contribute to a more stable workforce and lower turnover rates compared with the private sector. See https://news.va.gov/1129/rand_study_201/.

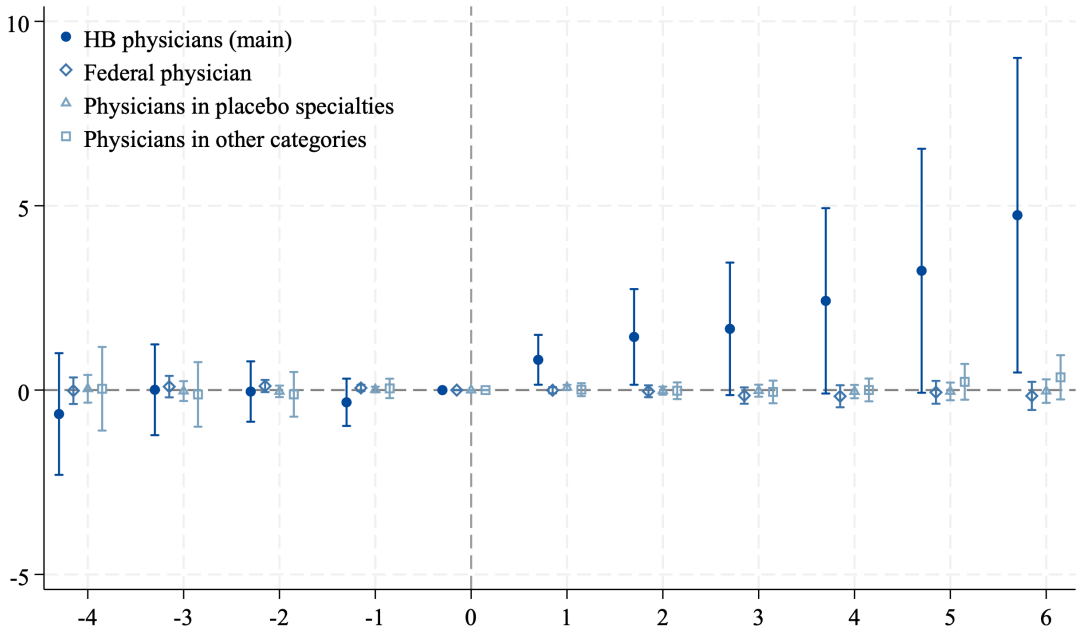


Figure 4: Effect of HIT diffusion on HB physician density, main results and falsification tests

Notes: The figure presents the main results alongside effects for physicians less likely to be affected by HIT adoption. Treatment (i.e., sharp HIT adoption) occurred in year 1. *Federal physicians* are those employed by the federal government, including the Army, Navy, Air Force, Veterans Administration, Public Health Service, and other federally funded agencies. *Physicians in other categories* are those not providing patient care but instead working in research, teaching, and administration, etc. *Placebo specialties* include Dermatology, Aerospace Medicine, Forensic Pathology, Medical Genetics, Occupational Medicine, Nuclear Medicine, Pathology (Anatomic/Clinical), Physical Medicine/Rehabilitation, and Public Health & General Preventive Medicine. The event-study coefficient estimates are based on Equation (2), with the unit of observation at the county-year level. Regressions are weighted by population at the county-year level. Fixed effects at the county and year levels are always included. Controls include state-specific time trends and 2005 county demographics (share aged 65+, poverty rate, income per capita, Medicare Advantage penetration, share eligible for Medicaid, and college attainment rate), each interacted with a linear time trend to capture time variation while mitigating endogeneity from treatment, following Dranove et al. (2014). The whiskers show 95% confidence intervals, with standard errors clustered at the state level.

Table A3, Panel A, Column (1) reports the estimated average treatment effect from Equation (1). The results show that treated counties experienced an average increase of 2.16 HB physicians per 100k population, representing a 11.1% gain ($= 2.16 \div 19.4 \times 100\%$) relative to the control group. The p-value from the joint significance test of the pre-treatment interaction terms indicates that we cannot reject the hypothesis that these coefficients are jointly zero, supporting the parallel trends assumption. These results suggest that local HIT adoption affects aggregate physician location choices, *ceteris paribus*. This could happen, as areas with higher HIT adoption may attract HB physicians by offering comprehensive, real-time patient data that enhances clinical decision-

making. In addition, HIT can streamline ordering and documentation, reducing administrative burdens and potentially boosting workflow efficiency and revenues. Although adopting HIT may be difficult for some physicians, the aggregate effect of county-level HIT adoption on HB physician density remains positive.

We further explore heterogeneous effects across categories within HB physicians: medical specialties, surgical specialties, total general practice (GP), and other specialties. Common medical specialties include Internal Medicine, Pediatrics, and Cardiovascular Disease, while surgical specialties include Obstetrics and Gynecology, General Surgery, and Orthopedic Surgery. Total GP comprises General Practice and Family Medicine. Figure A2 presents the event-study estimates for these specialty groups. The results reveal a post-treatment increase in the number of HB physicians per 100k population in treated counties relative to control counties for both medical and surgical specialties. In contrast, the effects on total GP and other specialties are insignificant. Table A3 Columns (2)–(5) report the regression estimates. On average, the post-treatment interaction terms indicate a relative increase of 1.14 (17.6%) in medical specialties and 0.64 (17.1%) in surgical specialties. These results suggest that the observed overall increase in HB physician density is primarily driven by medical and surgical specialties.

This pattern likely arises as medical specialties depend on complex diagnostic data and coordinated chronic disease management, and surgical specialties rely on efficient scheduling, preoperative evaluations, and postoperative monitoring. All are processes that local HIT can help enhance. In contrast, hospital-based general practitioners typically provide broader, less specialized care that requires fewer advanced HIT functionalities. The "other specialties" category shows noisy estimates, likely reflecting the diverse HIT dependencies among these specialties. Importantly, our results reflect aggregate physician density rather than individual physician choices. For example, if a senior physician retires or shifts to office-based settings, hospitals can reallocate resources to hire multiple early-career, HIT-savvy physicians, leading to a net increase in physician rates.[22]

Because changes in HB physicians following HIT diffusion may depend on local hospital market competitiveness, we examine the moderating role of market structure. We calculate the

[22] Glenn (2024) finds that hospitalists, including those in general practice, family practice, and internal medicine, are more likely to retire or shift to office-based settings after EHR adoption. Our results are consistent with hers when considering specialty differences and aggregate effects. The first two specialties align with our total GP category, for which we observe null effects, while internal medicine, although part of medical specialties, may involve broader, generalist care with lower reliance on advanced HIT functionalities. Consistent with this reasoning, we also find no significant effect when focusing solely on HB physicians in internal medicine.

HHI for each county in 2005 (the baseline year) and classify counties into local monopoly markets (with a single hospital, HHI = 1) and non-monopoly markets (HHI < 1, more than one hospital in a county). Counties with only one hospital in 2005 account for roughly 65% of the sample. Figure A3 shows that both groups experienced similar post-treatment increases in HB physicians, though estimates for non-monopoly markets are slightly noisier, likely due to the smaller sample size.

5.2 HIT Diffusion or Physician Practice Consolidation?

The observed increase in HB physician density associated with HIT diffusion could reflect "expanding firm boundaries." As consolidation (e.g., M&As and VIs) has become increasingly common in the healthcare sector, it could also affect local HIT diffusion. For example, when a large health system acquires local physician practices, it may integrate them into hospital outpatient departments while adopting advanced HIT to coordinate care across the network. In such cases, the rise in HB physicians may simply reflect a change in the "employment status" of existing non-HB physicians resulting from consolidation, rather than an increase in physician density. McCullough and Snir (2010) find that demand for monitoring IT increases with physician–hospital integration, likely due to challenges in enforcing complete contracts between hospitals and physicians. To assess whether our findings are primarily driven by consolidation between hospitals and other healthcare organizations, we conduct the following analyses.

First, we compare the effects of HIT diffusion on total physicians—defined as the total number of physicians per 100k population in a county providing direct patient care—with those on HB physicians. If the diffusion of HIT merely alters employment structures (e.g., via integration of independent practices into hospital systems), we would expect an insignificant or smaller effect on total physicians relative to HB physicians. We also examine the effects on highly HB specialties, where the share of HB physicians exceeds the overall mean of 15.3%, since consolidation-related reclassification should primarily affect specialties more likely to work in hospital settings.[23]

Figure 5 presents the event-study estimates. During the post-treatment periods, treated counties experience a greater increase in total physicians than in HB physicians, indicating that consolidation or employment reclassification alone cannot explain the rise in HB physician density. Moreover, the effects for highly HB specialties closely mirror the main estimates, suggesting that HIT diffusion contributes directly to shaping the physician workforce rather than simply shifting em-

[23] Highly HB specialties are listed in Table A1. Results are robust to alternative thresholds.

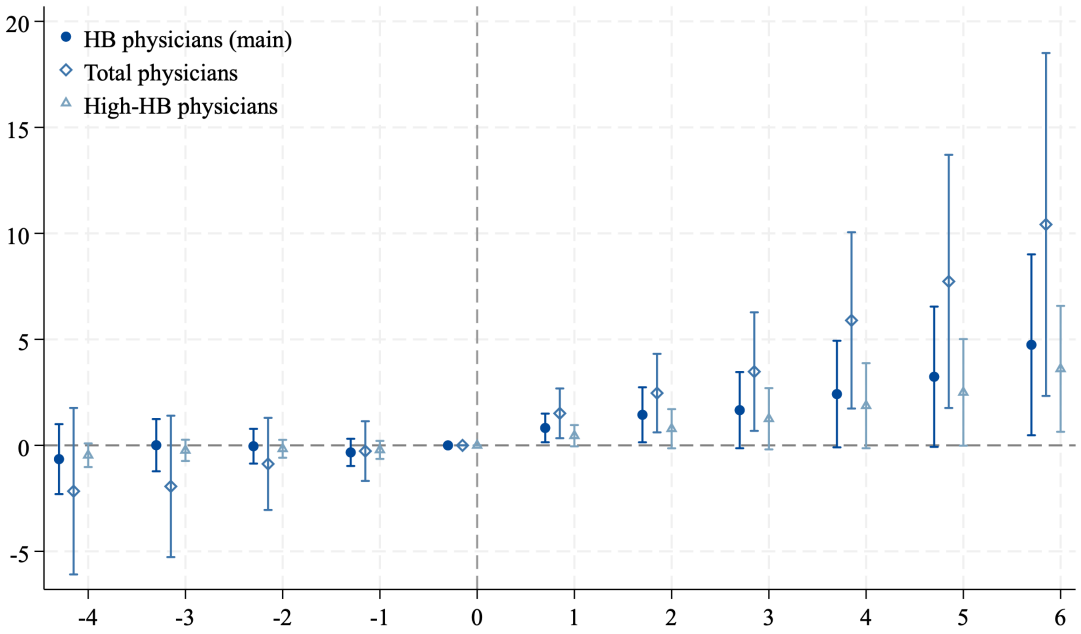


Figure 5: Effect of HIT diffusion on total physician versus HB physician densities

Notes: The figure compares the main result with effects on total physicians. The event-study coefficient estimates are based on Equation (2), with the unit of observation at the county-year level. Regressions are weighted by population at the county-year level. Fixed effects at the county and year levels are always included. The same set of controls and state-specific time trends are included as in the main specification. The whiskers show 95% confidence intervals, with standard errors clustered at the state level.

ployment status, which would otherwise suggest a much larger increase in high-HB physicians.[24]

Second, we re-estimate our main specifications after excluding counties that experienced substantial M&A or VI activities during the study period. The HIMSS data contain information on system affiliation for hospitals and affiliated non-hospital care facilities. A health *system* is defined as either an independent hospital *per se* or an integrated health care delivery network comprising multiple hospitals and affiliated non-hospital facilities. We consider a hospital system to have experienced an M&A (VI) in a given year if the number of hospitals (ambulatory care units) within the system increased compared to the previous year. At the aggregate level, a county is classified as experiencing substantial M&A (VI) activity in a given year if the share of local systems undergoing such changes exceeds the top 75th percentile across the sample, which is 0.10 for M&As and 0.14 for VIs. Excluding these counties allows us to test whether our main findings persist in markets less

[24]Total physicians include both HB physicians and office-based physicians practicing in non-hospital settings, such as solo or group practices. The larger increase in total physician density may partly reflect growth among office-based physicians, potentially driven by (i) spillover effects of hospital HIT diffusion and/or (ii) concurrent adoption of office-based HIT due to technological complementarities across care settings. However, examining office-based HIT diffusion is beyond the scope of this study due to data limitations.

affected by organizational consolidation, providing a cleaner view of HIT's independent impact.

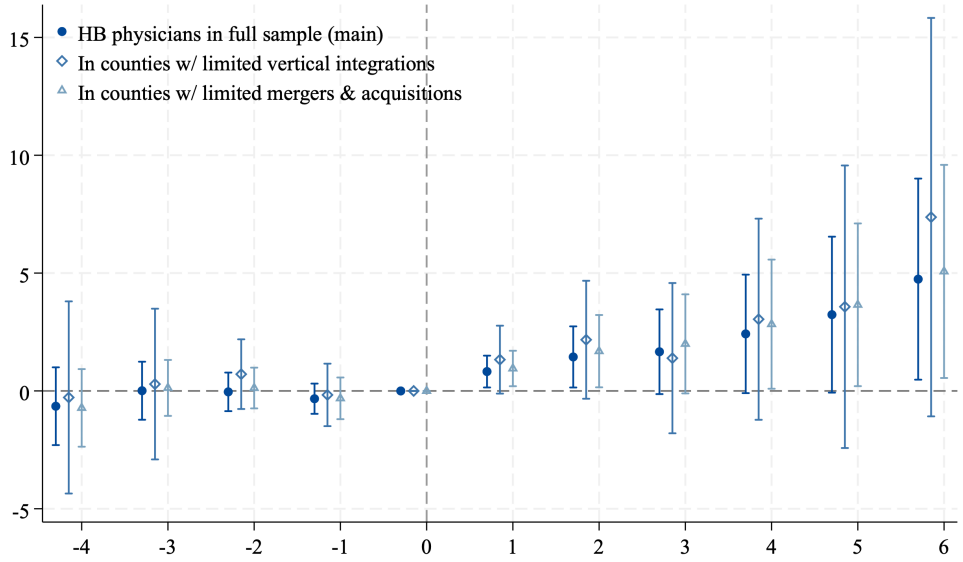


Figure 6: Effect of HIT diffusion on HB physician density in counties with less consolidation

Notes: This figure compares the result in subsamples characterized by limited VIs and limited M&As. The event-study estimates and 95% confidence intervals are based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

Figure 6 presents the event-study estimates, and Table A4 (Columns (3)-(4)) reports the corresponding regression results. The results indicate that even after excluding counties with substantial M&A activities (triangles), treated counties still exhibit a significant increase in HB physician density relative to controls, suggesting that HIT diffusion independently affects the rate of HB physicians. For counties without substantial VI activities (diamonds), the event-study estimates closely mirror the main results in magnitude and pattern, though the confidence intervals are notably wider. This test addresses the concern that large health systems may drive the observed results by consolidating to acquire physicians and expand their patient base while simultaneously adopting advanced HIT. Taken together, these analyses suggest that the observed rise in HB physician density reflects more than boundary shifts or consolidation. Rather, our results indicate that HIT adoption itself remains an independent driver of increased HB physician density.

5.3 Discussion on Sources of Increasing HB Physician Density

We find that the rapid HIT diffusion increases HB physician density. This increase could arise from several sources: (i) a net increase in the overall number of HB physicians, (ii) relocation of HB

physicians from less HIT-intensive to more HIT-intensive areas, or (iii) employment reclassification of physicians from non-hospital to hospital settings due to expanded firm boundaries.

While our analyses do not directly identify (i) as the main driver, we compare trends in average total physician density and average HB physician density (Figure A4).[25] The results show that average HB physician density rises gradually and modestly over time, whereas total physician density declines slightly in the first half of the sample period and then remains flat. These patterns suggest that our findings likely do not mainly reflect a large net expansion of the physician workforce, given the long training and licensing pipeline for new physicians.

We view (ii) (i.e., relocation across markets) as an important source of increase. In particular, the positive effect may reflect physicians moving from smaller hospitals or less-resourced counties to larger, more technologically advanced hospitals that adopted CPOE earlier and more extensively. To explore this possibility, we re-estimate our main specifications at the hospital referral region (HRR) level, a broader geographic unit for tertiary medical care.[26] Figure A5 (right panel) presents event-study results for overall HB physicians and by specialty.[27] We continue to observe increases in HB physician density, particularly among medical specialties, though estimates are less precise due to smaller variation. Because HRRs encompass much larger areas, we would expect weaker signals from within-region relocation. Thus, the persistent positive effects even at this level suggest that physician migration in response to HIT diffusion extends beyond localized movements.

Finally, our consolidation analyses (Section 5.2) indicate that while we cannot fully disentangle relocation (ii) from reclassification (iii), the evidence suggests that firm-boundary changes alone do not fully explain the observed increases in HB physician density.

5.4 Heterogeneity by Physician Career Stage and by Shortage Status

We explore how the effects of HIT diffusion vary by physician career stage and county-level physician shortage status, as these dimensions are crucial for understanding how HIT adoption may influence the distribution of physicians across experience levels and underserved areas.

Heterogeneity by Career Stage: We first examine heterogeneity by physicians' career stage.[28]

[25] Each measure averages the respective county-level physician counts per 100k population across counties.

[26] Each HRR, with a minimum population of 120k, includes at least one hospital performing major cardiovascular procedures and neurosurgery (https://www.dartmouthatlas.org/faq/).

[27] Figure A5 (left panel) shows that HIT diffusion patterns at the HRR level resemble those at the county level.

[28] The AHRF reports physician counts by age, though it does not distinguish between hospital-based and office-based physicians. Thus, the results by career stages reflect the effect on both groups.

Figure 7 (left panel) shows the event-study estimates for early-career (under 45), mid-career (45–64), and late-career (65+) active physicians. Table A5 presents corresponding regression estimates in Columns (1)–(3). We observe a significant post-treatment increase in early-career physicians (circles) in treated counties relative to controls, but the effects for mid- and late-career physicians are insignificant. This result suggests that the overall increase in physician density is primarily driven by younger physicians. The finding aligns with previous research showing that early-career physicians are more likely to (re)consider practice locations in response to external changes (Polsky et al., 2000; Kessler et al., 2005; Huh, 2021; Khoury et al., 2024; Huh and Lin, 2024). In terms of HIT adoption, younger physicians may face fewer barriers to navigating complex IT systems and may value faster access to patient information and streamlined workflows enabled by HIT. As a result, they appear more willing to practice in HIT-intensive environments, driving the observed aggregate effects. In contrast, inactive physicians show no response among younger groups but a mild rise among those 65+, reflecting selective retirement effects post-HIT adoption (Figure A6, right panel).

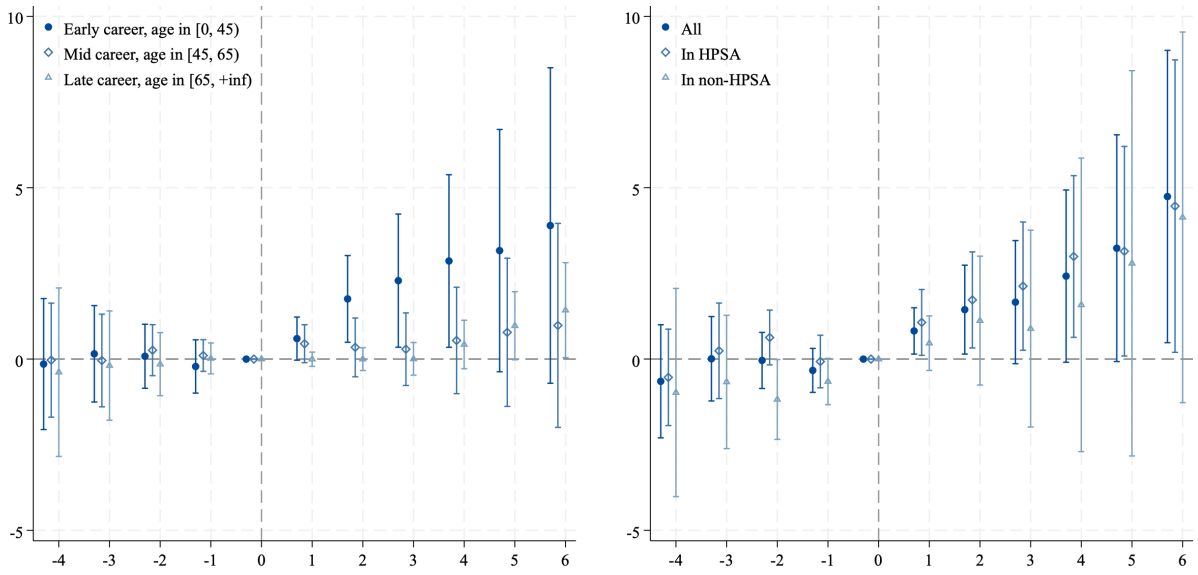


Figure 7: Effect of HIT diffusion on physician density, by career stage and HPSA status

Notes: Early, mid, and late career physicians are defined as those younger than 45, between 45 and 64, and 65 or older, respectively. Health Professional Shortage Area (HPSA) are designated areas with a shortage of primary care practitioners. The event-study estimates and 95% confidence intervals are based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

Heterogeneity by Physician Shortage Area Status: Next, we assess how the effects of HIT diffusion vary by Health Professional Shortage Area (HPSA) designation. We classify a county as ever-HPSA if at least part of the county was ever designated as having a shortage of primary care practitioners.[29] We re-estimate the main specifications for ever-HPSA counties and the remaining counties. Figure 7 (right panel) and Table A5 (Columns (4)–(5)) show that the treatment effect is significant among ever-HPSA counties, meaning a significant increase in HB physicians per 100k in treated HPSA-counties relative to control HPSA-counties. In contrast, HB physicians do not appear to change significantly post-treatment in never-HPSA counties. This indicates that the overall effects of HIT adoption on HB physician density are largely driven by improvements in shortage areas. One plausible explanation is that HIT adoption enhances the ability to provide high-quality care in resource-limited settings, making HPSA counties more attractive by improving clinical efficiency and offering better practice opportunities where physician demand remains high.

5.5 Financial Impacts of HIT Adoption

In this section, we explore the financial impacts of HIT diffusion for healthcare providers. We first examine whether HB physicians benefit financially from practicing in areas with more rapid HIT adoption. Specifically, we use two proxies for financial performance: (i) average Medicare-allowed amounts per HB physician, and (ii) average number of Medicare services conducted by each HB physician.[30] To construct these measures, we identify HB physicians as those furnishing at least 90% of their services in hospital inpatient or emergency room settings.[31] We then compute county-level averages by averaging (i) and (ii) across all HB physicians by county.

Figure 8 (left panel) presents the event-study estimates, with regression results in Table A6 (Columns (1)–(2)). The results show that HB physicians in treated counties receive significantly higher Medicare-allowed payments following sharp HIT adoption, compared to those in control counties. These positive effects remain statistically significant up to four years post-adoption. A similar pattern emerges for the average number of Medicare services per physician, suggesting that one way HIT adoption enhances physicians' reimbursement is by expanding their capacity to provide care. This is consistent with the proposed advantage of HIT: quicker service provision and

[29] HPSAs are geographic areas designated by the Health Resources and Services Administration as in shortages of health care providers. See https://bhw.hrsa.gov/workforce-shortage-areas/shortage-designation#hpsas.

[30] These two financial measures are analyzed over a shorter period due to data availability starting in 2013.

[31] We follow the definition set by CMS. See https://www.cms.gov/regulations-and-guidance/legislation/ehrincentiveprograms/downloads/mln_medicareehrprogram_tipsheet_ep.pdf.

easier ordering of additional procedures, enabling physicians to deliver care more efficiently and thereby increasing revenue.

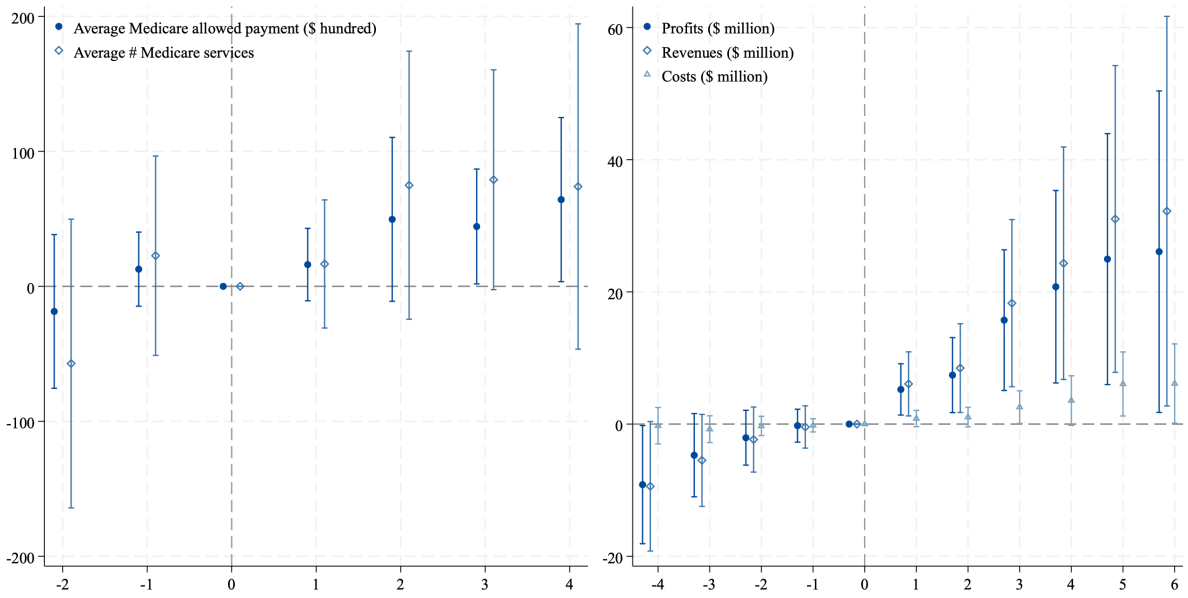


Figure 8: Effect of HIT diffusion on financial metrics

Notes: The figures report results using financing metrics as the outcomes, with shorter periods for two measures (left panel) due to data availability. Unit for the right panel: $ million. The event-study estimates and 95% confidence intervals are based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

Next, we examine hospital financial performance using three metrics: total patient revenue, total costs, and total profits (defined as the difference between the first two). We extract these hospital-level measures from the HCRIS data and compute county-level averages across all hospitals. As shown in Figure 8 (right panel) and Table A6 (Columns (3)-(5)), hospitals in treated counties experience sustained profit gains following HIT adoption relative to control counties, mainly driven by rising patient revenue. Post-treatment hospital revenues show a substantial upward pattern, while costs rise to a much smaller extent; all remain statistically significant.[32] These results indicate that higher hospital profitability is driven primarily by revenue expansion rather than cost reductions. The likely mechanism is that HIT adoption enhances physicians' capacity to deliver more services and improves operational efficiency through better coordination and information flow. In turn, stronger financial performance may enable hospitals to expand physician staffing, contributing to the continued growth in HB physician density observed after HIT diffusion.

[32] Although slight pre-trends are visible in average hospital revenue and profit, the sharp increase immediately after treatment and the persistent post-treatment rise suggest that the main findings remain robust.

Together, these findings point toward a financial mechanism through which HIT adoption attracts and retains HB physicians: by reducing operational inefficiencies, boosting physician earnings, and improving hospital profitability, HIT adoption plausibly creates a more rewarding practice environment for physicians and a more sustainable business model for hospitals.

5.6 Implications on Care Utilization

Building on the results that HIT diffusion boosts physician and hospital financial performance, we now examine the changes in patient care utilization, recognizing the interplay between service usage and provider capacity. Specifically, we examine the extent to which HIT diffusion influences subsequent service use. We focus on two main utilization measures: total outpatient and total inpatient surgical operations in hospitals, measured per 100k population at the county level using AHRF data. To capture heterogeneity, we categorize counties into tertiles based on pre-treatment care utilization, measured by standardized, risk-adjusted per capita Medicare costs in 2006. We use a uniform measure to divide the sample for all utilization analyses to ensure consistent baseline comparisons. We use the 2006 value, the first year this variable appears in AHRF, to avoid potential bias from utilization growth.[33] We also report alternative utilization measures, including outpatient visits and Medicare hospital inpatient discharges, and discuss why and how these utilization measures may respond differently.

Outpatient Surgery Volume: We first assess whether HIT diffusion affects subsequent patient utilization by examining outpatient surgeries per 100k population in hospitals. Figure 9 (left panel) shows that only mid-tertile counties exhibit a significant post-HIT increase in outpatient surgical procedures.[34] Providers or facilities in high-utilization areas may have reached capacity constraints even before HIT was widely adopted by local hospitals, leaving limited space for additional surgical operations that could have been facilitated by HIT, while low-utilization areas may simply lack sufficient demand. Mid-tertile counties likely represent an optimal balance, possessing room to accommodate extra services post-HIT diffusion. Since outpatient surgeries often involve elective or less complex procedures that can be more easily scheduled and scaled when HIT streamlines administrative tasks such as scheduling, documentation, and care coordination, this increase in high-margin outpatient surgeries aligns with our earlier finding of greater average hospital profits

[33] An arguably better measure is healthcare expenditure from both Medicare and non-Medicare populations, but only Medicare costs are available in the AHRF data.

[34] Table A7 reports the regression estimates for outpatient and inpatient surgery volumes.

in treated counties.

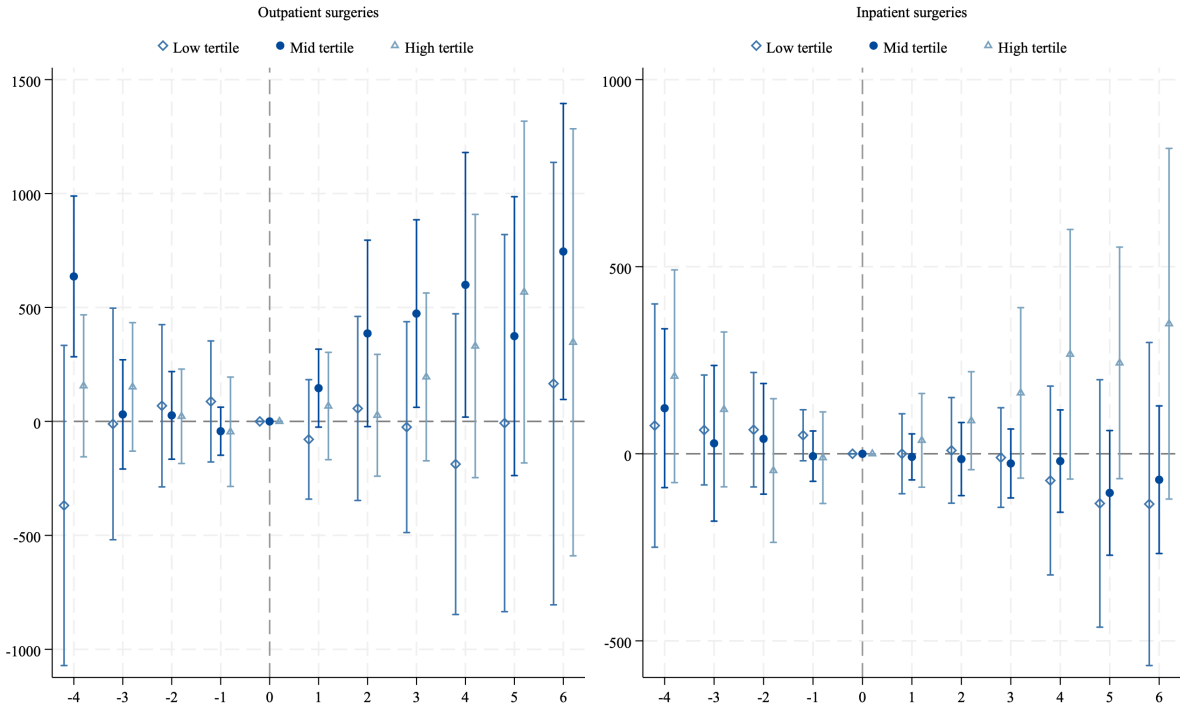


Figure 9: Effect of HIT diffusion on outpatient/inpatient surgery volume

Notes: The figures show results by tertiles of pre-treatment care utilization, measured by standardized, risk-adjusted per capita Medicare costs in 2006. The event-study estimates and 95% confidence intervals are based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

Inpatient Surgery Volume: We then repeat this analysis for inpatient surgical operations and report the results in Figure 9 (right panel). There is no corresponding rise in inpatient surgeries across any tertile, suggesting that the value of HIT may be less pronounced in inpatient settings, where surgeries are often more invasive, urgent, or involve higher-risk patients, making volumes less responsive to operational efficiencies. Inpatient procedures also typically require longer recovery periods and greater resource commitments, limiting hospitals' ability to scale up volumes quickly, even with improved HIT infrastructure. Given that outpatient services generally represent a higher-margin revenue stream, this difference complements our earlier finding of greater hospital profits in treated counties, highlighting that HIT-driven efficiencies may have stronger financial impacts in outpatient settings where service expansion is more flexible.[35]

[35] See https://www.hfma.org/finance-and-business-strategy/strategic-planning/hospitals-see-a-margin-advantage-as-care-migrates-to-the-outpatient-department/.

Outpatient Visits and Medicare Discharges: Figure A7 examines heterogeneity by pre-treatment care utilization for outpatient visits and Medicare inpatient discharges. Both panels show that these utilization measures remain largely unaffected by HIT diffusion. The absence of significant effects on outpatient visits may reflect the nature of these encounters, which are typically shorter, less complex, and generate lower revenue per encounter than surgical procedures. Similarly, the lack of growth in Medicare inpatient discharges may stem from capacity constraints or the less flexible nature of inpatient care. Compared with the clearer patterns observed in surgical operations, these utilization measures exhibit greater variability, likely due to differences in case complexity and preferences for less invasive treatments for Medicare patients. Overall, the results suggest that HIT's impact is most pronounced in complex surgical care, where efficiency and coordination gains are more important.

5.7 Robustness Checks

We conduct several analyses to assess the robustness of our results. First, we re-estimate the main specifications using alternative subsamples. We restrict the sample to counties with no more than five distinct HIT adoption rates, as more gradual adopters may exhibit fewer discrete changes (Figure A8, diamonds). Next, we exclude counties that ever recorded zero per-capita HB physicians to ensure that results are not driven by those with no hospital-based workforce (Figure A8, triangles). We also drop counties with extreme population sizes (top or bottom 10%; Figure A8, squares). Finally, we perform a balanced event study including only counties with at least four pre- and post-treatment periods (Figure A8, solid diamonds).[36] Across all these subsample analyses, our main findings remain consistent.

Second, we explore alternative model specifications. Removing state-specific time trends yields estimates similar to the main results (Figure A9, diamonds). The findings remain robust when we exclude county-year level controls (Figure A9, triangles), and when we further exclude both state-specific time trends and county-level or county-year observables (Figure A9, squares).[37] Next, we apply alternative staggered DiD estimators from recent Econometric literature (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). As shown in Figure A10, the results are generally consistent across estimators, with all showing similar trends and magni-

[36] The four-period threshold balances the availability of pre-treatment observations against sample size retention; observations beyond this window are excluded.

[37] Table A8 shows the regression estimates corresponding to Figures A8 and A9.

tudes of treatment effects. The estimates from the Callaway-Sant'Anna estimator are slightly less precise but follow the same overall pattern as the alternative methods.[38]

Finally, we test the robustness of our findings using two alternative definitions of HIT adoption. The first is based on the adoption of either CPOE or physician documentation (PD) systems, following prior work (e.g., Dranove et al., 2014). The results remain robust, though slightly less precise (Figure A11, right panel), consistent with most key variation and advanced automation features being driven by CPOE, as discussed in Section 2.2.[39] The second alternative definition focuses on the adoption of the clinical data repository (CDR), a more basic HIT component that serves as a centralized database for storing and managing patient information. Under this definition, the estimated effects on HB physician density become statistically insignificant both before and after treatment. This likely reflects that basic components such as CDR were adopted earlier and more gradually (Figure A11, left panel), and lack the advanced automation and clinical integration features of CPOE that drive meaningful organizational change.

Overall, these robustness checks confirm that our main results are consistent across alternative sample definitions, model specifications, and HIT adoption measures.

5.8 Limitations

Our study has some limitations. First, we rely on aggregate datasets, which mitigate concerns about patient sorting, but limit our ability to disentangle changes at the physician level. For example, a net increase in HB physicians could reflect compositional shifts, such as changes in the mix of primary care providers and specialists, or evolving physician roles and responsibilities. Similarly, without granular data, we cannot fully isolate the mechanisms through which HIT affects physicians' labor supply decisions, including potential changes in working hours or task allocation. Second, although our data do not measure interoperability, greater information exchange across providers may help explain the positive physician responses observed. Future work incorporating interoperability metrics could assess this channel more directly.

Third, our focus on HIT diffusion could be enriched by examining how digital and physical

[38] We also implemented a continuous DiD estimator by De Chaisemartin and d'Haultfoeuille (2024), obtaining positive and significant results consistent with our main findings. Interpretation of point estimates at full treatment scales remains under methodological development, and we therefore refrain from emphasizing these results.

[39] PD allows physicians to transition from paper-based to electronic (unstructured) notes (Dranove et al., 2014). Unlike CPOE, PD is not a core component of the Meaningful Use criteria under the HITECH Act but an optional menu item. The correlation coefficient between CPOE adoption and CPOE/PD adoption rates is 0.94.

medical technologies jointly affect physician density, but data limitations prevent such analysis. Nevertheless, our extensive controls mitigate concerns that other technological investments drive the results. Finally, it would be valuable to examine the impact on downstream health outcomes, but this remains beyond the scope of our study. As HIT is only one element within broader, team-based care delivery processes, isolating its impact is challenging, let alone distinguishing between direct and indirect effects through physician density. These remain valuable future directions.

6 Conclusion

This study examines how the rapid diffusion of advanced HIT influences HB physician density across US counties. Leveraging sharp local HIT adoption, we find that treated counties experienced a 11.1% increase in HB physicians per 100k population relative to control counties, with the growth primarily driven by early-career physicians and concentrated in areas that faced physician shortages. HIT adoption leads to higher Medicare-allowed payments per physician, more Medicare services delivered, and increases in average hospital profits. In addition, we find increases in outpatient surgical volumes, particularly in counties with moderate pre-treatment utilization levels, suggesting that HIT-enabled efficiencies in outpatient settings enhance patient throughput and revenue generation. These findings remain robust after accounting for healthcare consolidation, various model specifications, alternative DiD estimators, and analyses across multiple subsamples.

Our results have implications for health policy and management. For policymakers, investing in HIT may help attract and retain physicians, particularly in areas with physician shortages and, thus, excess demand for medical care. Such investments could complement existing incentive programs by making HIT-enabled environments more appealing to early-career physicians, who may be more comfortable with advanced HIT. For hospital managers, aligning digital investments with workforce strategies is essential for improving physician productivity and retention. Recognizing the role of HIT in affecting physician supply can help hospitals align digital investments with hiring strategies to sustain growth and meet evolving patient care demands.

Our findings contribute to the broader discussion on automation and the future of work in health care. Advanced HIT adoption over an extended period has laid the groundwork for the data-rich environments that modern digital tools rely on. At the aggregate county level, we find that advanced HIT appears to complement physician labor, enhancing productivity and patient

access rather than displacing physician jobs. Future research could explore how burgeoning digital innovations, such as AI tools and interoperable systems, can be optimally integrated within HIT to further support physicians in delivering better patient care.

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A Figures and Tables

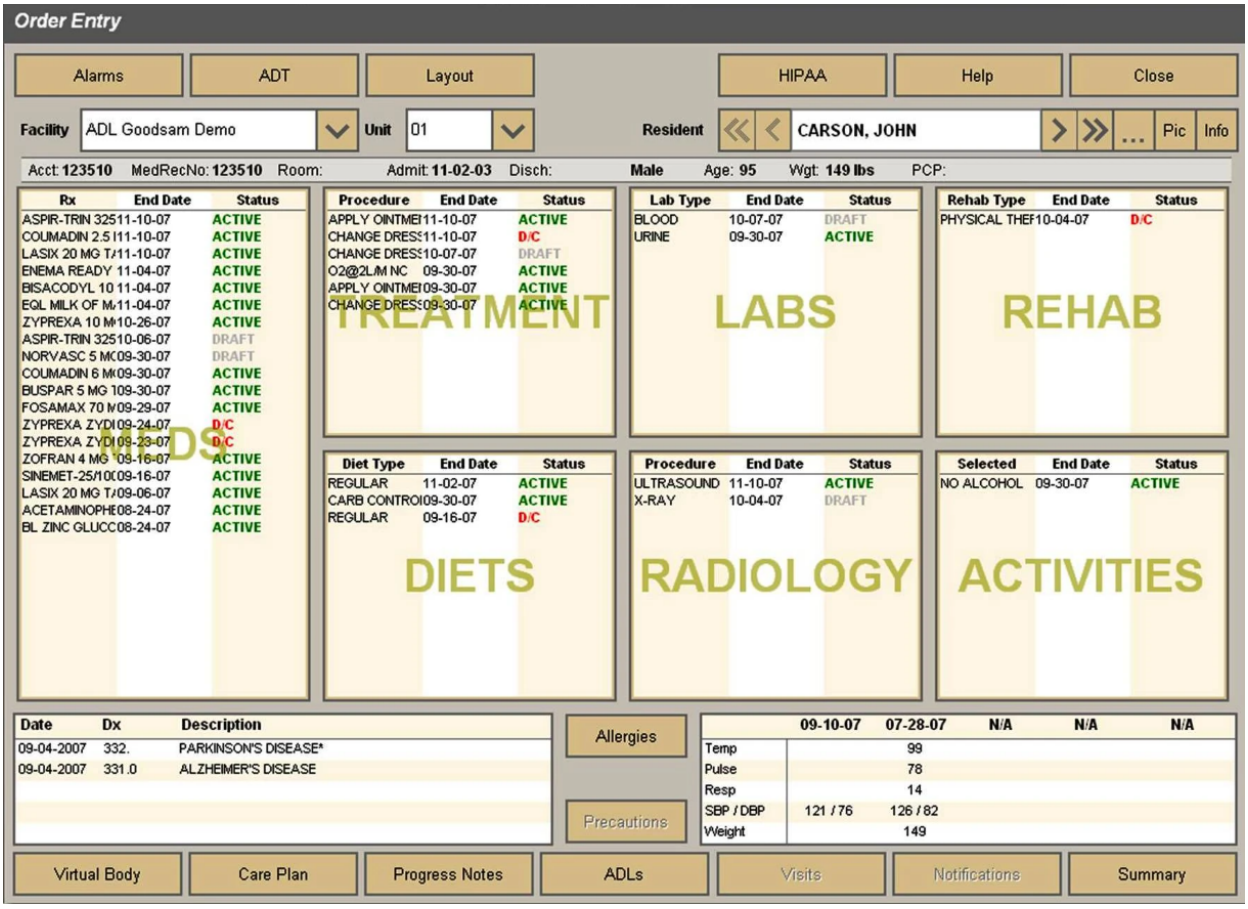


Figure A1: Example of a Computerized Physician Order Entry (CPOE) Interface

Notes: This figure shows a CPOE interface, which enables health care providers to electronically enter and manage medical orders. Source: *Hitman Wiki* (https://hitm.fandom.com/wiki/Computerized_physician_order_entry).

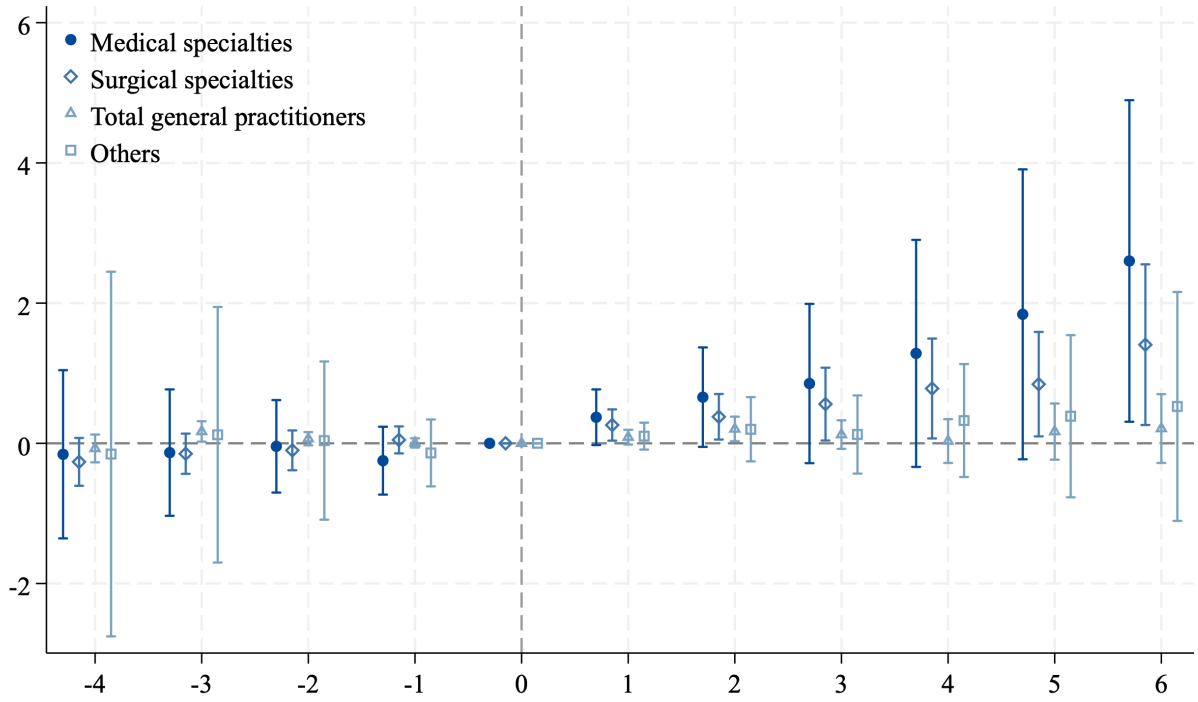


Figure A2: Effect of HIT diffusion on HB physician density, by main specialty

Notes: The four specialties shown are AHRF-defined categories: medical specialties, surgical specialties, total general practitioners (GP), and others. Common *medical specialties* include Internal Medicine, Pediatrics, and Cardiovascular Disease. Common *surgical specialties* include Obstetrics Gynecology, General Surgery, and Orthopedic Surgery. Common *total GP* refers to General Practice and Family Medicine. *Others* capture the remaining specialties. Appendix Table A1 provides more information on each specialty category. The figures present event-study estimates and 95% confidence intervals based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

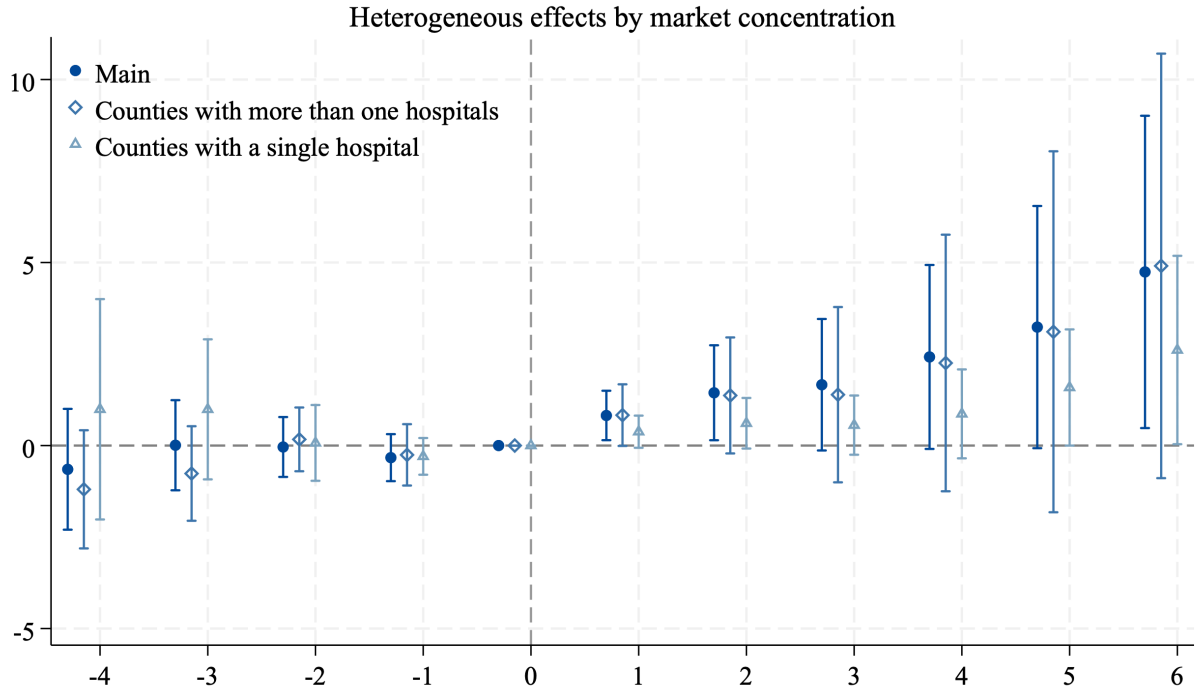


Figure A3: Effect of HIT diffusion on physician density, by hospital market concentration

Notes: The figures show event-study estimates from subsample analyses defined by HHI in 2005: counties with local monopoly markets (with a single hospital, HHI = 1) and non-monopoly markets (HHI < 1, more than one hospital in a county). The figures present event-study estimates and 95% confidence intervals based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

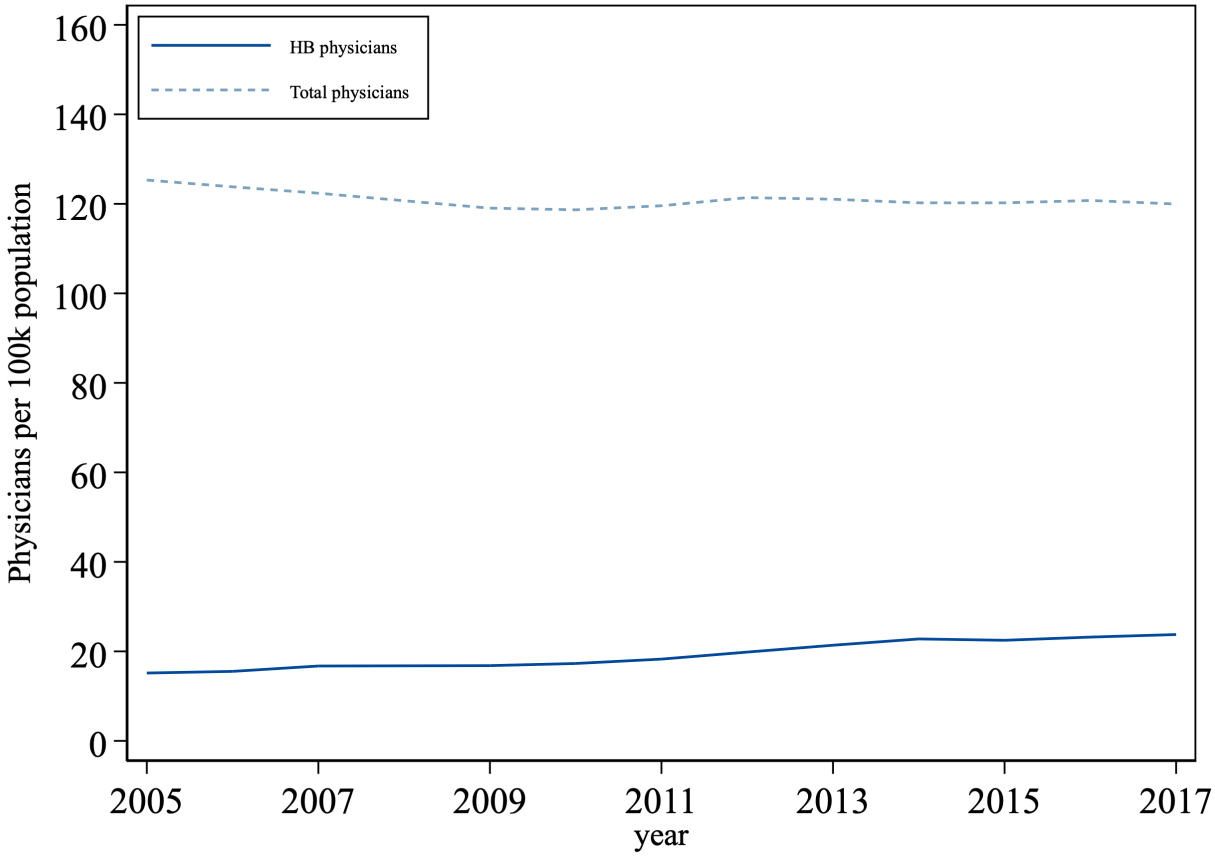


Figure A4: Trends of total physician density vs. HB physician density

Notes: The figure shows the trends of average total physician density vs. average HB physician density.

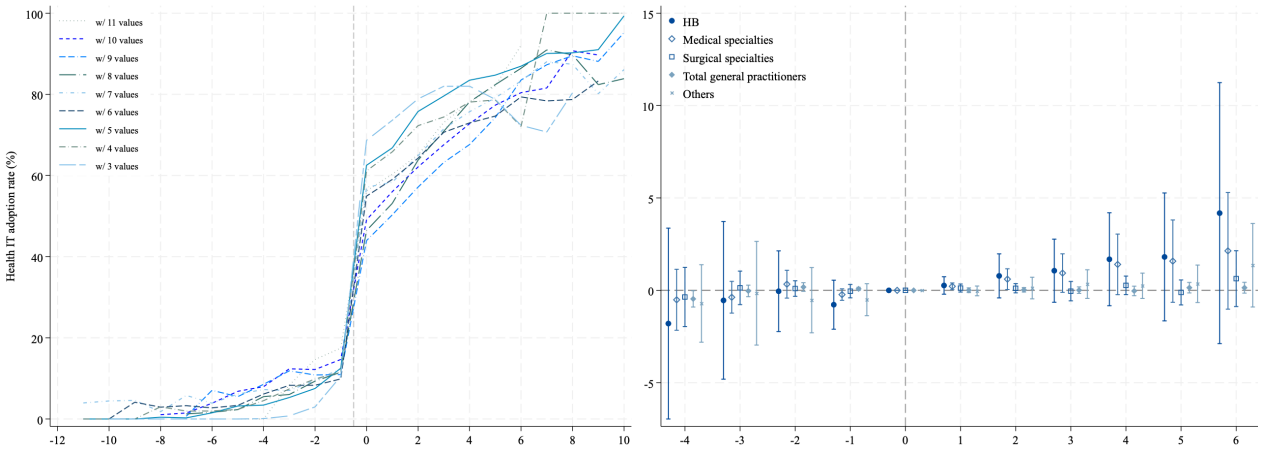


Figure A5: Effect of HIT diffusion on HB physician density, in HRRs

Notes: The figures show results based on HRRs. The left panel plots HIT adoption rates over time relative to the treatment year for treated HRRs. Different legends represent subsamples of HRRs encountering various values in HIT adoption rates as defined in Figure 2. The right panel presents event-study estimates and 95% confidence intervals based on Equation (2). The unit of observation is at the HRR-year level. Regressions are weighted by population at the HRR-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

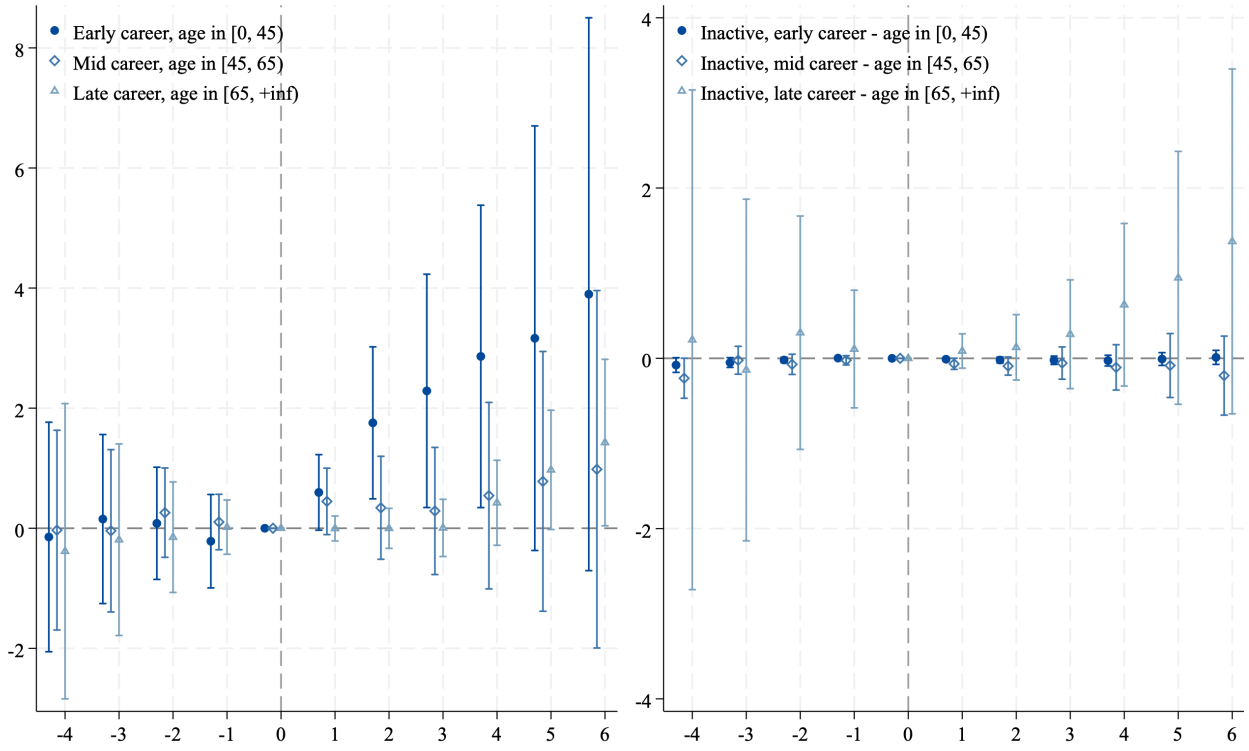


Figure A6: Effect of HIT diffusion on physician density, by career stage and active vs. inactive status

Notes: Early, mid, and late career physicians are defined as those younger than 45, between 45 and 64, and 65 or older, respectively. Inactive physicians include those "who are retired, semiretired, working part time, temporarily not in practice, or not active for other reasons and indicated they worked 20 hours or less per week" (AHRF, 2018). The event-study estimates and 95% confidence intervals are based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

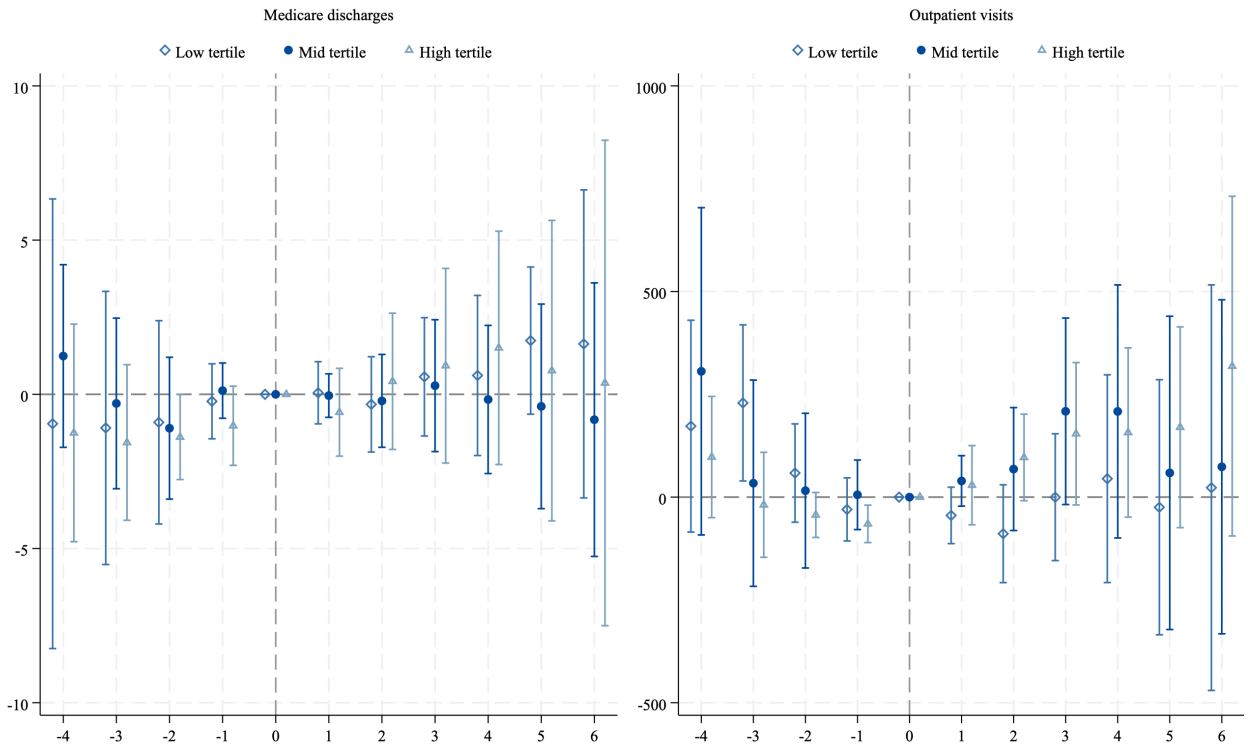


Figure A7: Effect of HIT diffusion on Medicare inpatient discharges and outpatient visits, by pre-treatment care utilization

Notes: The figures show results by tertiles of pre-treatment care utilization, measured by standardized, risk-adjusted per capita Medicare costs in 2006. The event-study estimates and 95% confidence intervals are based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

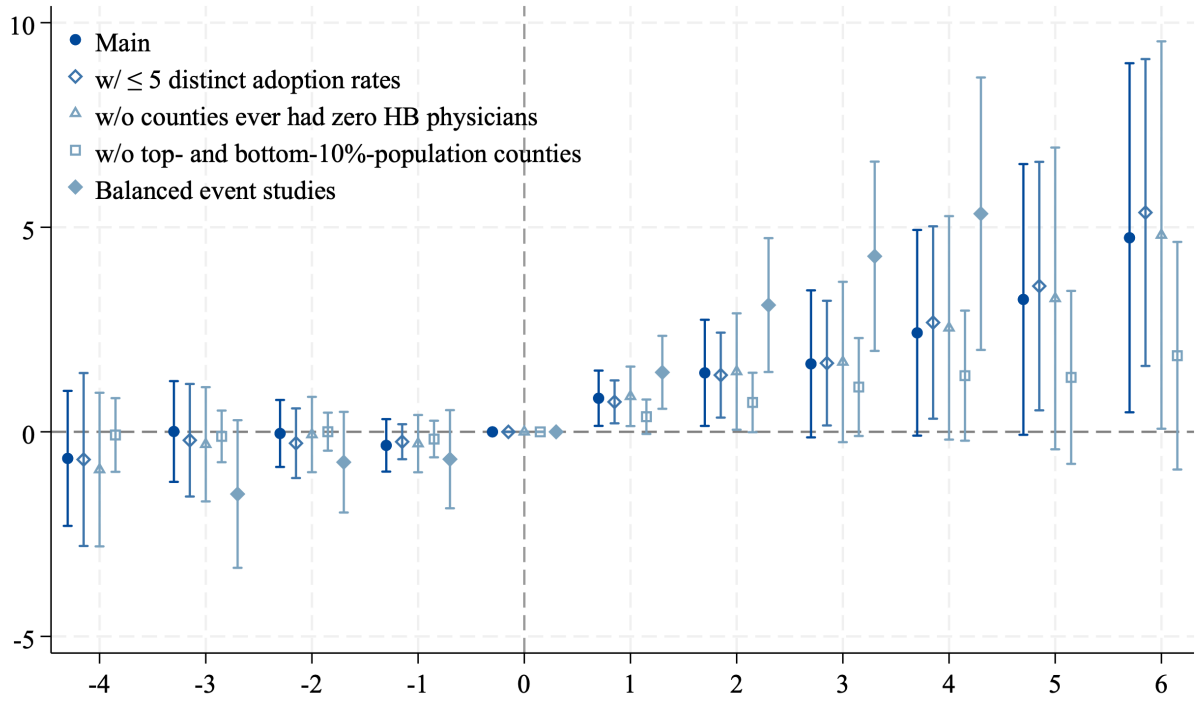


Figure A8: Effect of HIT diffusion on HB physician density: robustness checks

Notes: For "w/ $\leq$ 5 distinct adoption rates," we include only counties with no more than five distinct HIT adoption rates. For "w/o counties ever had zero HB physicians," we exclude counties that ever had zero HB physicians during the study period. For "w/o top- and bottom-10%-population counties," we exclude counties without extremely large/small populations (i.e., the top/bottom 10%). For "balanced event studies," we include only counties with at least four periods before and after treatment. Section 5.7 provides more details on the sample for each figure. The figures show event-study estimates and 95% confidence intervals based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

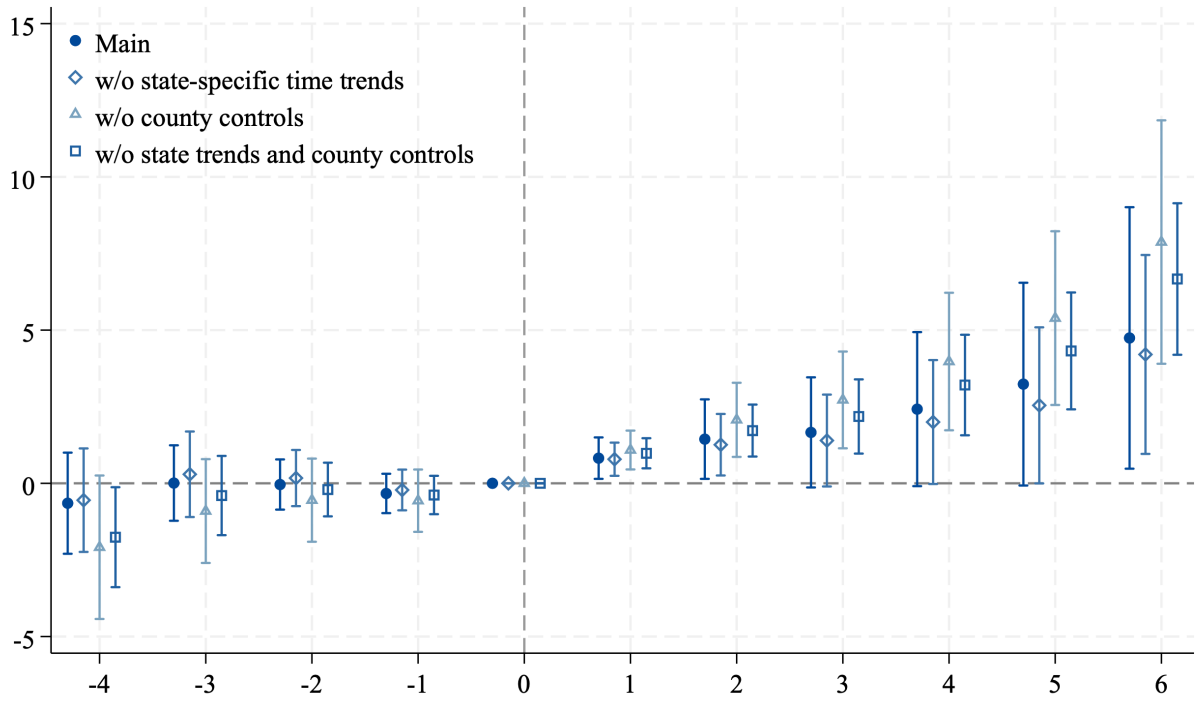


Figure A9: Effect of HIT diffusion on HB physician density: specification checks

Notes: We conduct specification checks by (a) excluding state-specific time trends, (b) excluding county-level controls, and (c) excluding both state-specific time trends and county-level observable controls. The figures show event-study estimates and 95% confidence intervals based on Equation (2). The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

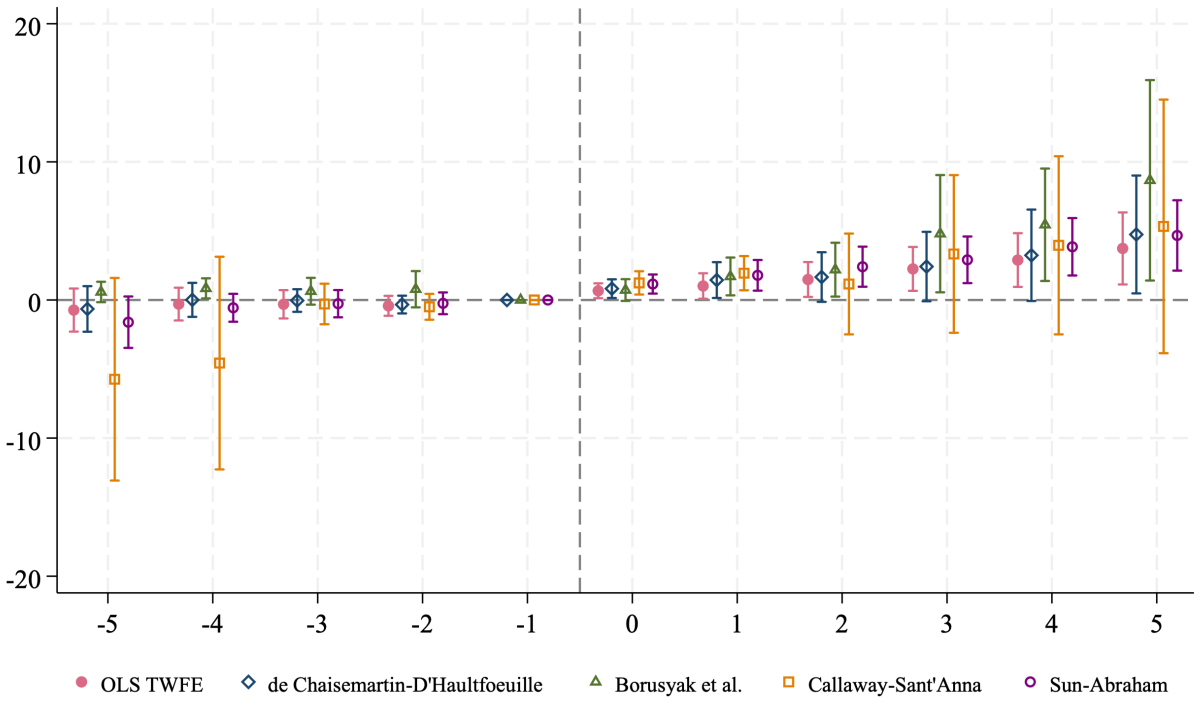


Figure A10: Effect of HIT diffusion on HB physician density: alternative DiD estimators

Notes: The figures present event-study estimates and 95% confidence intervals using alternative DiD estimators. The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 0, which we relabeled to ease the comparison across various DiD estimators. All estimators use -1 period as the reference except Borusyak et al., which uses the earliest period as the baseline period. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

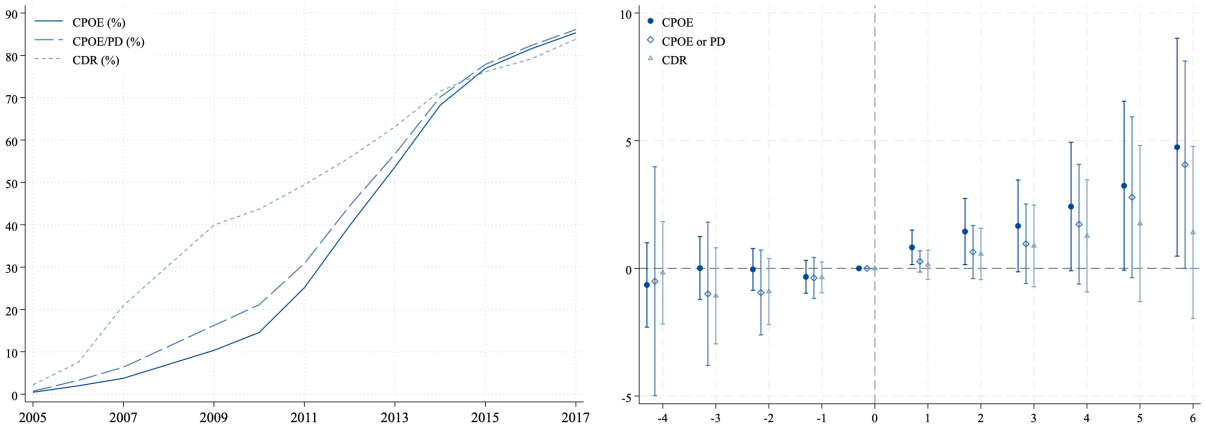


Figure A11: Effect of HIT diffusion on HB physician density: alternative HIT measures

Notes: The left panel shows average health IT adoption rates of alternative HIT measures across counties each year during our sample period. The right panel presents event-study estimates and 95% confidence intervals using alternative HIT adoption measures, i.e., county-level sharp adoption of either CPOE or physician documentation (PD), or adoption of clinical data repository (CDR). PD is another advanced HIT component, but not a core component for HITECH Act meaningful use criteria. The unit of observation is at the county-year level. Regressions are weighted by population at the county-year level. Treatment occurred in year 1. All specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

Table A1: List of specialties in each HB physician category

Total General Practice	**Medical**	**Surgical**	**Others**
General Practice	Allergy and Immunology	Colon/Rectal Surgery	Aerospace Medicine*
Family Medicine, General	Cardiovascular Disease	General Surgery‡	Anesthesiology‡
Family Medicine Subspecialties	Dermatology*	Neurological Surgery‡	Radiology
	Gastroenterology	Obstetrics-Gynecology, General	Diagnostic Radiology‡
	Internal Medicine, General‡	Obstetrics-Gynecology Subspecialties	Emergency Medicine‡
	Internal Medicine Subspecialties‡	Ophthalmology	Forensic Pathology*
	Pediatrics, General	Orthopedic Surgery	General Preventive Medicine
	Pediatric Subspecialties‡	Otolaryngology	Medical Genetics*
	Pediatric Cardiology‡	Plastic Surgery	Neurology
	Pulmonary Disease	Thoracic Surgery‡	Nuclear Medicine*
		Urology	Occupational Medicine*
			Pathology, Anatomic/Clinical*
			Physical Medicine/Rehabilitation*
			Public Health & General Preventive Medicine*
			Radiation Oncology‡
			Transplant Surgery‡
			Vascular Medicine
			Other Specialties‡
			Unspecified

Notes: This table lists the specialties for each category within HB physicians that provide physical care. These specialties are self-designated practice specialties determined by physicians from a list of codes included with the Physicians' Practice Arrangements questionnaire. * denotes specialties excluded from our main outcome measure of HB physicians due to limited HIT relevance; these specialties are collectively used in a placebo test. ‡ denotes highly HB specialties we discussed in Section 5.2.

Table A2: Summary statistics for variables over time

Year	2006	2007	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
HB physician counts per 100k population	15.17 (32.56)	15.54 (37.22)	16.74 (40.49)	16.82 (33.68)	17.30 (34.07)	18.28 (35.23)	19.84 (37.10)	21.38 (39.20)	22.78 (41.44)	22.48 (41.46)	23.20 (42.63)	23.77 (43.14)
Health IT diff--usion rate (%)	0.46 (4.00)	1.98 (11.77)	3.76 (16.62)	10.35 (27.55)	14.56 (32.14)	25.15 (39.88)	39.81 (45.25)	53.63 (46.27)	68.21 (43.36)	76.90 (39.23)	81.50 (35.92)	85.33 (32.47)
% treated	0 (0)	1.67 (12.83)	3.80 (19.13)	11.16 (31.49)	15.80 (36.48)	27.30 (44.56)	42.74 (49.48)	57.25 (49.48)	72.05 (44.89)	80.83 (39.37)	85.64 (35.08)	89.64 (30.48)
Medical HB physicians per 100k population	5.08 (14.27)	5.13 (16.41)	5.49 (17.39)	5.40 (14.48)	5.62 (14.76)	5.90 (15.05)	6.49 (15.95)	7.10 (16.74)	7.65 (17.74)	7.66 (17.88)	7.89 (18.44)	7.90 (18.39)
Surgical HB physicians per 100k population	2.81 (8.79)	2.87 (9.48)	3.11 (10.74)	3.21 (9.13)	3.39 (9.34)	3.58 (9.74)	3.98 (10.23)	4.24 (10.56)	4.49 (11.06)	4.39 (10.91)	4.44 (11.20)	4.55 (11.41)
Total GPs per 100k population	3.73 (6.99)	3.69 (6.89)	3.95 (7.10)	3.83 (6.66)	3.80 (6.84)	3.95 (6.71)	4.13 (6.68)	4.39 (6.94)	4.67 (7.63)	4.47 (7.43)	4.49 (7.36)	4.66 (7.85)
Other HB physicians per 100k population	3.55 (8.79)	3.85 (10.43)	4.18 (11.38)	4.38 (9.70)	4.49 (9.74)	4.86 (10.31)	5.25 (10.87)	5.65 (11.66)	5.97 (12.19)	5.96 (12.21)	6.37 (12.63)	6.67 (12.94)
Federal physicians per 100k population	3.50 (7.17)	3.56 (6.92)	3.84 (7.38)	3.56 (6.42)	3.50 (6.25)	3.33 (5.82)	3.36 (5.82)	3.58 (5.82)	3.62 (5.83)	3.30 (5.56)	3.17 (5.46)	3.00 (5.17)
Placebo specialties per 100k population	0.82 (2.89)	0.89 (3.30)	0.93 (3.52)	0.89 (3.11)	0.86 (3.00)	0.88 (3.00)	0.95 (3.16)	1.01 (3.39)	1.06 (3.60)	1.04 (3.50)	1.03 (3.59)	1.04 (3.60)
Physicians in other catego- per 100k population	4.31 (11.02)	4.38 (11.50)	4.24 (10.98)	3.87 (8.98)	3.71 (8.77)	3.68 (8.64)	3.89 (9.46)	3.86 (9.23)	3.75 (8.94)	3.63 (8.63)	3.63 (8.49)	3.58 (8.26)
Total physicians per 100k population	125.3 (117.6)	123.8 (121.4)	122.4 (122.8)	119.0 (112.6)	118.7 (114.2)	119.6 (115.7)	121.4 (119.2)	121.0 (120.0)	120.2 (120.5)	120.2 (121.5)	120.8 (123.2)	120.0 (123.6)
Early-career physicians per 100k population	46.38 (63.05)	44.76 (67.90)	43.31 (67.93)	40.42 (59.60)	40.32 (60.46)	40.48 (61.08)	40.20 (61.40)	39.57 (61.71)	38.93 (62.38)	38.57 (63.73)	38.68 (64.51)	37.80 (64.78)
Mid-career physicians per 100k population	62.90 (54.30)	63.04 (54.77)	62.95 (54.62)	62.58 (52.80)	62.11 (52.64)	62.04 (52.56)	61.59 (52.70)	61.15 (52.96)	60.64 (53.42)	60.27 (53.72)	59.34 (53.75)	58.44 (53.53)
Old-career physicians per 100k population	13.18 (12.91)	13.82 (13.96)	13.80 (14.13)	14.73 (13.82)	14.62 (13.36)	15.37 (13.84)	16.36 (14.54)	17.56 (15.43)	18.23 (15.83)	19.34 (16.71)	20.68 (17.63)	21.88 (18.58)
Inactive early-career physicians per 100k population	0.25 (0.94)	0.22 (0.90)	0.21 (0.76)	0.17 (0.59)	0.16 (0.55)	0.16 (0.59)	0.15 (0.53)	0.14 (0.48)	0.15 (0.59)	0.14 (0.55)	0.13 (0.56)	0.12 (0.57)
Inactive mid-career physicians per 100k population	3.24 (4.47)	3.17 (4.32)	3.34 (4.63)	3.28 (4.68)	3.31 (4.53)	3.22 (4.46)	3.11 (4.29)	3.10 (4.50)	3.15 (4.60)	3.19 (4.74)	2.92 (4.49)	2.65 (3.84)
Inactive old-career physicians per 100k population	21.53 (20.11)	21.73 (20.39)	22.58 (21.10)	23.04 (21.52)	24.00 (22.23)	25.51 (23.58)	26.38 (24.25)	27.03 (24.51)	28.11 (25.65)	29.27 (26.37)	30.62 (27.35)	32.05 (28.56)
Avg. Medicare allowed payments per physician ($ hundred)							718.8 (468.8)	721.9 (461.6)	728.9 (449.3)	730.4 (451.5)	735.5 (541.2)	722.5 (462.3)
Avg. # Medicare services per physician							1110.9 (1139.3)	1064.9 (1045.9)	1062.7 (986.0)	1047.1 (990.6)	1015.6 (995.1)	990.2 (981.3)
Avg. profits per hospital ($ million)	71.82 (116.1)	79.22 (126.9)	86.66 (135.8)	107.9 (170.1)	117.2 (183.8)	128.5 (199.6)	138.1 (213.9)	151.0 (232.8)	166.1 (256.6)	182.8 (283.7)	200.4 (315.2)	218.0 (348.0)
Avg. revenues per hospital ($ million)	127.6 (178.3)	138.0 (192.1)	149.8 (205.8)	175.2 (245.3)	187.1 (261.9)	200.3 (280.7)	211.5 (297.0)	227.5 (320.4)	246.4 (350.5)	267.6 (384.4)	289.3 (421.6)	311.4 (461.6)
Avg. costs per hospital ($ million)	55.76 (70.01)	58.75 (73.40)	63.18 (79.27)	67.26 (84.03)	69.92 (87.55)	71.87 (91.26)	73.44 (93.41)	76.44 (98.55)	80.38 (106.08)	84.77 (114.40)	88.97 (121.03)	93.36 (128.56)
Outpatient surgeries per 100k population	6361.7 (6428.1)	6276.3 (6476.1)	6386.6 (6419.7)	6272.5 (5389.2)	6292.8 (5473.3)	6253.0 (5396.3)	6174.4 (5399.3)	6200.5 (5542.6)	6308.7 (5628.7)	6582.7 (5869.7)	6576.9 (5749.9)	6641.3 (5886.7)
Inpatient surgeries per 100k population	2449.1 (2898.3)	2431.0 (3042.4)	2356.5 (2778.5)	2179.0 (2258.6)	2079.9 (2186.3)	2037.7 (2317.7)	1950.0 (2109.0)	1865.9 (2052.7)	1818.8 (1946.4))	1837.7 (1983.5)	1829.5 (1960.8)	1797.1 (1986.6)
Outpatient visits per 100k population	2701.0 (2853.6)	2724.4 (2851.4)	2780.5 (3032.2)	2787.3 (2737.9)	2784.1 (2484.7)	2854.6 (2683.7)	2887.1 (2769.7)	2903.3 (2628.5)	3001.6 (2761.6)	3119.1 (2976.3)	3117.6 (2867.9)	3124.5 (2977.7)
Medicare discharges per 100k population	51.28 (42.09)	50.66 (43.12)	49.95 (40.71)	45.56 (31.77)	44.77 (31.26)	43.05 (30.67)	41.94 (30.68)	40.25 (31.13)	40.06 (30.00)	39.36 (29.82)	39.56 (30.51)	39.22 (30.95)
# counties	2,392	2,391	2,393	2,393	2,393	2,392	2,389	2,386	2,386	2,379	2,374	2,375

Notes: This table reports summary statistics of the variables we use in the analyses by year over our sample period. Standard deviations are in parentheses.

Table A3: Treatment effects on physician density by main specialty and falsification tests

	Overall	By main HB specialty				Falsification tests		
		Medical	Surgical	Total GP	Others	Federal physicians	Other categories	Placebo specialties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Treatment Effect	2.162**	1.136*	.641**	.132	.252	-.09	.062	-.007
	(1.043)	(.627)	(.257)	(.111)	(.35)	(.102)	(.144)	(.076)
Panel B								
Event time −4	-.649	-.157	-.265	-.073	-.154	-.017	.036	.035
	(.842)	(.612)	(.174)	(.101)	(1.327)	(.183)	(.579)	(.191)
Event time −3	.008	-.133	-.149	.169**	.122	.094	-.118	-.027
	(.628)	(.46)	(.146)	(.074)	(.93)	(.149)	(.447)	(.137)
Event time −2	-.04	-.043	-.101	.065	.039	.11	-.116	-.035
	(.418)	(.337)	(.145)	(.048)	(.576)	(.084)	(.309)	(.079)
Event time −1	-.331	-.248	.049	.005	-.137	.058	.046	.016
	(.327)	(.247)	(.098)	(.034)	(.244)	(.044)	(.134)	(.04)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	.821**	.372*	.261**	.087	.102	-.004	.012	.075**
	(.345)	(.203)	(.114)	(.054)	(.098)	(.043)	(.09)	(.034)
Event time 2	1.442**	.658*	.378**	.205**	.201	-.032	-.018	-.016
	(.662)	(.362)	(.166)	(.089)	(.234)	(.082)	(.116)	(.056)
Event time 3	1.661*	.853	.559**	.124	.126	-.148	-.051	-.017
	(.917)	(.58)	(.265)	(.104)	(.285)	(.113)	(.157)	(.083)
Event time 4	2.42*	1.282	.781**	.032	.325	-.168	.004	-.041
	(1.283)	(.826)	(.364)	(.159)	(.411)	(.153)	(.158)	(.092)
Event time 5	3.236*	1.84*	.843**	.167	.386	-.06	.224	-.036
	(1.688)	(1.055)	(.38)	(.204)	(.59)	(.158)	(.248)	(.122)
Event time 6	4.744**	2.601**	1.407**	.21	.526	-.158	.346	-.028
	(2.177)	(1.17)	(.585)	(.25)	(.833)	(.195)	(.306)	(.163)
Mean DV	19.43	6.438	3.752	4.145	5.094	3.444	3.879	.949
N	28,426	28,426	28,426	28,426	28,426	28,426	28,426	28,426
P-value of testing joint significance of pre trends	.125	.719	.136	.001	.313	.141	.106	.517

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). The unit of observation is at the county-year level. Coefficients are reported as the number of physicians per 100k population. Regressions are weighted by county-year population. Controls include state-specific time trends and 2005 county demographics (share aged 65+, poverty rate, income per capita, Medicare Advantage penetration, share eligible for Medicaid, and college attainment rate), each interacted with a linear time trend to capture time variation while mitigating endogeneity from treatment, following Dranove et al. (2014). "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Treatment effects associated with consolidation or by market concentration

	Total physicians	Highly HB physicians	Excluding MAs	Excluding VIs	Counties w/ >1 hospitals	Counties w/ one hospital
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Treatment Effect	4.717***	1.561**	2.463**	2.743	2.077	.922**
	(1.72)	(.79)	(1.122)	(1.847)	(1.435)	(.469)
Panel B						
Event time -4	-2.162	-.465	-.721	-.277	-1.196	.99
	(2.003)	(.285)	(.84)	(2.08)	(.824)	(1.536)
Event time -3	-1.936	-.236	.127	.291	-.764	.989
	(1.702)	(.256)	(.605)	(1.632)	(.659)	(.976)
Event time -2	-.875	-.161	.122	.711	.168	.072
	(1.108)	(.215)	(.441)	(.754)	(.444)	(.528)
Event time -1	-.27	-.213	-.315	-.169	-.255	-.296
	(.718)	(.217)	(.451)	(.677)	(.428)	(.256)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	1.511**	.454*	.952**	1.327*	.831*	.378*
	(.598)	(.256)	(.384)	(.735)	(.43)	(.224)
Event time 2	2.465***	.785*	1.687**	2.17*	1.369*	.609*
	(.945)	(.472)	(.783)	(1.277)	(.809)	(.353)
Event time 3	3.479**	1.255*	1.996*	1.39	1.389	.557
	(1.427)	(.737)	(1.073)	(1.627)	(1.222)	(.413)
Event time 4	5.895***	1.87*	2.832**	3.042	2.255	.865
	(2.122)	(1.024)	(1.398)	(2.178)	(1.789)	(.62)
Event time 5	7.734**	2.499*	3.654**	3.571	3.108	1.586*
	(3.047)	(1.283)	(1.761)	(3.059)	(2.516)	(.81)
Event time 6	10.419**	3.61**	5.07**	7.373*	4.908*	2.61**
	(4.126)	(1.515)	(2.307)	(4.313)	(2.959)	(1.313)
Mean DV	121.041	10.279	17.696	23.214	29.096	12.728
N	28426	28426	24076	6501	11756	16268
P-value of testing joint significance of pre trends	.788	.399	.252	.839	.335	.016

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). The unit of observation is at the county-year level. Coefficients are reported as the number of physicians per 100k population. Regressions are weighted by county-year population. The same set of controls and state-specific time trends are included as in the main specification. "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Treatment effects on physician density by age and HPSA

	By career stage			By HPSA	
	Early-career	Mid-career	Late-career	Ever HPSA	Never HPSA
	(1)	(2)	(3)	(4)	(5)
Panel A					
Treatment Effect	2.263**	.523	.375	2.401**	1.588
	(1.034)	(.638)	(.269)	(.991)	(1.539)
Panel B					
Event time −4	-.145	-.032	-.383	-.534	-.978
	(.975)	(.849)	(1.254)	(.717)	(1.55)
Event time −3	.153	-.042	-.191	.24	-.668
	(.718)	(.69)	(.814)	(.711)	(.993)
Event time −2	.082	.26	-.149	.629	-1.179**
	(.477)	(.38)	(.469)	(.408)	(.595)
Event time −1	-.216	.104	.018	-.072	-.655*
	(.397)	(.236)	(.231)	(.391)	(.345)
Event time 0	omitted	omitted	omitted	omitted	omitted
Event time 1	.597*	.447	-.004	1.07**	.463
	(.321)	(.282)	(.106)	(.49)	(.406)
Event time 2	1.755***	.341	-.001	1.726**	1.122
	(.646)	(.438)	(.17)	(.715)	(.959)
Event time 3	2.288**	.288	.006	2.128**	.888
	(.991)	(.54)	(.243)	(.955)	(1.465)
Event time 4	2.862**	.543	.424	2.994**	1.582
	(1.285)	(.792)	(.361)	(1.204)	(2.185)
Event time 5	3.165*	.781	.972*	3.147**	2.794
	(1.804)	(1.104)	(.507)	(1.561)	(2.869)
Event time 6	3.898*	.982	1.427**	4.464**	4.136
	(2.349)	(1.518)	(.707)	(2.177)	(2.759)
Mean DV	40.797	61.428	16.619	17.919	20.949
N	28,426	28,426	28,426	14,332	14,086
P-value of testing joint significance of pre trends	.763	.738	.699	.262	.152

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). The unit of observation is at the county-year level. Coefficients are reported as the number of physicians per 100k population. Regressions are weighted by county-year population. The same set of controls and state-specific time trends are included as in the main specification. "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Treatment effects on financial metrics

	Physician financial incentive		Hospital financial incentive		
	Avg. Medicare allowed payments	Avg. Medicare services	Profits	Revenue	Costs
	(1)	(2)	(3)	(4)	(5)
Panel A					
Treatment Effect	40.855**	57.82*	14.959***	17.846***	2.886**
	(17.594)	(35.027)	(5.447)	(6.546)	(1.328)
Panel B					
Event time −4			-9.16**	-9.414*	-.254
			(4.562)	(4.999)	(1.405)
Event time −3			-4.713	-5.49	-.776
			(3.211)	(3.552)	(1.035)
Event time −2	-18.605	-57.202	-2.062	-2.343	-.281
	(29.055)	(54.575)	(2.118)	(2.513)	(.742)
Event time −1	12.713	22.667	-.244	-.441	-.197
	(14.012)	(37.676)	(1.271)	(1.632)	(.508)
Event time 0	omitted	omitted	omitted	omitted	omitted
Event time 1	16.103	16.558	5.241***	6.078**	.836
	(13.695)	(24.221)	(1.98)	(2.474)	(.631)
Event time 2	49.607	74.909	7.413**	8.473**	1.06
	(30.969)	(50.676)	(2.893)	(3.425)	(.759)
Event time 3	44.311**	78.976*	15.728***	18.295***	2.567**
	(21.725)	(41.547)	(5.43)	(6.453)	(1.257)
Event time 4	64.234**	73.922	20.78***	24.334***	3.555*
	(31.024)	(61.485)	(7.429)	(8.974)	(1.914)
Event time 5			24.965***	31.032***	6.066**
			(9.687)	(11.839)	(2.474)
Event time 6			26.085**	32.216**	6.131**
			(12.409)	(15.038)	(3.058)
Mean DV	730.807	1055.842	137.426	211.13	73.704
N	10,969	10,969	27,663	27,663	27,663
P-value of testing joint significance of pre trends	.268	.246	.087	.183	.69

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). The unit of observation is at the county-year level. The units for Column (1), (2), and (3)-(5) are $, number, and $ millions, respectively. Regressions are weighted by county-year population. The same set of controls and state-specific time trends are included as in the main specification. "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Treatment effects on surgery volumes by pre-treatment care utilization

	DV: Outpatient surgeries			DV: Inpatient surgeries		
	Low tertile	Mid tertile	Top tertile	Low tertile	Mid tertile	Top tertile
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Treatment Effect	40.753	482.044**	93.047	10.024	17.16	33.293
SE	(242.507)	(202.699)	(192.316)	(77.525)	(50.38)	(49.837)
Panel B						
Event time −4	-416.751*	538.131**	519.832	-89.032	48.189	169.756
	(216.869)	(242.995)	(322.453)	(71.042)	(70.142)	(112.93)
Event time −3	7.282	223.915	257.421	-51.586	169.006*	106.245
	(168.937)	(156.906)	(206.746)	(58.454)	(95.827)	(91.566)
Event time −2	251.357**	29.046	-20.602	92.914**	99.795***	31.391
	(127.431)	(122.127)	(138.51)	(37.095)	(35.187)	(54.183)
Event time −1	85.476	-147.234	-61.381	14.714	11.754	-9.056
	(102.159)	(95.706)	(116.346)	(20.894)	(23.934)	(36.965)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	19.095	200.339**	161.525	21.049	20.395	43.648*
	(113.637)	(85.271)	(148.966)	(61.082)	(24.681)	(23.708)
Event time 2	229.47	441.551**	-13.171	84.829	53.334	26.503
	(154.23)	(198.859)	(156.105)	(69.627)	(53.102)	(41.037)
Event time 3	58.021	470.605**	201.637	13.23	26.566	63.498
	(191.741)	(233.4)	(243.738)	(64.812)	(58.059)	(64.827)
Event time 4	-103.41	597.151**	305.18	-22.668	18.719	65.354
	(302.496)	(275.518)	(314.426)	(95.502)	(60.872)	(96.615)
Event time 5	28.025	590.172*	58.267	-43.193	-29.815	-10.31
	(423.208)	(322.35)	(302.155)	(131.867)	(81.434)	(108.682)
Event time 6	-62.154	840.255**	-418.067	-40.944	-19.849	-42.088
	(667.391)	(372.019)	(403.439)	(171.226)	(96.879)	(97.122)
Mean DV	7075.771	6179.145	5838.662	2418.903	2070.661	1678.348
N	9,371	9,519	9,536	9,371	9,519	9,536
P-value of testing joint significance of pre trends	.021	.039	.026	0	.031	.303

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). The unit of observation is at the county-year level. Coefficients are reported as annual surgery volumes per 100k population. Regressions are weighted by county-year population. The same set of controls and state-specific time trends are included as in the main specification. "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Treatment effects on HB physician density: robustness checks

	Different subsamples				Different specifications		
	≤5 adopt--ion rates	Counties w/o zero HB physicians	Balanced eve--nt studies	Excluding top-/ bottom-10%	No state--year trends	No county controls	No state/cou--nty controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Panel A							
Treatment Effect	2.227**	2.218*	1.026*	3.519***	1.846**	3.461***	2.866***
	(.868)	(1.146)	(.611)	(.986)	(.804)	(.925)	(.62)
Panel B							
Event time −4	-.676	-.922	-.077		-.55	-2.087*	-1.758**
	(1.078)	(.958)	(.46)		(.862)	(1.194)	(.832)
Event time −3	-.206	-.305	-.111	-1.52*	.295	-.905	-.399
	(.702)	(.712)	(.322)	(.92)	(.712)	(.864)	(.66)
Event time −2	-.279	-.066	.004	-.742	.172	-.55	-.203
	(.434)	(.47)	(.237)	(.627)	(.468)	(.692)	(.447)
Event time −1	-.242	-.288	-.176	-.669	-.217	-.567	-.382
	(.218)	(.357)	(.228)	(.612)	(.339)	(.519)	(.319)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	.732***	.867**	.369*	1.454***	.786***	1.086***	.98***
	(.267)	(.371)	(.215)	(.455)	(.276)	(.323)	(.251)
Event time 2	1.386***	1.474**	.718*	3.099***	1.259**	2.072***	1.721***
	(.53)	(.726)	(.371)	(.835)	(.512)	(.617)	(.433)
Event time 3	1.679**	1.707*	1.095*	4.291***	1.396*	2.721***	2.181***
	(.777)	(1)	(.611)	(1.18)	(.765)	(.806)	(.618)
Event time 4	2.672**	2.541*	1.373*	5.332***	2*	3.974***	3.207***
	(1.2)	(1.393)	(.811)	(1.699)	(1.032)	(1.145)	(.837)
Event time 5	3.562**	3.261*	1.331		2.544*	5.391***	4.321***
	(1.55)	(1.882)	(1.078)		(1.299)	(1.446)	(.973)
Event time 6	5.361***	4.81**	1.86		4.205**	7.873***	6.667***
	(1.914)	(2.415)	(1.419)		(1.656)	(2.026)	(1.262)
Mean DV	17.645	28.03	15.963	18.701	19.43	19.43	19.43
N	27,610	17,120	22,788	12,895	28,426	28,426	28,426
P-value of testing joint significance of pre trends	.558	.356	.847	.339	.275	.16	.011

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). The unit of observation is at the county-year level. Coefficients are reported as the number of physicians per 100k population. Regressions are weighted by county-year population. Control variables include county fixed effects, year fixed effects, state time trends, per capita income, unemployment rate, fraction of the population aged 65 or above, fraction of Black population, population density, the county-level hospital market HHI, and the following variables (in 2005 value) interacted with a linear time trend: Medicare Advantage penetration rate and the fraction of the population with a college degree or higher. "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.