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 an increase in the HB physician rate in treated counties relative to control counties, with medical and surgical specialties accounting for most of the increase. Moreover, this growth holds independent of major consolidation activity 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, as reflected in higher Medicare reimbursement, productivity, and hospital profits. Non-physician clinicians also change in line with the new schedule. Outpatient surgeries rise the most in counties with moderate pre-period care utilization. Various robustness checks across methods, estimators, specifications, and samples 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: Physician geographic distribution, technology adoption, financial incentives, health care utilization, hospitals, healthcare consolidation

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. Our 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). However, these systems 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). Despite its direct relevance to physician shortages, how CPOE affects physicians' geographic allocation and care provision remains understudied.

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 implementation 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 by De Chaisemartin and d'Haultfoeuille (2024) as our main estimator, and we demonstrate robustness using other recent DiD estimators (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Roth, 2022; 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. The 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 post-treatment, 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. We also explore how HIT adoption impacts non-physician workforce, such as physician assistants and registered nurses, and find that the effect varies depending on the specific nature of each role's interaction with physicians.

A potential threat to identification is that HIT diffusion may be correlated with unobserved county characteristics that also affect physician location decisions. For example, counties with more developed economies or stronger IT infrastructure may experience faster HIT diffusion, as their financial resources or existing technological ecosystems can lower the barriers to adopting new systems (Dranove et al., 2014). These areas may also attract physicians who seek better economic

prospects and prefer digitally integrated workplaces. To address this concern, we control for a rich set of county characteristics and extensive fixed effects. We also employ Hausman instruments (Hausman, 1996; Nevo, 2001), leveraging the fact that healthcare systems operate across multiple counties, and find similar results. Additionally, we conduct a systematic assessment of which factors correlate with treatment, using county-year-level observable characteristics as the outcome measures. The lack of significant effects on these outcomes, combined with the absence of differential pre-trends in HB physician density between treated and control counties, further lends support to the identifying assumption. Another potential threat to identification is the spillover effect of HIT diffusion. The rapid adoption in one county may make a neighboring, less HIT-intensive county less attractive to physicians and draw them away. To address this concern, we perform a matching-based DiD estimation, using distant but otherwise comparable counties as controls, and an analysis based on broader geographic units. Our results are consistent in both specifications.

Another 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). Therefore, the increasing HB physicians may be mainly driven by "expanding firm boundaries" (McCullough and Snir, 2010) rather than a true expansion of HB physician workforce. To test for this possibility, 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 expanding firm boundaries *cannot* be the main driver of the observed increase in HB physician density among HIT-heavy counties.

We also explore the implications of HIT for downstream patient care. We find no significant differences in the utilization measures we consider, except for some suggestive increases in outpatient surgery volumes in treated counties following HIT adoption. We then split the sample into tertiles by pre-period utilization and find that treated counties in the middle tertile exhibit notable increases in outpatient surgical services post-treatment. 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 due to substantially increased revenues despite a modest rise in costs. This pattern suggests that HIT allows hospitals to expand outpatient surgical capacity, potentially through improved coordination and patient throughput.

We conduct extensive robustness checks and placebo tests. Pre-trend tests à la Roth (2022) assure that our results are not sensitive to underpowered pre-trends, and leave-one-out analysis supports that unobserved, specialty-specific factors do not drive our results. Placebo tests show no significant changes in physician density among groups less likely to be influenced by HIT adoption, including physicians primarily engaged in research or teaching, those in specialties less HIT-relevant (e.g., aerospace medicine and forensic pathology), 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 (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 other recent staggered DiD estimators yield consistent results. Furthermore, our results are robust to alternative definitions of HIT adoption when combining CPOE with physician documentation systems, 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).

Like other enterprise information systems, HIT adoption involves major operational changes, making its effects on clinicians' productivity, workflow, and mobility complex. Whether HIT com-

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

plements or disrupts clinicians' work, and thus affects retention, depends on the specific applications, individual characteristics, and organizational context (Greenwood et al., 2019).[2] Related evidence from nursing homes indicates that HIT reduces nurse staffing in high-end facilities but increases it in low-end ones, with little net effect overall (Lu et al., 2018). Recent work finds that hospital HIT adoption can increase exit through retirement or shifts to office-based practice among hospitalists, particularly older physicians (Glenn, 2026).[3] We extend this literature by examining how advanced HIT diffusion affects local physician density across a wider range of specialties and practice settings than previously studied, an outcome directly linked to patient access to care.

Second, our study complements the broad literature on physician labor supply, most of which 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 shortages.[4] A growing literature explores this dimension by studying how providers 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 the 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 and managerial relevance. Early hospital experience suggests that advanced HIT improved clinician recruitment and retention (Silow-Carroll et al., 2012) and generated sizable returns through reductions in preventable medical errors (Everett et al., 2008). Consistent with this, some physicians value access to advanced HIT over higher pay when choosing jobs, as these technologies reduce administrative burden (DeSilva, 2025). As HIT investment

[2]The study by Greenwood et al. (2019), 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).

[3]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.

[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.

continues to expand globally (Wang and Bloch, 2023), our results provide timely evidence related to patients' access to care, providers' geographic distribution, and related financial sustainability. For hospital administrators, advanced HIT can ease cross-department coordination and serve as a strategic lever for physician recruitment and retention. For policymakers, understanding how digital adoption interacts with physician density can inform workforce sustainability and equitable access policies. Targeted digital investments may function as market-based tools to attract physicians.

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.

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 healthcare 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 had received over $21 billion in incentive payments (CMS, 2018a).

[5] See https://www.extractsystems.com/a-brief-history-of-the-emr/.
[6] See https://www.practicefusion.com/blog/emrs-hospital-vs-ambulatory-solutions/.

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, which all depend 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.

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 an example of 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, which were 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

[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.

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

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-to-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, 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' perspectives, 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 increasing care efficiency and potential earnings. In contrast, physicians less comfortable with digital technology may be discouraged by the demands of practicing in HIT-intensive environments.

From patients' perspectives, 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 main dataset is the Area Health Resources Files (AHRF) (AHRF, 2018), which aggregates information from over 50 sources on health professionals by specialty, healthcare utilization, facilities, and demographic characteristics. 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 mainly for physical health.[9] Our main out-

[9]We focus on physical care, where treatment processes and outcomes are relatively standardized. HB physicians include 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 exclude those employed by federal agencies (e.g., military, Veterans Administration, Public Health Service), who operate under distinct structures and are unlikely to be affected by HIT adoption.

come is the number of HB physicians per 100k population at the county-year level.[10] To isolate physicians likely affected by HIT adoption, we exclude specialties with limited HIT relevance: 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. We also conduct a leave-one-out analysis for specialties included in the main sample.

The AHRF provides data on physician characteristics, including age 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.

The AHRF also provides rich county-level demographic 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).

Finally, the AHRF contains information on non-physician clinicians and healthcare utilization, the outcome measures we use to explore implications for productivity and downstream care utilization. Our analysis of non-physician clinicians includes registered nurses (RNs), nurse practitioners (NPs), and physician assistants (PAs), all of whom may serve as either complements to or substitutes for physician roles.[13] We use the following measures to analyze care utilization:

[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 can handle zero values, modern DiD estimators are better suited to linear regression-based models. As a robustness check, we re-estimate the main specifications excluding counties that ever had zero HB physicians during our sample period, finding similar results (Section 5.6).

[11] The excluded specialties were selected based on discussions with physicians and medical school faculty. We especially thank Dr. Keith Joiner for valuable insights. Some exclusions are consistent with provider categories ineligible for HIT incentive payments (Dougherty et al., 2013)

[12] The 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] Note that the data for non-physician clinicians only include individuals with National Provider Identifiers (NPIs). We believe it still provides a representative proxy for the NP and PA workforces, given the high rates of NPI registration required for their clinical duties (American Association of Nurse Practitioners, 2022; National Commission

total outpatient and inpatient surgical operations at hospitals, outpatient visits, Medicare inpatient discharges, and emergency room visits.[14]

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 local hospital bed sizes.[15] Our one-year lagged CPOE data (à la Lu et al., 2018) span 2005–2017, a period marked by rapid US HIT adoption (Figure 1).[16] The left panel of the figure plots the average county-level adoption rate, starting below 0.5% in 2005 and exceeding 85% by 2017.[17]

Following the general strategy developed in East et al. (2023), we divide the sample into treatment and control groups based on whether a particular county ever experienced a substantial increase in adoption rates. Specifically, our sample begins with all counties untreated. We define a county as switching from control to treated in year τ if it satisfies either of the following conditions: (i) for a county with zero adoption in $\tau-1$, the change in adoption between $\tau-1$ and τ is the largest over the sample period; or (ii) for a county with positive adoption in $\tau-1$, the adoption rate increases by more than 100% in τ *and* such an increase is the largest during the sample period.[18] In either (i) or (ii) above, the identified sharp jump reflects a substantial change in HIT adoption, either transitioning from none to some adoption or undergoing a significant expansion, so that pre- and post-adoption statuses are meaningfully distinct.[19]

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on Certification of Physician Assistants, 2023). While NPIs are not a requirement for practicing RNs, this measure remains informative for tracking directional changes, provided that the discrepancy between RNs with and without NPIs does not follow a systematic pattern that would bias the observed trend.

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

[15] 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.

[16] We also use contemporaneous HIT adoption rates as a robustness check, and the main findings are similar (Section 5.6). Following the prior literature, we use one-year lagged data in our main analyses to allow sufficient time for the effect to materialize.

[17] Table A2 provides year-by-year adoption rates, highlighting the magnitude of this nationwide diffusion.

[18] The identification of the *largest* jump year is not sensitive to the precise cutoff. Conditions (i)–(ii) formalize the classification of sharp jumps. Imposing an alternative cutoff based on the sample median increase (154%) yields nearly identical treatment timing across counties.

[19] We experiment with a continuous DiD estimator by De Chaisemartin and d'Haultfoeuille (2024), obtaining posi-

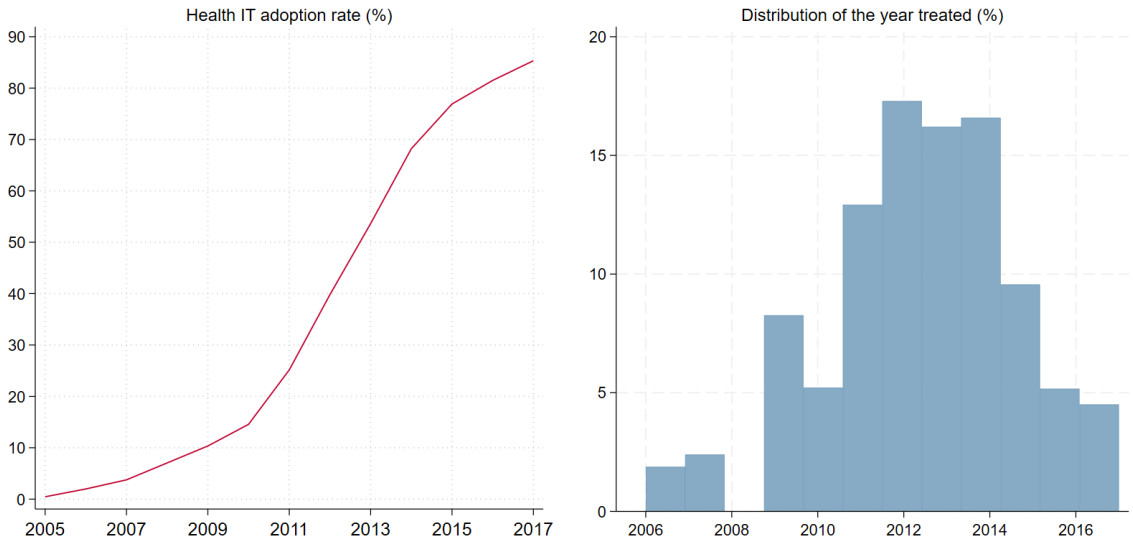


Figure 1: Health IT diffusion pattern

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, following Lu et al. (2018)

Our classification captures substantial changes in HIT adoption status for counties (Figure 2).[20] 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.[21] Although adoption trajectories vary across groups, a common pattern emerges: adoption rates remain relatively flat before treatment but rise sharply at the time of treatment. We exploit both the variation in HIT 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.

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 clas-

tive and significant results consistent with our main results. Since continuous treatment DiD remains under active methodological development, we refrain from emphasizing these results. Our results are also robust to alternative classifications of treatment (Section 5.6)

[20] Figure 1 (right panel) shows the distribution of treatment years based on this classification.

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

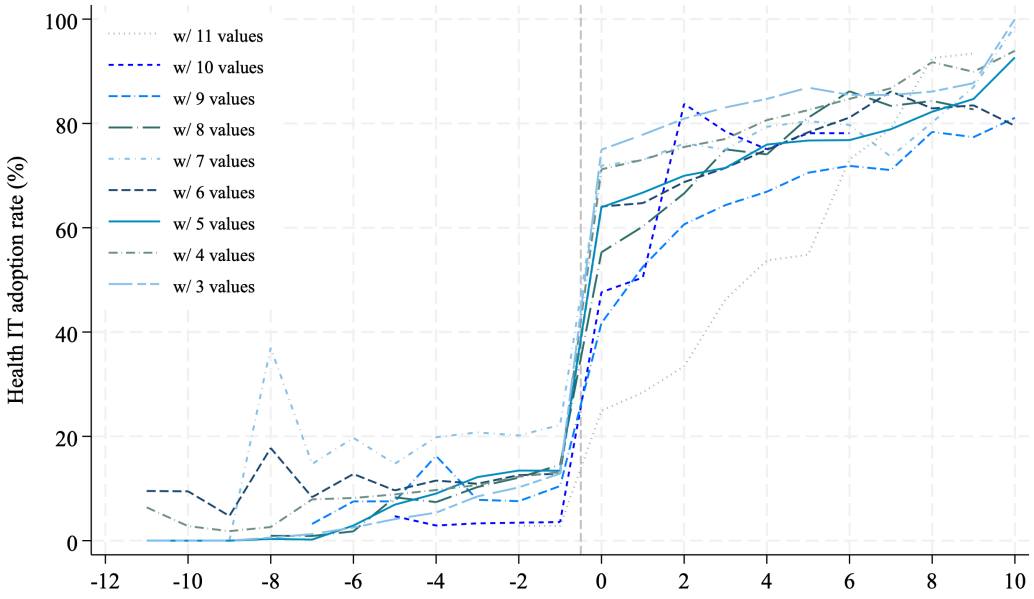


Figure 2: Health IT adoption rate relative to treatment year

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.

sifications, 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 next data source is the Medicare Physician & Other Practitioners by Provider and Service dataset (CMS). We extract two physician-level measures: (1) the total allowed amounts a physician receives for treating Medicare beneficiaries, including Medicare payments, patient deductibles and coinsurance, and any third-party contributions, and (2) the number of Medicare services conducted by each physician. These measures assess whether physicians benefit financially from practicing in areas with higher HIT adoption. Since this dataset starts in 2013, relevant analyses are limited to a shorter time frame.

Market Structure and Financial Performance Data: We supplement our 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 concen-

tration at the county level, we construct the Herfindahl-Hirschman Index (HHI), defined as the sum of squared market shares in hospital beds of all local hospitals in the county.[22] A higher HHI indicates a more concentrated market. 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 means of these measures by averaging across all hospitals in 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 2,394 counties for 2006–2018, excluding 2009 due to missing AHRF data.[23] When merging datasets, we apply a one-year lag between HIT adoption and outcomes to account for response time following Lu et al. (2018).[24] The reduction in our merged sample size is primarily due to missing data in 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 adoption rates derived from HIMSS accurately represent the overall HIT adoption status across most counties.[25]

3.2 Summary Statistics

Figure 3 shows the geographic distribution of HIT adoption (top) and HB physician counts per 100k population (bottom) 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 regional variation in both HIT adoption and physician supply suggests potential associations between these trends, motivating a

[22] 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.

[23] The empirical analysis does not have the year 2009 as a result.

[24] For example, we tie 2008 adoption to 2009 outcomes.

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

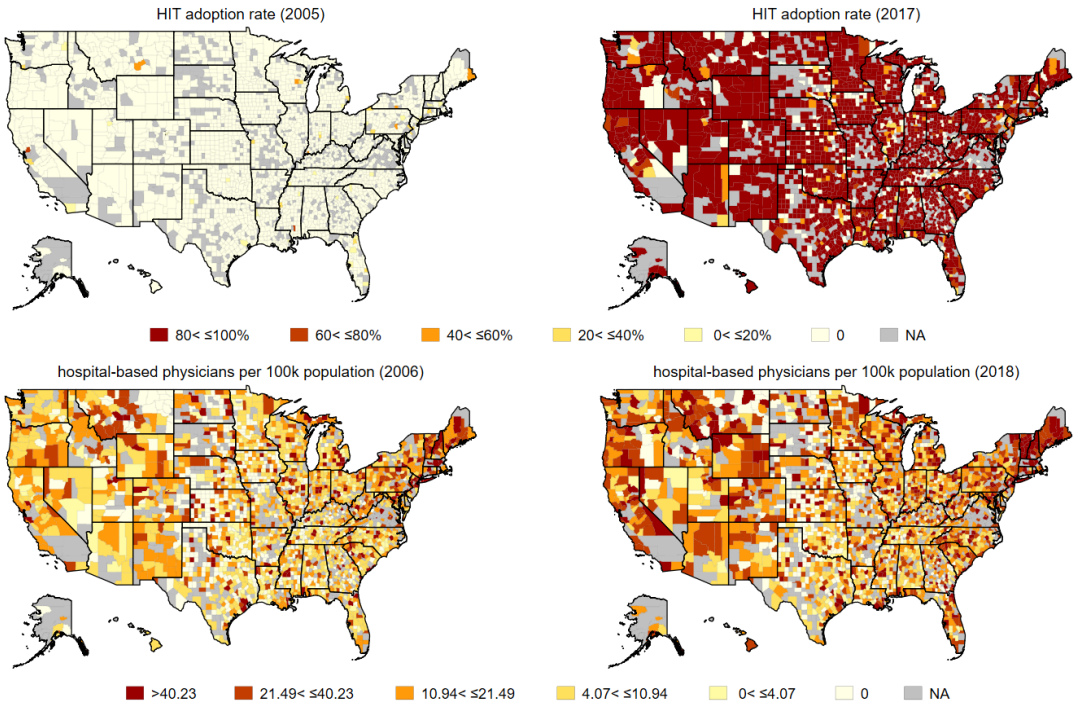


Figure 3: Geographic distribution of HIT adoption and hospital-based physician density

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.

more systematic analysis to determine the extent to which they reflect causal relationships.

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 adoption rates. The statistics by treatment status reveal that HB physician density was lower in never-treated counties. Both groups were similar across most observable county-level characteristics, except that ever-treated counties were more densely populated, had larger populations, less concentrated hospital markets, smaller aging populations, and higher Medicare Advantage penetration rates prior to HIT adoption. We also examine the differential change in these characteristics over time between never-treated and ever-treated counties, analogous to a difference-in-differences measure (Table A3). Most of the differences in these changes are statisti-

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 (37.8)	13.0 (17.0)	17.7 (39.6)
Health IT adoption rate (%)	1.46 (5.39)	0 (0)	1.64 (5.69)
% 65+ population	15.7 (4.07)	17.2 (4.35)	15.5 (4.00)
Poverty rate (%)	15.9 (5.95)	16.6 (6.10)	15.8 (5.92)
Income per capita	32,356 (8,325)	34,872 (10,304)	32,046 (7,996)
Medicare Advantage penetration rate (%)	4.06 (7.73)	2.87 (5.58)	4.21 (7.95)
% Medicaid eligibles	20.3 (8.35)	21.1 (9.10)	20.2 (8.25)
% above college degree	12.6 (5.7)	11.4 (5.1)	12.8 (5.7)
Hospital HHI	0.80 (0.27)	0.92 (0.15)	0.78 (0.27)
Population size	88,067 (195,643)	37,219 (39,620)	94,333 (206,021)
Population density	239 (1,722)	107 (520)	256 (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. The majority of variation comes from the timing group (i.e., ever-treated units at different times).

cally insignificant, except for population size and Medicaid eligibility rates, though the difference in the second control is very small in magnitude. While ever-treated counties have a relatively larger population, the estimated effect of HIT adoption on HB physician counts is steeper than that on population size (Section 5.6), suggesting that our main estimates are, if anything, downward biased. 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.

4 Empirical Strategy

4.1 Main Specifications

We investigate how HB physician density changes in response to the rapid diffusion of advanced HIT 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, the 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.

To examine the effect of HIT diffusion on HB physician density, we estimate the following regression equation in a staggered DiD framework:

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_{it-1} + \gamma X_{i,2005} * t + \lambda_{st} + \delta_i + \delta_t + \varepsilon_{it}, \tag{1}$$

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 (Lu et al., 2018). 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. $X_{i,2005} * t$ includes a rich set of county-year level variables valued in 2005, as described in Section 3.1, interacted with a time trend.[26] λ_{st} represents 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.[27] δ_i denotes

[26] We follow this strategy in Dranove et al. (2014) to mitigate potential concerns that contemporary observables may be affected by HIT.

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

county fixed effects, controlling for time-invariant county characteristics that might simultaneously affect local physician workforce and HIT diffusion. Time fixed effects, δ_t, account for changes over time that affect all counties. Our key coefficient of interest, β_1, measures the effect of HIT adoption on local HB physician density.

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:

$$Y_{it} = \beta_0 + \sum_{\tau=-4,\, \tau\neq 0}^{6} \beta_1^{\tau} \times \mathbb{1}\{t = \tau\}\text{EverTreated}_i + \gamma X_{i,2005} * t + \lambda_{st} + \delta_i + \delta_t + \varepsilon_{it}, \tag{2}$$

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 year 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.

We estimate the main specifications in Equations (1) and (2) following De Chaisemartin and d'Haultfoeuille (2024) that accounts for staggered treatment timing and heterogeneous treatment effects. Recent econometric literature highlights that traditional TWFE estimators may produce biased estimates in such settings. To ensure robustness, we also report results using alternative estimators from Borusyak et al. (2024), Callaway and Sant'Anna (2021), Roth (2022), and Sun and Abraham (2021) (Section 5.6). 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).

4.2 Discussion on Identification

Our key identifying assumption is that county-level HIT adoption is exogenous to unobserved factors influencing local physician rates. However, a potential concern is that divergent adoption trajectories between treatment and control counties may reflect underlying differences in demographic and economic conditions, or in the availability of local IT-complementary resources; these

factors could also affect physician practice decisions. To address this concern, we control for a rich set of county characteristics and extensive fixed effects. We confirm no differential pre-trends in HB physician density between treated and control counties, supporting the identifying assumption. Moreover, we employ Hausman instruments (Hausman, 1996; Nevo, 2001), exploiting the structure of healthcare systems that span multiple counties, and we use adoption rates in non-local associated counties as instrumental variables (IVs). These are counties where "sibling" hospitals—those belonging to the same system as hospitals in the focal county—are located. To further mitigate concerns regarding local spillovers, we restrict the associated counties to those located in different states than the focal county. The results are in line with our main findings (Section 5.1).

In addition, we examine how common county characteristics evolved before and after treatment and find no evidence that they are correlated with the timing of rapid adoption (Section 5.1). In fact, the rapid diffusion of HIT was largely driven by the HITECH Act and HIT-related ACA incentives that tied hospital payments to HIT adoption (Adler-Milstein and Jha, 2017; Dougherty et al., 2013). These policy-driven incentives reduce concerns that HIT diffusion was primarily shaped by local endogenous factors.

Another concern may arise due to potential spillovers of local HIT diffusion. Rapid HIT adoption in one county may create a competitive disadvantage for neighboring, less HIT-intensive counties, pulling physicians away from those areas. To address this concern, we apply a matching-based DiD method, following the procedure à la Deryugina et al. (2018). Specifically, for each ever-treated county, we identify the top 10 control counties based on the following county characteristics in 2000–2004: HB physician density, annual percentage change in HB physician density, Medicare Advantage penetration rate, % 65+ population, income per capita, and unemployment rate. We further restrict the control counties to be sufficiently far away ($\geq$300 miles and in a different census region from the focal county). This exercise yields results in the absence of local spillovers and tests whether our main results are robust to constructing control counties that are geographically distant but otherwise similar to treated counties in observables. We also conduct the analysis based on a larger geographic unit, Hospital Referral Regions (HRRs), where spillover concerns are less salient. Our results are robust to all these alternative specifications.

A third potential concern involves health care consolidation, where large hospital systems acquiring physician practices may adopt HIT simultaneously, resulting in observed physician increases. We thus test whether rapid HIT adoption leads to a net increase in total physician density.

The intuition is as follows: if our main results are primarily driven by the reclassification of local, previously non-HB physicians, then the increase in total physician density should be no greater than that in HB physician density. We also conduct robustness checks that exclude counties with substantial mergers, acquisitions, or vertical integrations and the main findings hold (Section 5.2).

4.3 Heterogeneity, Mechanism, and Robustness Checks

We examine heterogeneity along various dimensions. First, we compare physician specialties, as responses to HIT may differ between general practitioners and medical/surgical specialties due to varying HIT reliance. Second, we assess differences by career stage, hypothesizing that early-career physicians, who are typically more IT-savvy and movable, are more likely to adopt new technologies and adjust location choices. Third, we analyze variation across areas with and without prior physician shortages, accounting for geographic differences in access to care. Fourth, we explore heterogeneity across counties with varying levels of market concentration or urbanicity. Together, these analyses examine whether the effects are concentrated among certain types of physicians, such as those facing stronger incentives or lower costs to adopt HIT, or within certain areas, such as those that are less competitive, with greater physician shortages, or are more urban.

To understand factors that may impact physician density responding to HIT diffusion, we examine whether HIT-intensive environment yields measurable financial benefits for healthcare providers, including HB physicians and hospitals. We also examine the effect of HIT diffusion on non-physician clinicians, e.g., registered nurses, nurse practitioners, and physician assistants. Moreover, we explore heterogeneity across counties with different levels of pre-existing healthcare utilization and assess how adoption of HIT may influence subsequent patient care utilization. Finally, we perform a series of sensitivity checks to evaluate the robustness of our main findings, ensuring that specific sample compositions or model specifications do not drive the results.

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 Equation (2). The figure shows results for four physician categories: HB physicians (circles), federal physicians (diamonds), physi-

cians 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. There is no visual evidence of differential pre-trends in HB physician supply between the treatment and control groups. Table A4 (Panel A, Column (1)) reports the corresponding average treatment effect estimated from Equation (1). It shows that treated counties experienced an average increase of 2.16 HB physicians per 100k population, representing an 11.1% gain ($= 2.16 \div 19.4$). The joint significance test (p-value $= 0.125$) of the pre-treatment interaction terms indicates that we cannot reject the hypothesis that these coefficients are jointly zero, supporting the parallel trends assumption.

Note that the "treatment" corresponds to an average increase in the adoption rate of approximately 65.5 percentage points, as shown in Figure A2, where we re-estimate Equation (2) using the actual, continuous adoption rate as the dependent variable. Thus, counties that switched from no adoption to full adoption experienced, on average, a relative increase of 3.30 ($= 2.16 \div 0.655$) HB physicians per 100k population, which is broadly aligned with the estimates from the continuous DiD estimator by De Chaisemartin and d'Haultfoeuille (2024) (Figure A3). These results suggest that local HIT adoption affects aggregate physician location choices, *ceteris paribus*. It shows the importance of advanced HIT, which can be a bargaining point for hospitals, in physician recruitment and retention (e.g., Silow-Carroll et al., 2012; DeSilva, 2025).

The remainder of Figure 4 serves as falsification tests, 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.[28] 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. We find no significant effects of HIT adoption on physician density across these placebo

[28] 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/.

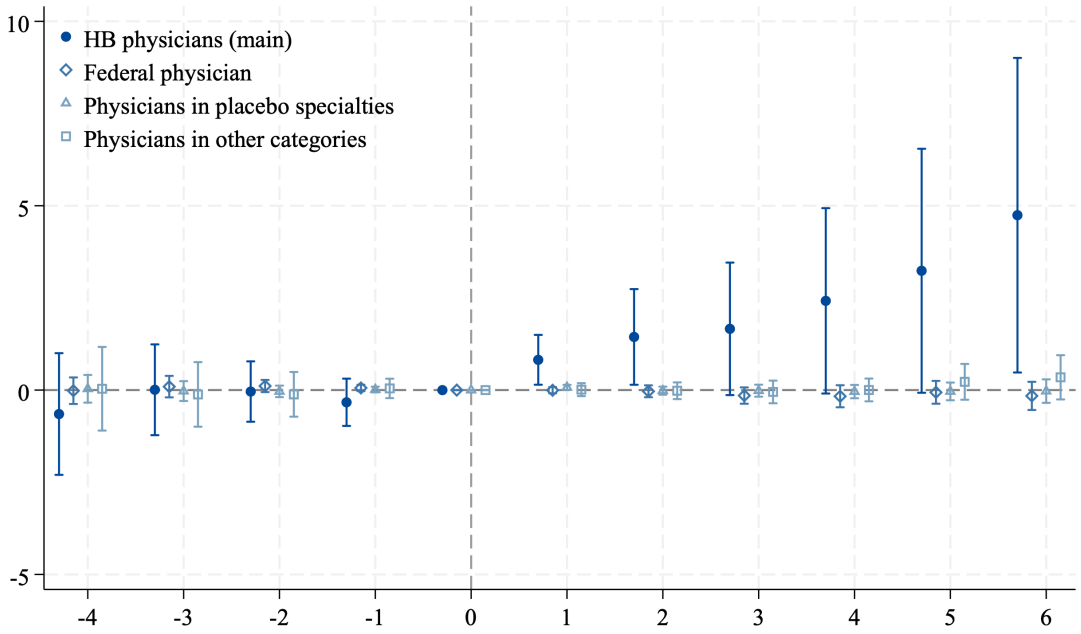


Figure 4: Effect of HIT diffusion on HB physician density, main results and falsification tests

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.

groups, reinforcing the validity of our main findings.

We further explore heterogeneous effects across categories within HB physicians: medical specialties, surgical specialties, total general practice (GP), and other specialties.[29] Figure A4 presents the event-study estimates for these specialty groups. The figure shows 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. On average, the post-treatment interaction terms indicate a relative in-

[29]Common medical specialties: Internal Medicine, Pediatrics, and Cardiovascular Disease. Surgical specialties: Obstetrics and Gynecology, General Surgery, and Orthopedic Surgery. Total GP: General Practice and Family Medicine.

crease of 1.14 (17.6%) in medical specialties and 0.64 (17.1%) in surgical specialties (see Columns (2)–(5) in Table A4). 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. Local HIT can help enhance all these processes. 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, which may lead to a net increase in physician rates.[30]

Unobserved County Heterogeneity: As discussed in Section 4.2, a potential concern for identification is that the distinctive HIT diffusion patterns across counties may reflect unobserved county-level heterogeneity. To address this concern, we re-estimate the main specifications, replacing HB physician density with certain common county characteristics. Figure A5 (left panel) presents the event-study results. None of these outcome measures show significant changes following HIT adoption, suggesting that they are not correlated with local HIT diffusion patterns.

To further address this endogeneity issue, we use adoption rates from outside associated counties as instruments and implement a two-step estimator. First, we regress the treatment variable on the instruments, along with the same set of county controls and fixed effects as in the main specification, and obtain the predicted values from this regression. Then, we apply the continuous DiD estimator by De Chaisemartin and d'Haultfoeuille (2024), replacing the treatment variable with the predicted values from the first step. Figure A6 and Table A5 report the IV results. These are consistent with our main findings, despite wider confidence intervals.[31]

[30] Glenn (2026) 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.

[31] Note that the IV sample includes fewer than 1,000 counties because (1) not all focal counties have hospitals affiliated with healthcare systems, and (2) we restrict the associated counties to those located in different states from the focal county. Also, the second-stage standard errors do not account for the estimation uncertainty from the first stage, as we manually implement the two-step procedure to accommodate the modern DiD framework.

Addressing concerns about local spillovers: To address potential concerns that HIT adoption may generate spillover effects that influence nearby counties with slower diffusion, we conduct a matching-based DiD analysis. Specifically, we follow Deryugina et al. (2018) (discussed in Section 4.2) to identify observably similar but distant counties as control units. We find overall similar results to our main analysis (Figure A7). Since not all ever-treated counties have strictly matched controls, we lose about 5% of counties in total and 0%, 3%, 7%, and 5% in the Northeast, Midwest, South, and West census regions, respectively.[32] Regardless, we find consistent patterns in overall stacked regression and in separate analyses by census region.

Moreover, to alleviate the concern that the positive effect may reflect physicians moving disproportionately from less-resourced counties to more technologically advanced counties nearby, we re-estimate our main specifications at the hospital referral region (HRR) level (Figure A8, right panel), a broader geographic unit for tertiary medical care.[33] We continue to observe increases in HB physician density in treated HRRs relative to control HRRs post-treatment, particularly among medical specialties, though the 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 geographic level suggest that HIT attracts physician inflows *beyond* local movements.

5.2 HIT Diffusion or Physician Practice Consolidation?

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.[34] In such cases, the observed rise in HB physician density may simply reflect a change in the "employment status" of previously non-HB physicians due to consolidation, rather than a genuine increase in physician density.

To assess whether our findings are driven by consolidation between hospitals and other healthcare organizations, we conduct the following analyses. First, we compare the effects of HIT diffu-

[32] Our preferred specification is also simpler and easier to transition to other analyses.

[33] HIT diffusion patterns at the HRR level resemble those at the county level (Figure A8, left panel). Each HRR, with a minimum population of 120k, includes at least one hospital performing major cardiovascular procedures and neurosurgery (https://www.dartmouthatlas.org/faq/).

[34] McCullough and Snir (2010) find that the demand for monitoring IT increases with physician-hospital integration, likely due to challenges in enforcing complete contracts between hospitals and physicians.

sion 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 (particularly through the acquisition of ambulatory practices) should primarily affect specialties less likely to work in hospital settings.[35]

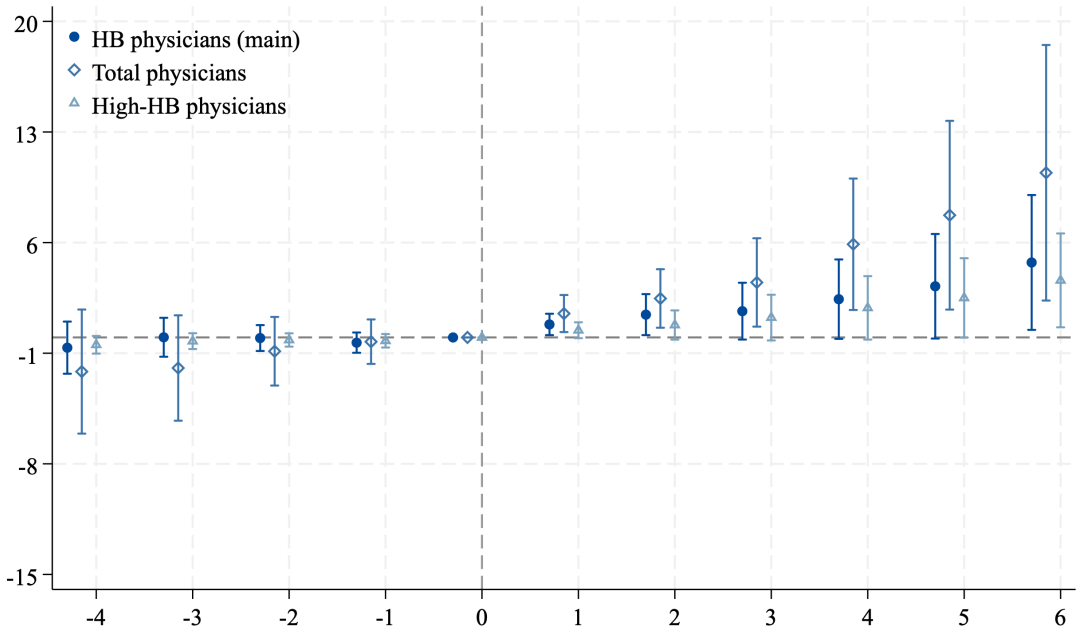


Figure 5: Effect of HIT diffusion on total physician versus HB physician densities

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 county-year level population. Fixed effects at the county and year levels are always included. The same set of controls and state-specific time trends as in the main specification are included. The whiskers show 95% confidence intervals, with standard errors clustered at the state level.

Figure 5 and Table A6 (Columns (1)–(2)) report the results. In the post-period, treated counties exhibit a greater increase in the total physician rate compared to the HB physician rate, indicating that consolidation or employment reclassification alone cannot explain the rise in HB physician density. Despite a slight visual pre-trend in total physician density, the joint test of the pre-treatment coefficients fails to reject the null hypothesis (Table A6), and the pre-trend test à la Roth (2022)

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

(Table A7) supports a significant increase in this measure post-treatment. Moreover, the effects for highly HB specialties closely mirror the main estimates, suggesting that HIT diffusion does not differentially affect employment reclassification, which would otherwise suggest a much larger increase in high-HB specialty physician density.[36]

Second, we re-estimate our main specifications after excluding counties that experienced substantial M&A or VI activities during the study period. 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. We classify a county as experiencing substantial M&A (VI) activity in a given year if the share of local systems undergoing such changes exceeds the 25th percentile of the sample distribution.[37] Excluding these counties allows us to test whether our main findings persist in markets less affected by organizational consolidation, providing a cleaner view of HIT's independent impact.[38]

Figure 6 presents the event-study estimates, and Table A6 (Columns (3)–(4)) reports the corresponding regression results. We find 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. 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. 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 Heterogeneity Analysis

We explore how the effects of HIT diffusion vary across different types of physicians (e.g., by career stage) and across different types of counties (e.g., by physician shortage status, urban

[36] 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.

[37] We also try alternative cutoffs, such as the 50th percentile, and the results are robust.

[38] We also use the share of systems with VI/MA activities as the outcome variable. We find no evidence of increasing VI/MA activities post-treatment (Figure A5, right panel), assuring our results are not driven by consolidation.

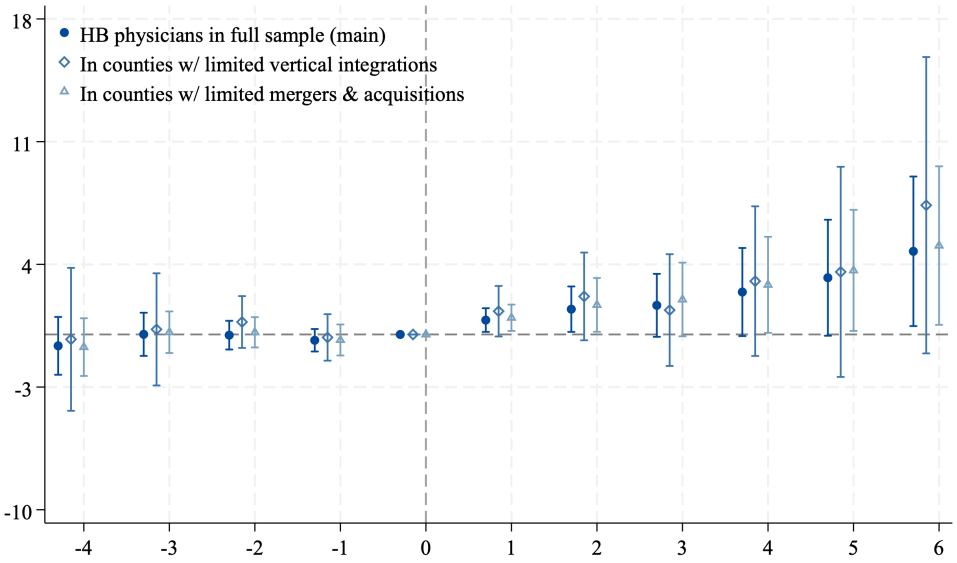


Figure 6: Effect of HIT diffusion on HB physician density in counties with less consolidation

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.

status, or hospital market concentration). Exploring those heterogeneity helps us understand how HIT adoption affects the distribution of physicians across experience levels and geographic areas.

Heterogeneity by Career Stage: Figure 7 (left panel) shows the event-study estimates for early-career (under 45), mid-career (45–64), and late-career (65+) active physicians.[39] We observe a significant post-treatment increase in early-career physicians (circles) in treated counties relative to controls, but no evidence of changes for mid- and late-career physicians. These results suggest that the overall rise in physician density is primarily driven by younger physicians. The finding aligns with previous work showing that early-career providers 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). Younger physicians may face fewer barriers to navigating complex IT systems and may value faster access to patient data and streamlined workflows enabled by HIT. In contrast, inactive physicians show no response among younger groups but a mild rise among those 65+, reflecting selective retirement after HIT adoption (Figure A9, right panel).

Heterogeneity by Physician Shortage Area (HPSA) Status: Next, we assess how the effects

[39]Table A8 reports regression results (Columns (1)–(3)). The AHRF provides physician counts by age but does not distinguish between hospital- and office-based settings, so results by career stage reflect the effects on both groups.

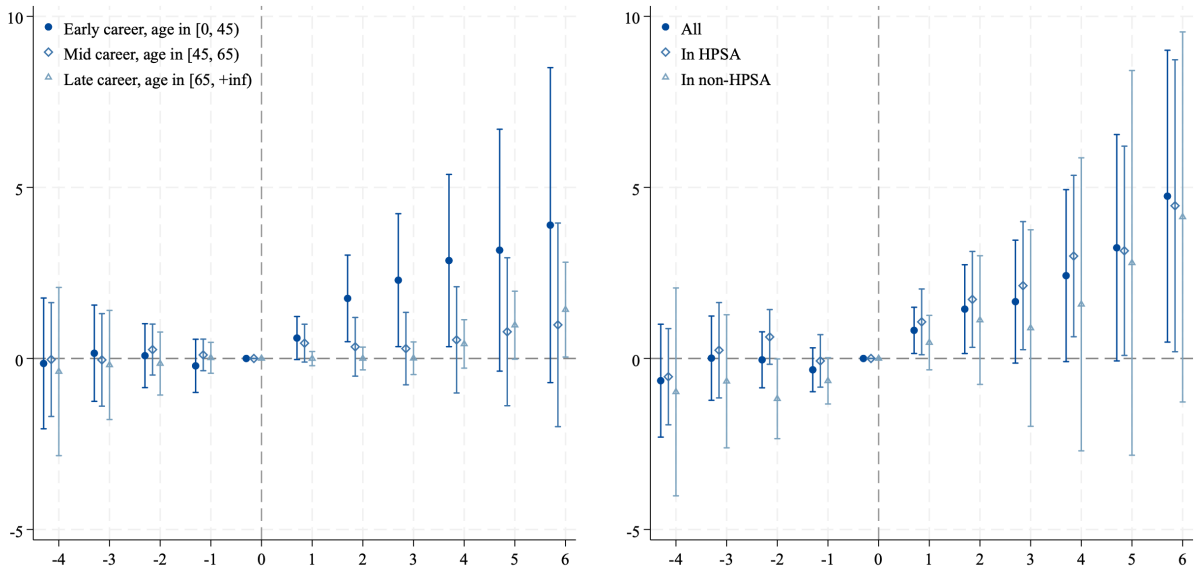


Figure 7: Effect of HIT diffusion on physician density, by career stage and HPSA status

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.

of HIT diffusion vary by 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 during our sample period.[40] Figure 7 (right panel) and Table A8 (Columns (4)–(5)) show that the treatment effect is concentrated among ever-HPSA counties, with a significant increase in HB physicians density in treated HPSA-counties relative to control HPSA-counties. This suggests that HIT enhances the ability to provide high-quality care in resource-limited settings. The estimates for never-HPSA counties are noisy and show no evidence of increases in physician density post-treatment.

Heterogeneity by Urban/Rural Status: To examine heterogeneity by local population density or urban classification, we split the sample at the median population density and by metropolitan versus non-metropolitan statistical area status (Figure A10). The positive effect on HB physician density is concentrated in above-median-density areas (left panel) and metropolitan statistical areas (right panel), with no evidence of significant changes in physician density in other areas. This pattern suggests that denser, urban areas have more resources and higher potential patient vol-

[40]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.

umes that give HIT more scope to justify expanded physician staffing. This result complements the HPSA finding: HIT can improve access in underserved areas with excess demand, while baseline patient volume shapes how much hospitals can expand physician staffing sustainably.

We further split counties by HPSA designation and by population density (above vs. below median), then re-estimate the main specifications for each combination of the two (Figure A11). While post-treatment increases in HB physician density are concentrated in HPSA counties, the estimates are statistically significant only in more densely populated areas. It is possible that HIT makes HPSA counties more attractive to physicians by improving clinical efficiency and offering better practice opportunities where physician demand remains high.

Heterogeneity by Hospital Market Concentration: Since 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 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. Both groups experienced similar post-treatment increases in HB physician density, though the estimates for non-monopoly markets are slightly noisier (Figure A12), likely due to the smaller sample size.

Sources of Increasing HB Physician Density: The HIT-induced increase in physician density we found could arise from (i) relocation of HB physicians from less HIT-intensive to more HIT-intensive areas, (ii) employment reclassification of physicians from non-hospital to hospital settings due to expanded firm boundaries, or (iii) a net increase in the overall number of HB physicians. The results from the matching-based DiD and HRR analyses suggest that physician migration in response to HIT diffusion extends beyond localized movements. Our analyses in Section 5.2 show that firm-boundary changes alone do not fully explain the observed increases in HB physician density. Despite the long training and licensing pipeline for new physicians, our findings may also reflect a net expansion of the physician workforce, given that our study spans over a decade and density gains are concentrated among younger physicians. Future research using more micro-level data, such as physician-level records, could further distinguish between these sources of growth.

5.4 Mechanism: Financial and Productivity 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.[41] To construct these measures, we identify HB physicians as those furnishing at least 90% of their services in hospital inpatient or emergency room settings.[42] We then compute county-level means by averaging (i) and (ii) across all HB physicians by county.

Figure 8 (left panel) and Table A9 (Columns (1)–(2)) present the results, showing that HB physicians in treated counties receive significantly higher Medicare-allowed payments following HIT adoption, compared to those in control counties. These positive effects remain statistically significant up to four years post-treatment. 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 productivity increase is consistent with the proposed advantage of HIT: quicker service provision and easier ordering of additional medical procedures, enabling physicians to deliver care more efficiently and increase revenue.

Next, we examine hospital financial performance using three metrics: total patient revenues, total costs, and total profits. Hospitals in treated counties experience sustained profit gains following HIT adoption relative to control counties, mainly driven by rising patient revenues (Figure 8 (right panel), Table A9 (Columns (3)–(5))). Post-treatment hospital revenues show a substantial upward pattern, while costs rise to a much smaller extent; all remain statistically significant.[43] These results suggest 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.

We then examine changes in non-physician clinicians (Figure A13). Physician assistants (PAs), whose scope of practice closely aligns with physicians, naturally expand at a similar rate,

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

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

[43] Although slight pre-trends are visible in average hospital revenues and profits, the pre-trend tests à la Roth (2022) assured that our results are robust to potential underpowered pre-trends (Table A7).

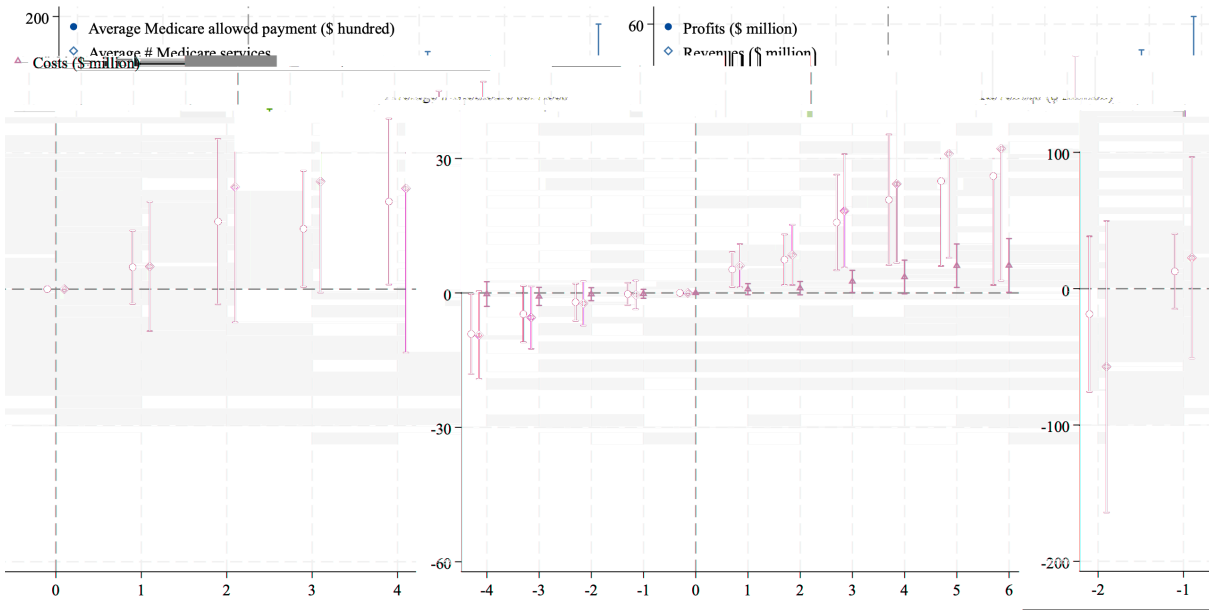


Figure 8: Effect of HIT diffusion on financial metrics

Notes: The figures report results using financial metrics as outcomes, with shorter periods for two measures (left panel) due to data availability. The event-study estimates are based on Equation (2). The unit of observation is at the county-year level. Regressions are unweighted in the physician-level and hospital-level analyses. 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.

keeping their ratio to physicians steady. Nurse staffing (NPs and RNs) also increases, but many routine tasks (e.g., charting and medication orders) are streamlined by HIT, freeing nurses' administrative time to manage more patients and focus on hands-on care. Such an efficiency gain can reduce the nurse-to-physician ratio while the PA-to-physician ratio remains flat. This pattern appears consistent with a care model that emphasizes physician-led teams supported by PAs, with nurses adopting more efficient, patient-centered roles.[44] This is also consistent with prior work showing that CPOE affects nurse staffing levels in nursing homes (Lu et al., 2018).

Together, these findings point toward a financial mechanism through which HIT adoption attracts and retains HB physicians. By reducing operational inefficiencies, boosting physician productivity (and thus earnings), and improving hospital profitability (by expanding revenue), HIT adoption plausibly creates a more rewarding practice environment for physicians and a more sustainable business model for hospitals. This financial mechanism is consistent with classical economic theory, which posits that growth is driven by capital and labor, and that as capital (i.e., HIT investment) increases, complementary human capital (i.e., physicians) becomes increasingly

[44] Our results suggest that NPs may be less of a complement (than PAs) to physicians in care provision, aligned with the findings in Kleiner et al. (2016).

important for overall growth.

5.5 Implications for Downstream Care Utilization

Building on the results that HIT diffusion boosts physician and hospital finances, we now examine the changes in patient care utilization, recognizing the interplay between service usage and provider capacity. Specifically, we study the extent to which HIT diffusion influences subsequent service use. We examine the following utilization measures: total outpatient surgeries (done in hospitals), total inpatient surgeries, total emergency department (ED) visits, total outpatient visits, and total Medicare inpatient discharges, all measured per 100k population at the county level using the AHRF data. Figure 9 and Table A10 present the results when we replace our outcome measure with one of these utilization measures. Visually, HIT diffusion has little impact on most of these outcomes, except for outpatient surgeries.

Intuitively, 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, thereby representing a higher-margin revenue stream. This extends our earlier finding that hospital profits increased in treated counties, suggesting that the financial benefits of HIT-driven efficiencies may be more pronounced for elective procedures, where hospitals have greater flexibility to expand services.[45] In contrast, inpatient procedures often require longer recovery periods and more resources, limiting hospitals' ability to scale up volumes quickly, even with improved HIT. Meanwhile, outpatient visits are typically shorter, less complex, and generate lower revenue per encounter than surgeries. Similarly, the lack of growth in Medicare inpatient discharges may stem from capacity constraints, case complexity, and preferences for less invasive treatments.

Diving deeper into heterogeneity in the growth of surgery volumes, we group counties into tertiles based on pre-treatment care utilization, measured by standardized, risk-adjusted per capita Medicare costs in 2006. We use the 2006 value, the first year this variable appears in AHRF, to avoid potential bias from utilization growth.[46] We find that only mid-tertile counties exhibit a significant post-HIT increase in outpatient surgeries per 100k population in hospitals (Figure

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

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

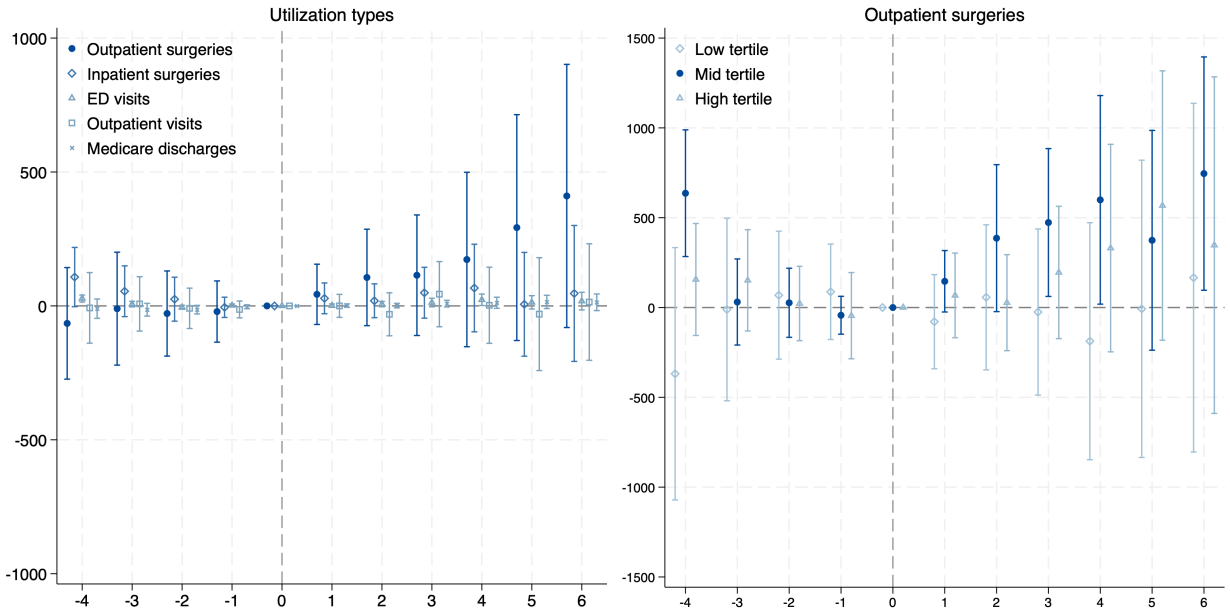


Figure 9: Effect of HIT diffusion on outpatient/inpatient surgery volume

Notes: The left panel shows the overall effect of HIT diffusion on surgery volumes, and the right panel shows 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.

9, right panel; Table A11).[47] 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 HIT could have facilitated, 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.

5.6 Robustness Checks

We conduct several analyses to assess the robustness of our results. First, we implement pre-trend tests à la Roth (2022) to examine how well-powered our event studies are by calculating the size of the largest potential biases. Table A7 reports the largest potential biases we cannot detect under 50% and 80% power for our main set of results, all of which are much smaller than the estimated effects in our event studies. Second, when re-estimating the effects by systematically excluding each specialty one by one (Figure A14), the overall patterns remain robust, suggesting

[47] While providing consistent evidence, the estimates are noisy.

that our findings are not driven by any single specialty.

Third, we re-estimate the main specifications using alternative subsamples, finding robust results (Figure A15 and Table A12). 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 (diamonds). We also drop counties with extreme population sizes (top or bottom 10%; triangles). Moreover, we perform a balanced event study including only counties with at least four pre- and post-treatment periods (squares).[48] Finally, we test the robustness of the classification of treatment by restricting the sample to counties that experienced no more than three changes in adoption rates over time. We also try restricting the sample to counties that experienced a *unique* largest jump in adoption, the one that represents a transition from non-adoption to adoption and that is at least twice the magnitude of the second-largest jump, where applicable. The estimates are similar to our main results (Figure A16).

Fourth, we explore alternative model specifications (Figure A17 and Table A12). The findings remain robust when we remove state-specific time trends (diamonds), exclude county-year level controls (triangles), or further exclude both state-specific time trends and county-level observables (squares). Using concurrent, instead of lagged, adoption rates also yields estimates similar to the main results (hollow diamonds). Fifth, we apply alternative staggered DiD estimators from the recent econometric literature (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). The results are generally consistent across estimators (Figure A18), with all showing similar trends and magnitudes of the treatment effects. The Callaway-Sant'Anna estimates are slightly less precise but follow the same pattern as other methods. Continuous DiD estimates are also similar and slightly larger in magnitude (Figure A3).

In addition, we re-run the main specification using physician counts (rather than rates) to avoid potential issues with transforming the outcome variable (Figure A19), while maintaining an intuitive interpretation with linear DiD models (Mullahy and Norton, 2024). We find increases in HB physicians (the numerator; left panel) and local population (the denominator; right panel), with the effect on the former steeper than the latter. It is consistent with our hypothesis that advanced HIT disproportionately pulls physicians to faster-adopting areas.

Finally, we test the robustness of our findings using two alternative definitions of HIT adoption (Figure A20). The first is based on adopting either CPOE or physician documentation (PD) sys-

[48] A 4-period cutoff balances pre-period windows with sample retention; we exclude observations beyond this window.

tems, following prior work (e.g., Dranove et al., 2014). The results remain robust, though slightly less precise (right panel), consistent with most key variation and advanced automation features being driven by CPOE, as discussed in Section 2.2.[49] The second 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 data. Under this definition, the estimated effects on HB physician density become statistically insignificant (left panel). This likely reflects that basic components such as CDR were adopted earlier and more gradually, and lack the advanced automation and clinical integration features of CPOE that drive meaningful organizational changes.

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

5.7 Limitations

Our study has some limitations. First, we rely on aggregate datasets, which mitigate concerns about patient sorting but limit our ability to disentangle physician-level changes. For instance, a net increase in HB physician rate 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' working decisions, including potential changes in working hours or task allocation. Second, although our data do not measure interoperability, greater information exchange across providers may improve care provision, and merits future studies on this aspect directly. Third, our focus on HIT diffusion could be enriched by examining how digital and physical medical technologies jointly affect physician density, but data limitations prevent such analysis. Nevertheless, our extensive control set mitigates 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.

[49] 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.

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 an 11.1% increase in HB physicians per 100k population relative to control counties, with medical and surgical specialties accounting for most of the increase. This growth is primarily driven by early-career physicians and concentrated in areas that face physician shortages. HIT adoption leads to higher Medicare-allowed payments per physician, more Medicare services delivered, and increases in average hospital profits. Moreover, our findings of stable physician assistant-to-physician ratios alongside declining nurse-to-physician ratios following HIT adoption suggest that this technology has varying impacts on the non-physician workforce, depending on the specific nature of each role's interaction with physicians in care delivery. In addition, our findings of increasing outpatient surgical volumes, particularly in counties with moderate pre-treatment utilization levels, suggest that HIT-enabled efficiencies in elective procedures enhance patient throughput and revenue generation. These findings remain robust after accounting for healthcare consolidation, various model specifications, alternative DiD estimators, and multiple subsamples.

Our results have important 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.

References

Adler-Milstein, J. and Jha, A. K. (2017). Hitech act drove large gains in hospital electronic health record adoption. *Health affairs*, 36(8):1416–1422.

Agha, L. (2014). The effects of health information technology on the costs and quality of medical care. *Journal of Health Economics*, 34:19–30.

AHRF (2006-2018). Area Health Resources Files. Available at https://data.hrsa.gov/data/download.

American Association of Nurse Practitioners (2022). 2022 NP practice report. Technical report, AANP. Accessed via AANP Research Department.

Baker, L. C., Bundorf, M. K., and Kessler, D. P. (2016). The effect of hospital/physician integration on hospital choice. *Journal of Health Economics*, 50:1–8.

Baker, L. C. and Royalty, A. B. (2000). Medicaid policy, physician behavior, and health care for the low-income population. *Journal of Human Resources*, 35(3):480–502.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event-study designs: robust and efficient estimation. *Review of Economic Studies*, page rdae007.

Bronsoler, A., Doyle, J., and Van Reenen, J. (2022). The impact of health information and communication technology on clinical quality, productivity, and workers. *Annual Review of Economics*, 14(1):23–46.

Buchmueller, T., Miller, S., and Vujicic, M. (2016). How do providers respond to changes in public health insurance coverage? Evidence from adult medicaid dental benefits. *American Economic Journal: Economic Policy*, 8(4):70–102.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Chen, J. and Roth, J. (2024). Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economics*, 139(2):891–936.

CMS (2013-2018b). Medicare Physician & Other Practitioners - by Provider and Service. Available at https://data.cms.gov/provider-summary-by-type-of-service/medicare-physician-other-practitioners/medicare-physician-other-practitioners-by-provider-and-service.

CMS (2018a). EHR Incentive Program Status Report May 2018. *EHR Incentive Program Status Report* . Available at https://www.cms.gov/regulations-and-guidance/legislation/ehrincentiveprograms/downloads/may2018_summaryreport.pdf.

CMS and HHS (2012). Medicare and Medicaid Programs; Electronic Health Record Incentive Program—Stage 2 . *Federal Register*, 77(171):53968–54162.

Curto, V. and Bhole, M. (2022). Impacts of early ACA medicaid expansions on physician participation. *Health Services Research*, 57(4):881–891.

De Chaisemartin, C. and d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, pages 1–45.

Deryugina, T., Kawano, L., and Levitt, S. (2018). The economic impact of hurricane katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2):202–233.

DeSilva, H. (2025). Physician compensation trends: Sign-on bonuses and top technology. Modern Healthcare. Accessed: 2026-01-27.

Dougherty, M., Williams, M., Millenson, M., and Harvell, J. (2013). EHR payment incentives for providers ineligible for payment incentives and other funding study. Accessed: 2026-02-11.

Dranove, D., Forman, C., Goldfarb, A., and Greenstein, S. (2014). The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy*, 6(4):239–270.

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The Stata Journal*, 3(2):168–177.

East, C. N., Miller, S., Page, M., and Wherry, L. R. (2023). Multigenerational impacts of childhood access to the safety net: Early life exposure to medicaid and the next generation's health. *American Economic Review*, 113(1):98–135.

Everett, W., Guilboard, B., and Nelson, K. (2008). 'stunning' cpoe study spurs immediate action in massachusetts. Clinician.com. Accessed: 2026-01-22.

Falcettoni, E. (2018). The determinants of physicians' location choice: Understanding the rural shortage. *Working Paper*.

Freedman, S., Lin, H., and Prince, J. (2018). Information technology and patient health: analyzing outcomes, populations, and mechanisms. *American Journal of Health Economics*, 4(1):51–79.

Gallego, B., Dunn, A. G., and Coiera, E. (2013). Role of electronic health records in comparative effectiveness research. *Journal of Comparative Effectiveness Research*, 2(6):529–532.

Ganju, K. K., Atasoy, H., and Pavlou, P. A. (2022). Do electronic health record systems increase Medicare reimbursements? The moderating effect of the recovery audit program. *Management Science*, 68(4):2889–2913.

Garthwaite, C. L. (2012). The doctor might see you now: The supply side effects of public health insurance expansions. *American Economic Journal: Economic Policy*, 4(3):190–215.

Glenn, H. (2026). Labor markets and technological change: Evidence from electronic health records. Working Paper.

Greenwood, B. N., Ganju, K. K., and Angst, C. M. (2019). How does the implementation of enterprise information systems affect a professional's mobility? an empirical study. *Information Systems Research*, 30(2):563–594.

Harvell, J., Dougherty, M., Millenson, M., and Williams, M. (2013). EHR payment incentives for providers ineligible for payment incentives and other funding study. *Report for Office of the Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services*.

Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The economics of new goods*, pages 207–248. University of Chicago Press.

HCRIS (2006-2018). Healthcare Cost Report Information System. Available at https://www.cms.gov/data-research/statistics-trends-and-reports/cost-reports.

HIMSS (2011). Essentials of the us hospital it market. *Chicago: Health Information Management and Systems Society*.

Huh, J. (2021). Medicaid and provider supply. *Journal of Public Economics*, 200:104430.

Huh, J. and Lin, J. (2024). More doctors in town now? Evidence from medicaid expansions. *Journal of Policy Analysis and Management*.

Kessler, D. P., Sage, W. M., and Becker, D. J. (2005). Impact of malpractice reforms on the supply of physician services. *Journal of the American Medical Association*, 293(21):2618–2625.

Khoury, S., Leganza, J., and Masucci, A. (2024). Health professional shortage areas and physician location decisions. *American Journal of Health Economics*.

Kleiner, M. M., Marier, A., Park, K. W., and Wing, C. (2016). Relaxing occupational licensing requirements: Analyzing wages and prices for a medical service. *Journal of Law and Economics*, 59(2):261–291.

Kulka, A. and McWeeny, D. (2018). Rural physician shortages and policy intervention. *Working Paper*.

Lin, J. and Olson, M. K. (2024). Reassessing the impact of health IT: Hidden costs and consequences of vendor heterogeneity. *Journal of Economics & Management Strategy*.

Lu, S. F., Rui, H., and Seidmann, A. (2018). Does technology substitute for nurses? Staffing decisions in nursing homes. *Management Science*, 64(4):1842–1859.

Malani, A. and Reif, J. (2015). Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics*, 124:1–17.

McCullough, J. S., Casey, M., Moscovice, I., and Prasad, S. (2010). The effect of health information technology on quality in us hospitals. *Health Affairs*, 29(4):647–654.

McCullough, J. S., Parente, S. T., and Town, R. (2016). Health information technology and patient outcomes: the role of information and labor coordination. *The RAND Journal of Economics*, 47(1):207–236.

McCullough, J. S. and Snir, E. M. (2010). Monitoring technology and firm boundaries: Physician–hospital integration and technology utilization. *Journal of Health Economics*, 29(3):457–467.

Miller, A. R. and Tucker, C. E. (2011). Can health care information technology save babies? *Journal of Political Economy*, 119(2):289–324.

Miller, D. L., Page, M. E., Stevens, A. H., and Filipski, M. (2009). Why are recessions good for your health? *American Economic Review*, 99(2):122–127.

Mullahy, J. and Norton, E. C. (2024). Why transform y? the pitfalls of transformed regressions with a mass at zero. *Oxford Bulletin of Economics and Statistics*, 86(2):417–447.

National Commission on Certification of Physician Assistants (2023). 2023 statistical profile of board certified physician assistants. Technical report, NCCPA, Johns Creek, GA.

Neprash, H. T., Zink, A., Gray, J., and Hempstead, K. (2018). Physicians' participation in medicaid increased only slightly following expansion. *Health Affairs*, 37(7):1087–1091.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2):307–342.

Polsky, D., Kletke, P. R., Wozniak, G. D., and Escarce, J. J. (2000). HMO penetration and the geographic mobility of practicing physicians. *Journal of Health Economics*, 19(5):793–809.

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights*, 4(3):305–22.

Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics*, 115(2):617–650.

Silow-Carroll, S., Edwards, J. N., and Rodin, D. (2012). Using electronic health records to improve quality and efficiency: The experiences of leading hospitals. Issue Brief (Pub. 1608, Vol. 17). Accessed: 2026-01-22.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Wang, L. X. (2021). The complementarity of drug monitoring programs and health it for reducing opioid-related mortality and morbidity. *Health Economics*, 30(9):2026–2046.

Wang, L. X. and Bloch, C. (2023). Digital interventions in the health sector—country cases and policy discussions. *IMF Notes*.

A Appendix Figures and Tables

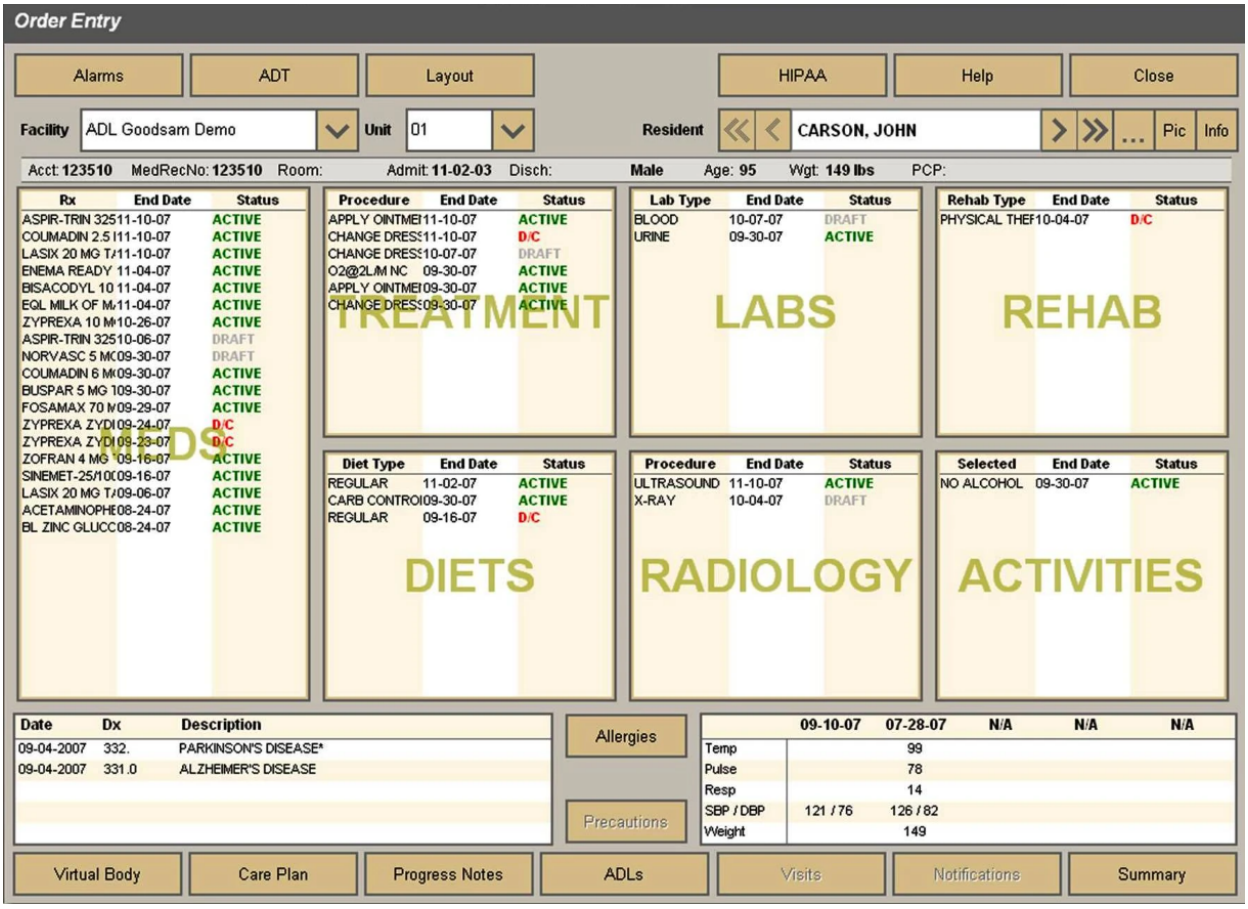


Figure A1: Example of a Computerized Physician Order Entry (CPOE) Interface

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).

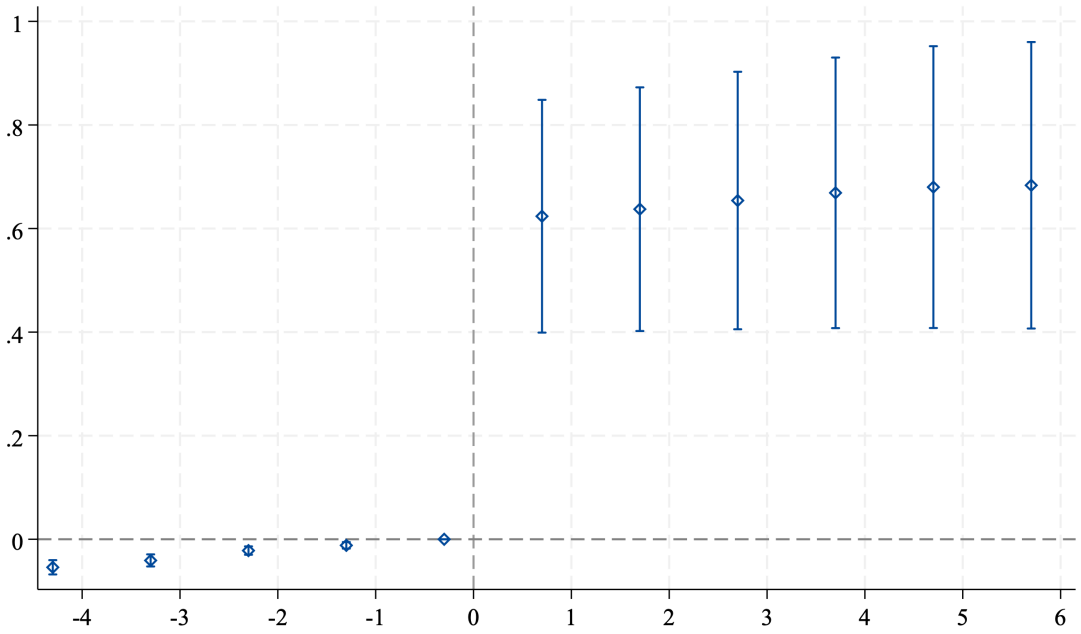


Figure A2: Health IT adoption rate relative to treatment year, based on event studies

Notes: The figure presents the results after applying the event study framework to the continuous adoption rates. The estimated average change in adoption rates from pre- to post-treatment among treated counties is 0.655*** (0.127). Treatment (i.e., sharp HIT adoption) occurred in year 1. 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.

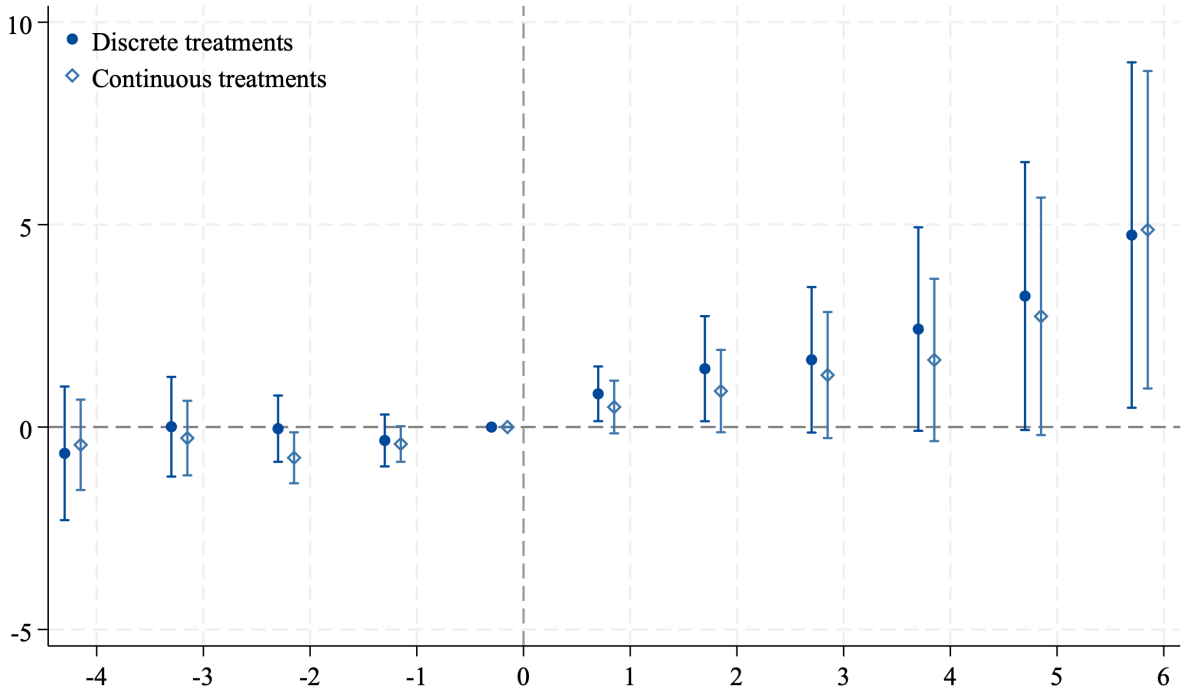


Figure A3: Effect of HIT diffusion on HB physician density, discrete vs. continuous treatments

Notes: This figure compares the results based on binary treatments (main results) versus continuous treatments. The estimated average treatment effect from a continuous DiD estimation approach is 2.72** (1.35), compared to our main estimates under discrete DiD of 2.16** (1.04). 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.

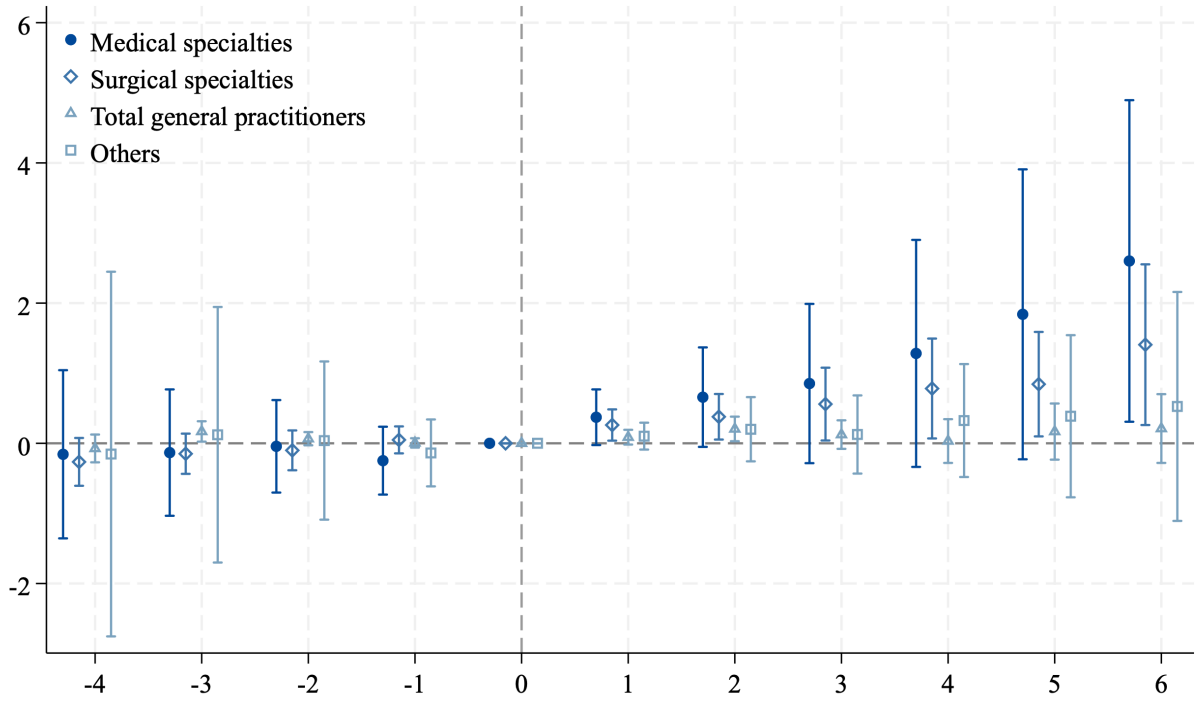


Figure A4: Effect of HIT diffusion on HB physician density, by main specialty

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. 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.

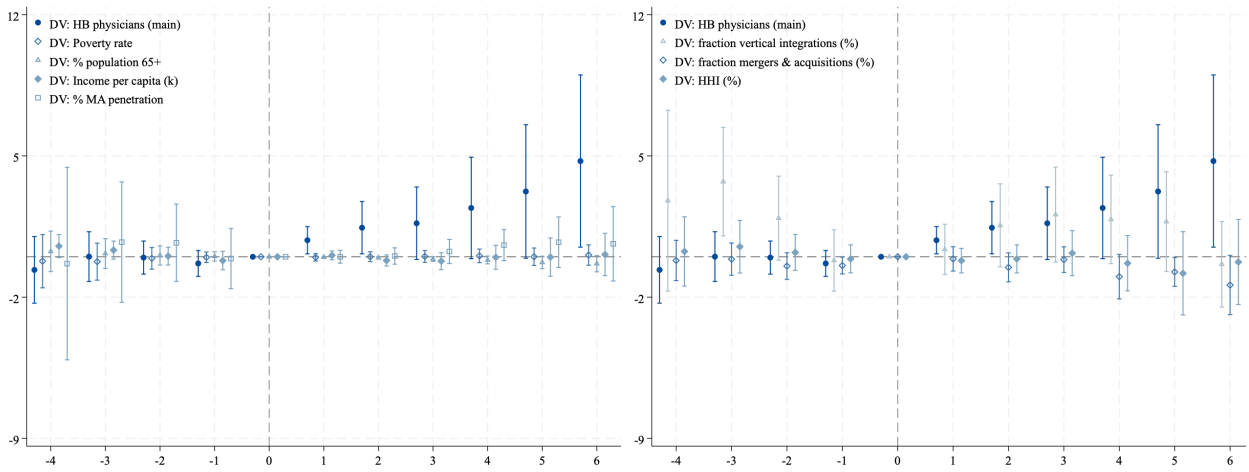


Figure A5: Effect of HIT diffusion on county characteristics

Notes: The figure presents the results using county characteristics as the outcome measures. We include the main results for comparison. Treatment (i.e., sharp HIT adoption) occurred in year 1. 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.

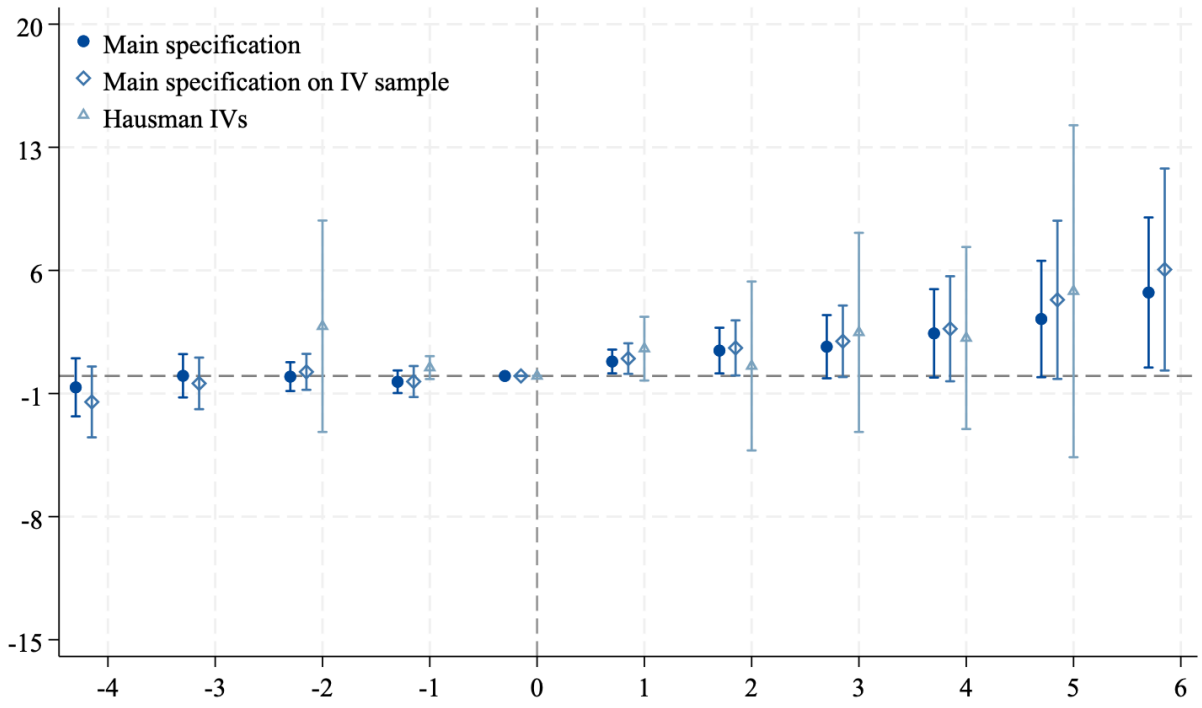


Figure A6: Effect of HIT diffusion on HB physician density, IV estimation

Notes: The figure presents the results from the two-step IV estimator. Treatment (i.e., sharp HIT adoption) occurred in year 1. Some pre- and post-treatment effects cannot be estimated due to a lack of variation in treatment during those periods in the continuous DiD framework. 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.

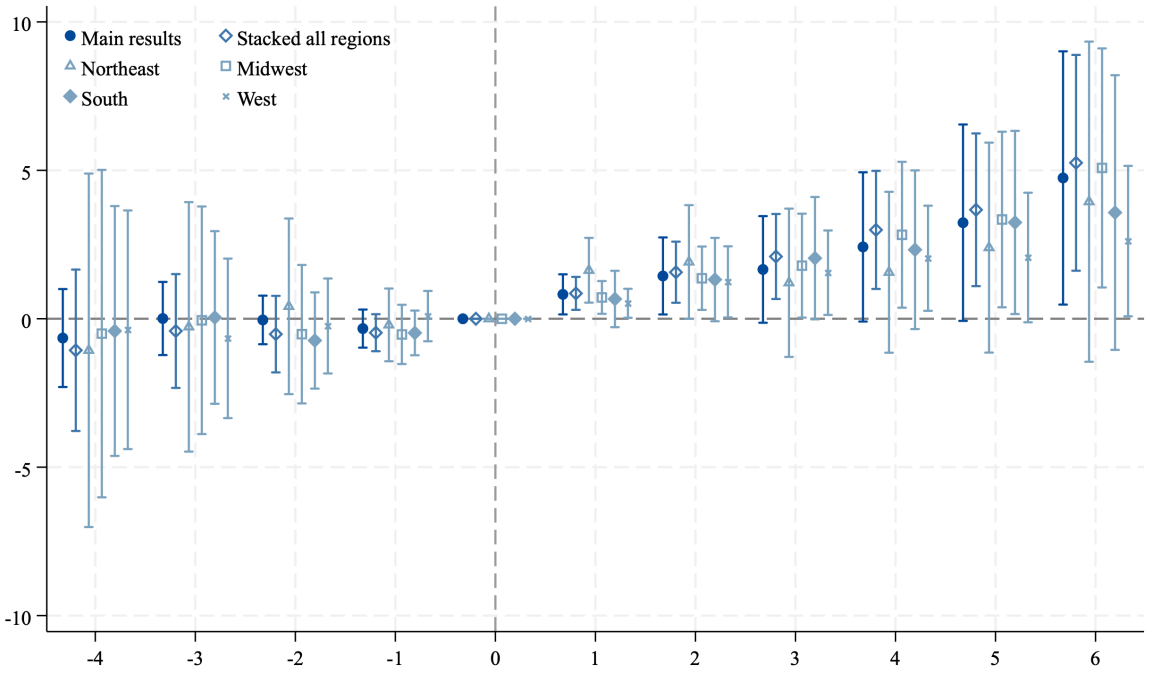


Figure A7: HIT diffusion and physician density: matching-based DiD analysis

Notes: This figure shows the event study estimates, accounting for potential local spillover effects by using a matching-based DiD procedure à la Deryugina et al. (2018). Regressions are weighted by county-year level population. 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.

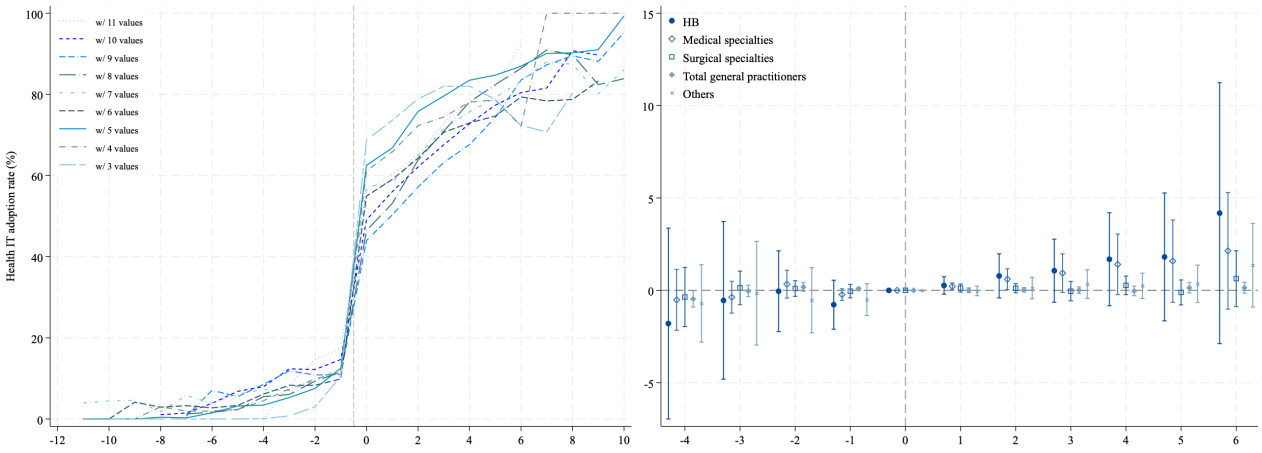


Figure A8: Effect of HIT diffusion on HB physician density, in HRRs

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.

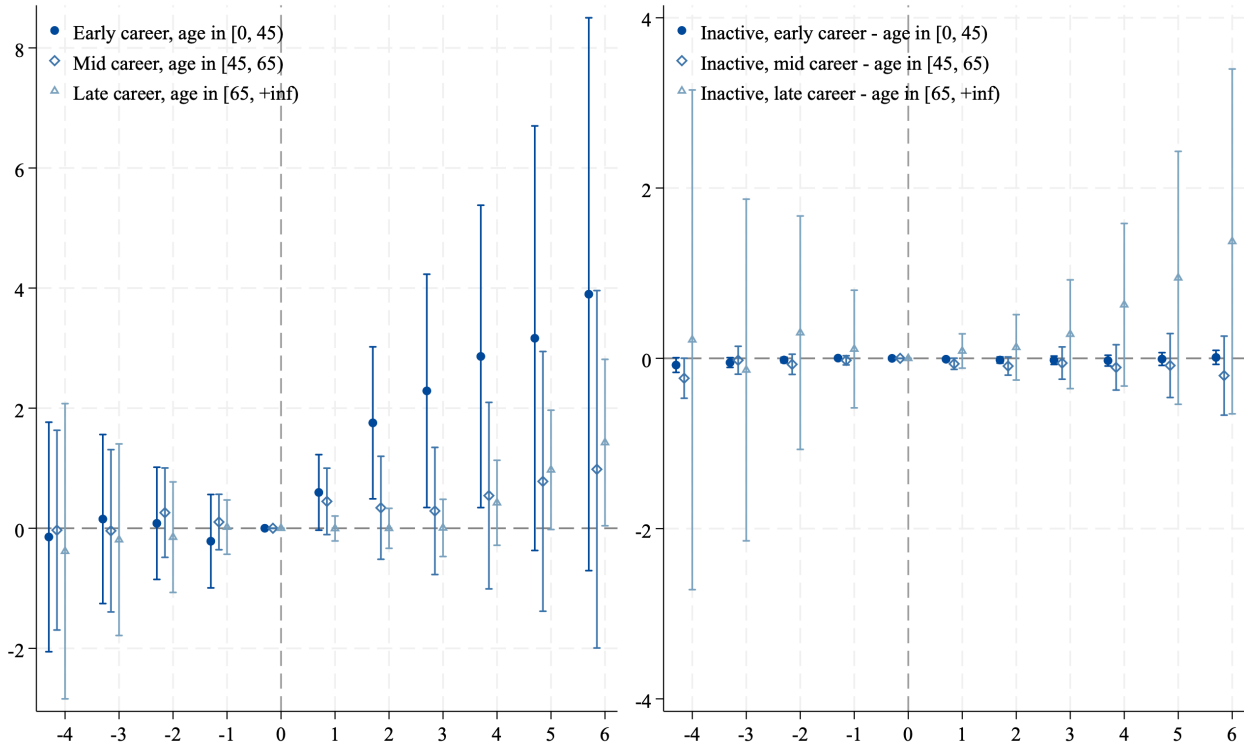


Figure A9: HIT diffusion and physician density: by career stage and active/inactive status

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.

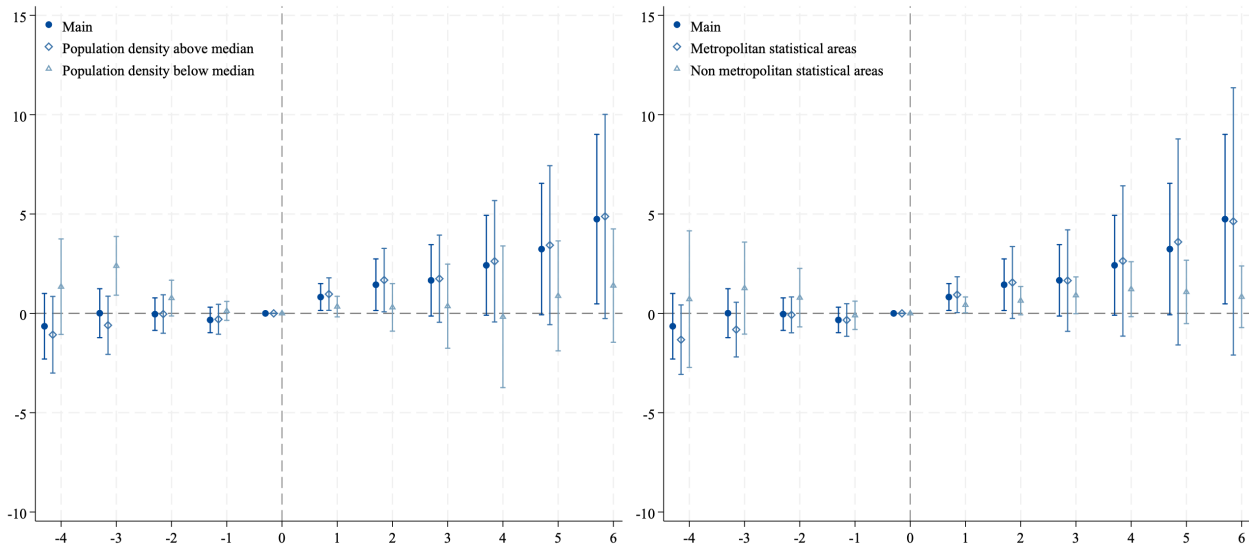


Figure A10: HIT diffusion and physician density: by population density and urban status

Notes: The left panel splits counties by median population density, and the right panel classifies counties by census metropolitan statistical areas (MSA) status. 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.

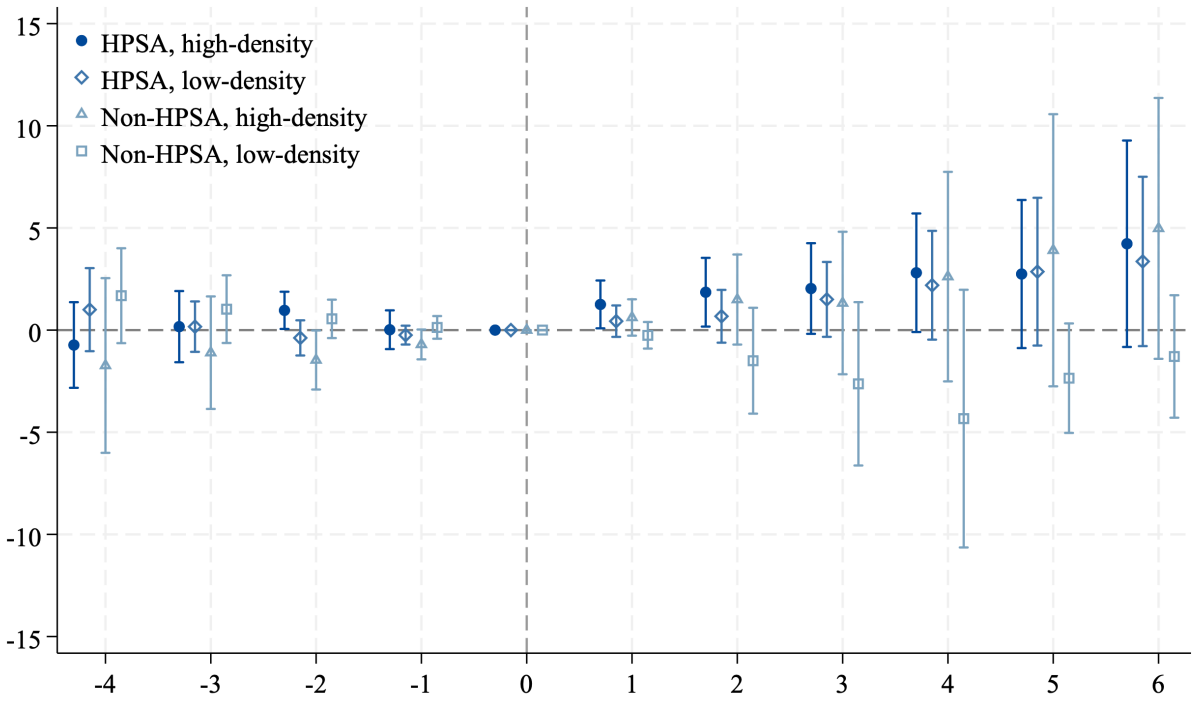


Figure A11: HIT diffusion and physician density: by HPSA × population density

Notes: The figure presents results by HPSA status interacted with population density. We re-estimate the main specification across four subgroups, splitting counties by HPSA designation and median population density. 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.

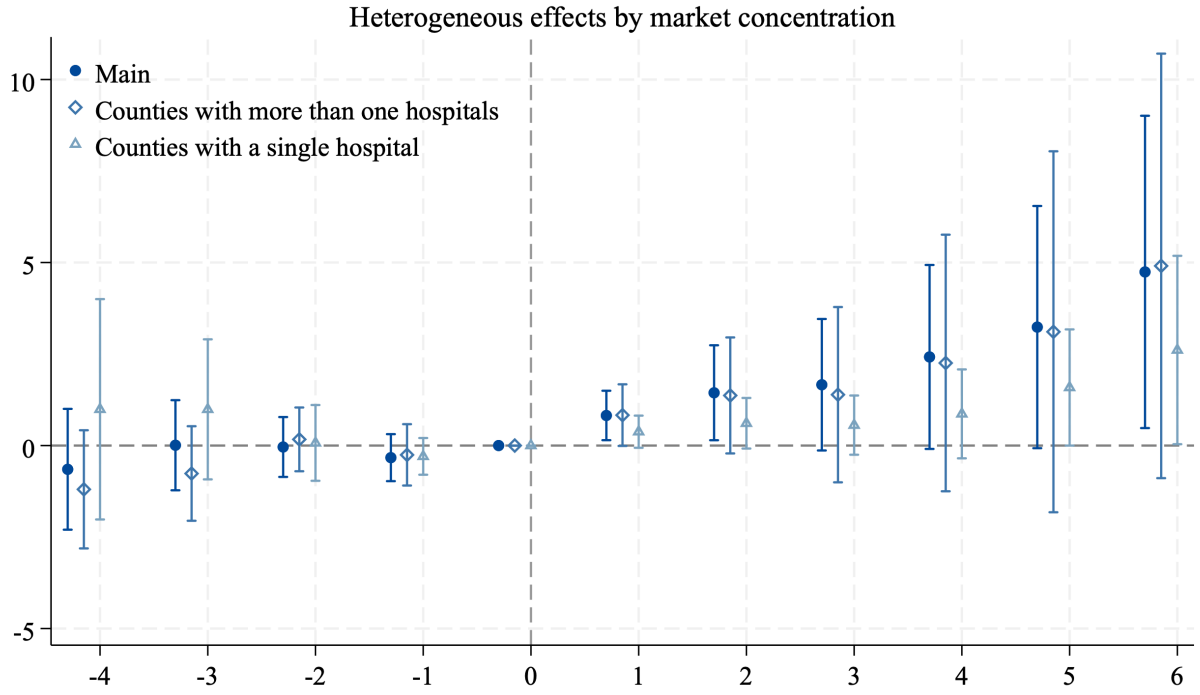


Figure A12: Effect of HIT diffusion on physician density, by hospital market concentration

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.

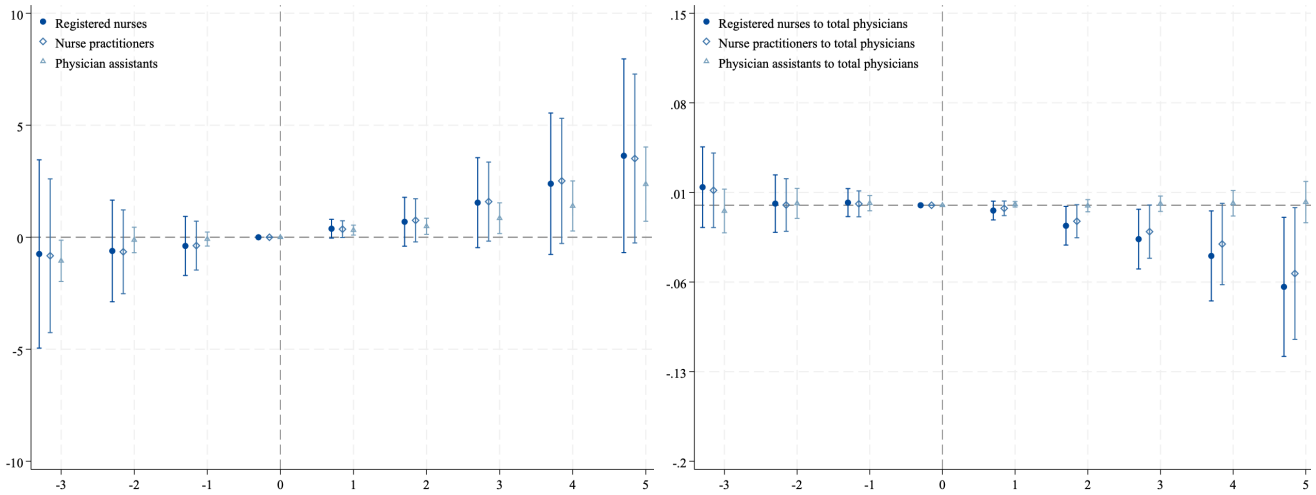


Figure A13: HIT and non-physician clinicians: nurse (PA) rates and nurse (PA)/physician ratios

Notes: This figure shows the event study estimates, focusing on supporting staff (nurses and physician assistants), both in rate (per 100 population) and their respective ratios to physicians. 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.

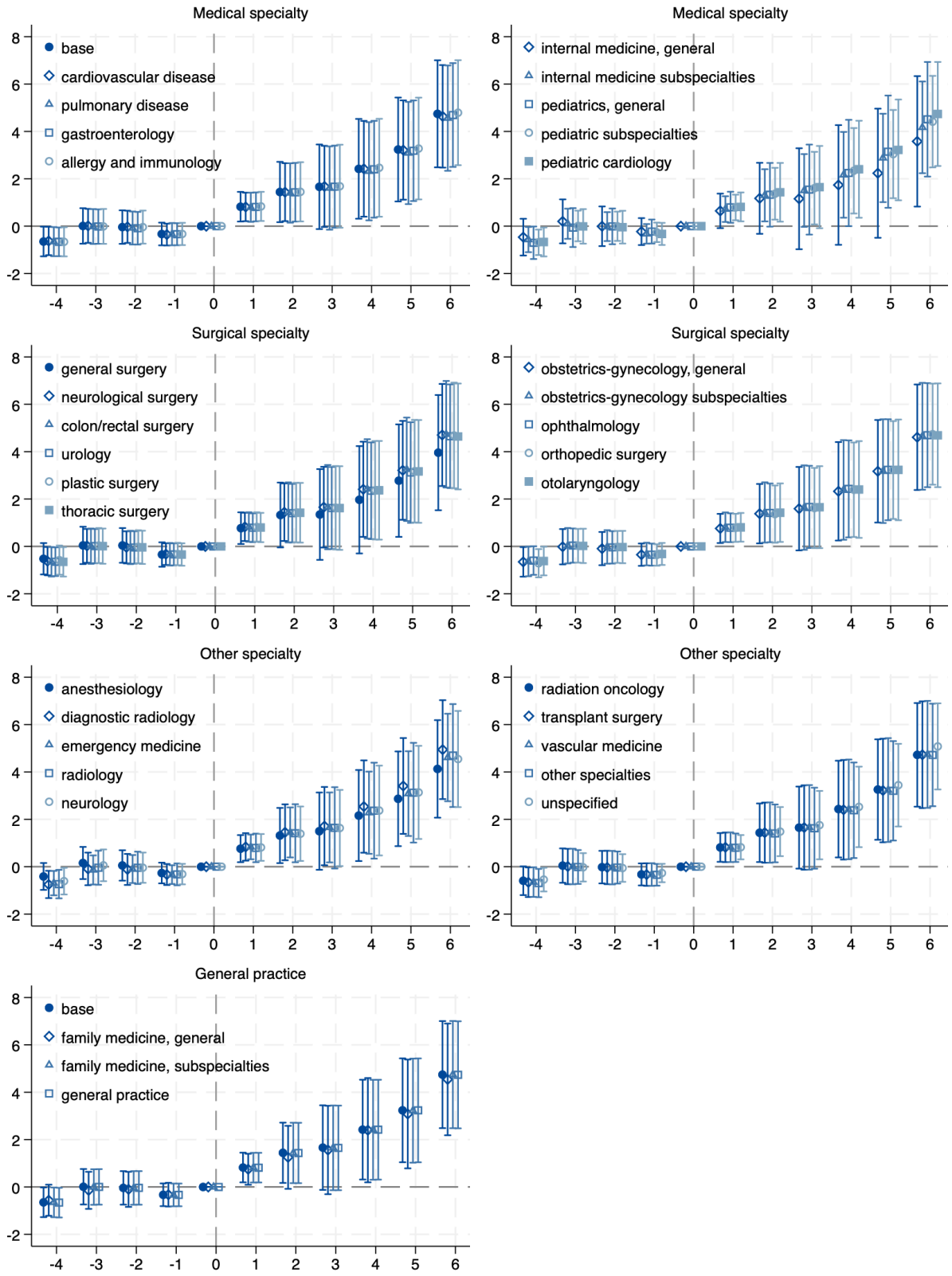


Figure A14: HIT diffusion and physician density: leave-one-out analysis

Notes: This figure shows the event study estimates, excluding one specialty at a time. 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.

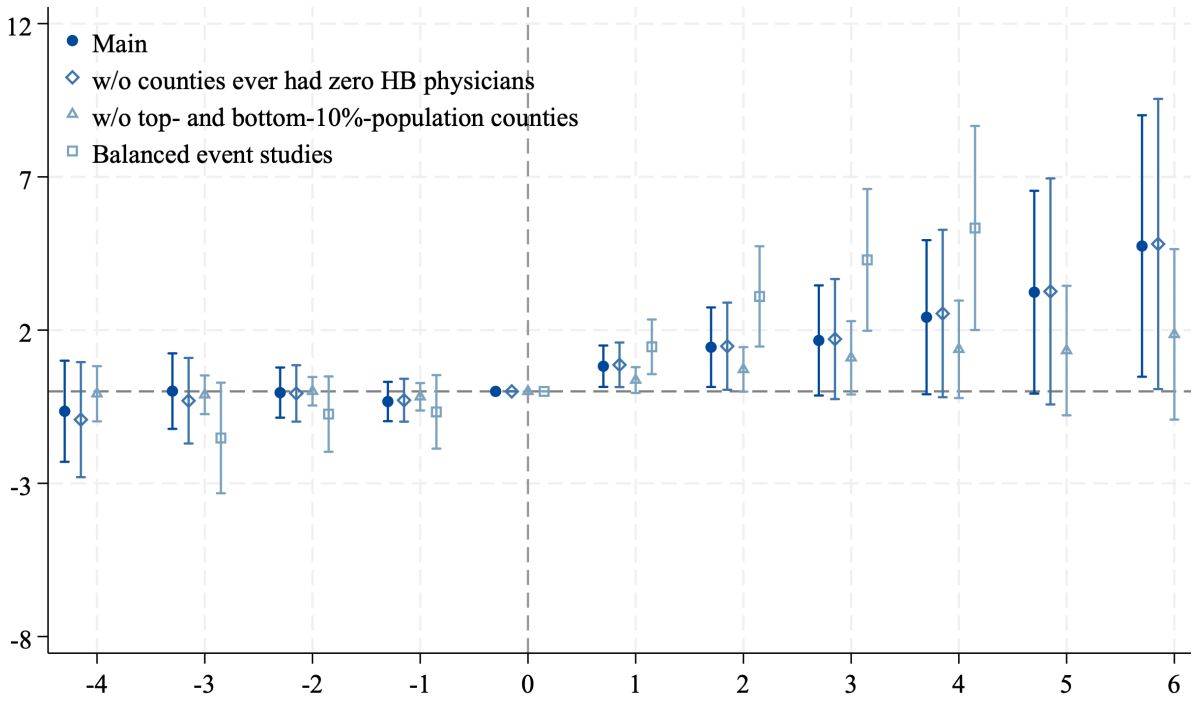


Figure A15: Effect of HIT diffusion on HB physician density: robustness checks

Notes: 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 5.6 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.

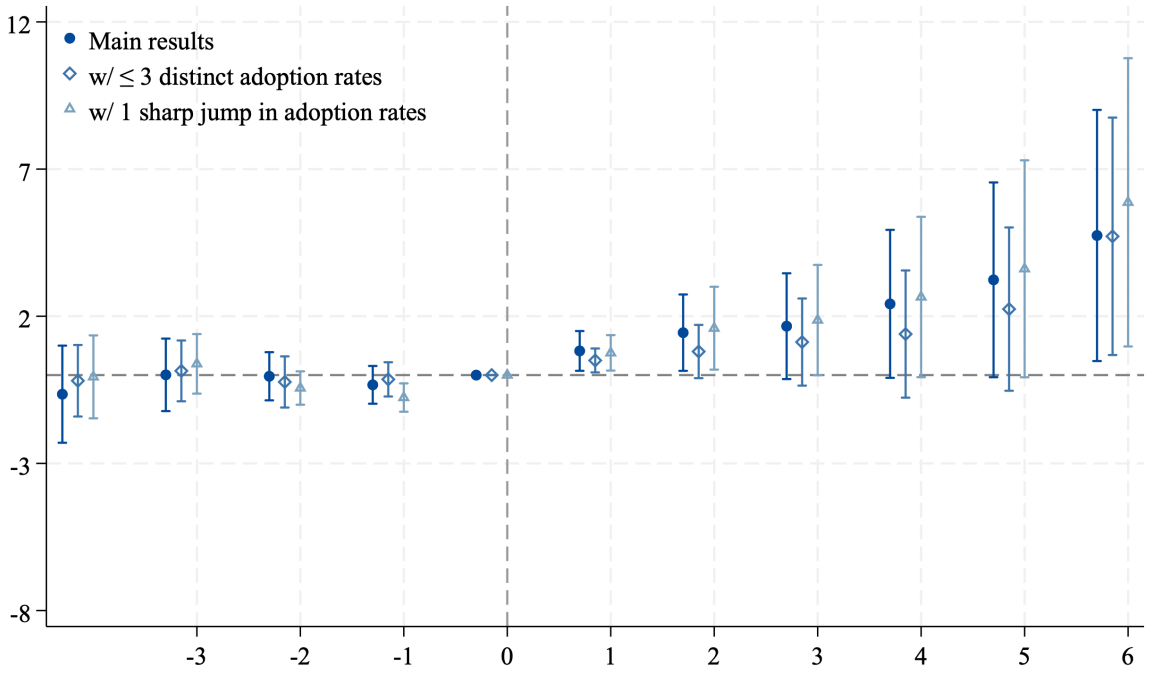


Figure A16: HIT diffusion and physician density: subsamples with limited big jumps

Notes: The figures present event-study estimates and 95% confidence intervals using two types of subsamples: (i) with counties experiencing no more than three distinct HIT adoption rates during the sample period; and (ii) counties that experienced a unique largest jump in adoption – one that represents a transition from non-adoption to adoption and that is at least twice the magnitude of the second-largest jump, where applicable. 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.

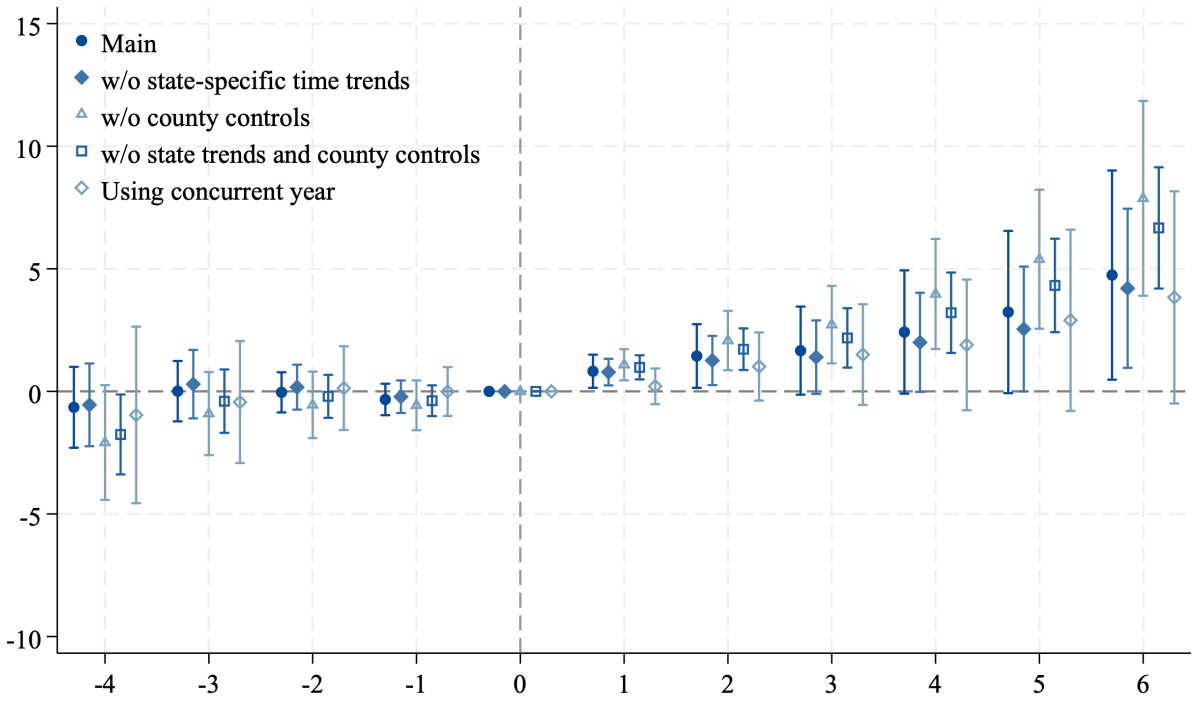


Figure A17: Effect of HIT diffusion on HB physician density: specification checks

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. **The treatment in hollowed diamonds 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.

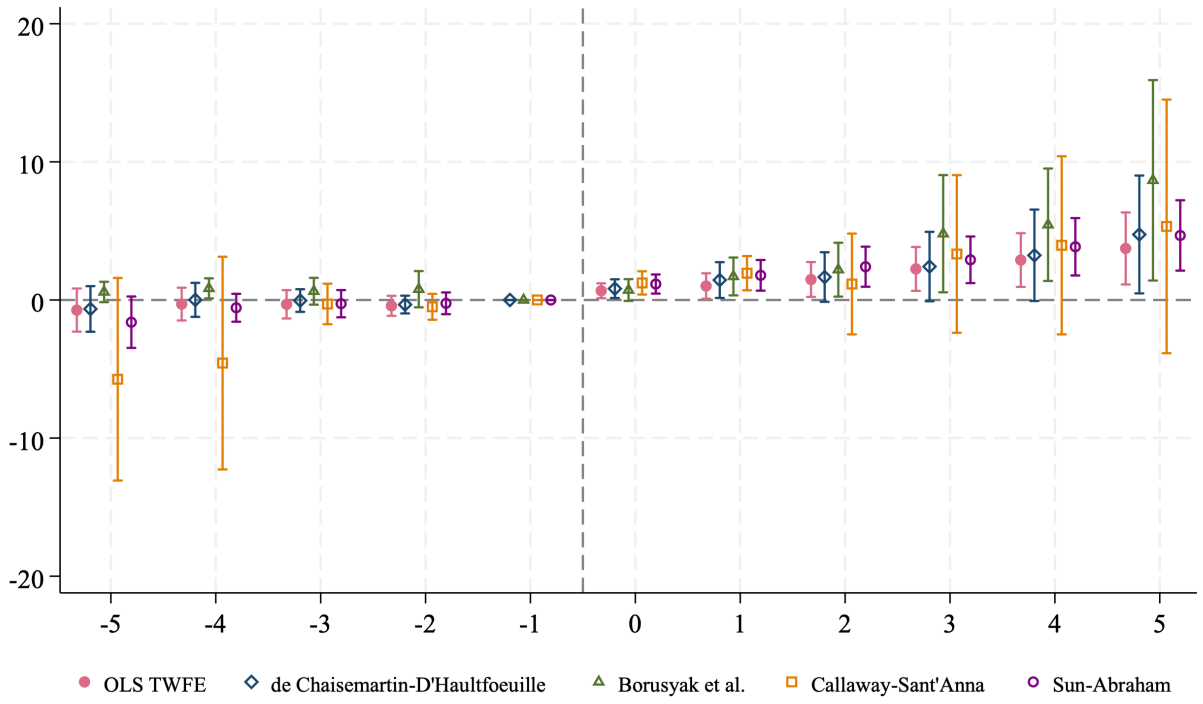


Figure A18: Effect of HIT diffusion on HB physician density: alternative DiD estimators

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.

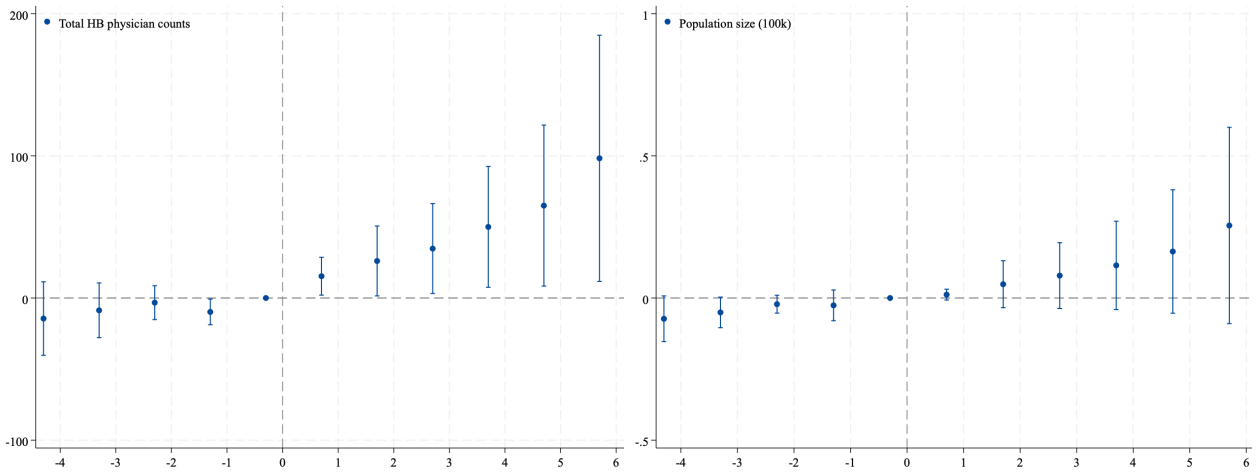


Figure A19: Effect of HIT diffusion on HB physician density: numerator vs. denominator

Notes: The figures present event-study estimates and 95% confidence intervals using numerator and denominator of the density measure. Importantly, we test the count data outcome measure of physician availability at the county level. 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 specifications use the full set of controls as in the main analysis. Standard errors are clustered at the state level.

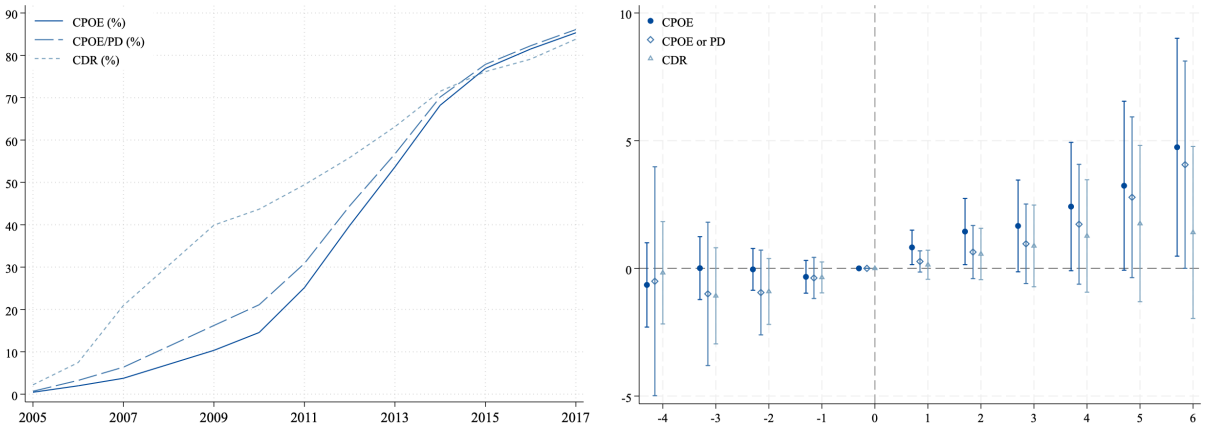


Figure A20: Effect of HIT diffusion on HB physician density: alternative HIT measures

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	2008	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: Summary statistics for key variables at the start/end of sample: by treatment status

	Never-treated		Ever-treated		Difference-in--differences
	Start	End	Start	End	
	(1)	(2)	(3)	(4)	(5)
HB physician counts per 100k population	9.91 (15.49)	16.04 (26.50)	15.85 (34.03)	25.06 (50.77)	-3.08** (1.49)
% 65+ population	15.59 (4.20)	19.22 (4.81)	14.88 (3.99)	18.41 (4.32)	0.10 (0.14)
Poverty rate (%)	15.61 (6.16)	15.86 (6.45)	15.10 (6.20)	15.20 (5.88)	0.15 (0.15)
Income per capita	26585.23 (6566.30)	40796.92 (14961.10)	27579.23 (6820.45)	41882.98 (11309.47)	-92.06 (433.79)
Medicare Advantage penetration rate (%)	3.75 (7.03)	22.14 (14.69)	4.96 (8.29)	24.22 (14.59)	-0.88 (0.76)
% Medicaid eligibles	21.39 (8.97)	22.82 (8.28)	20.64 (8.24)	22.77 (8.08)	-0.70** (0.22)
% above college degree	11.38 (5.13)	14.07 (5.87)	12.77 (5.69)	15.45 (6.61)	0.0039 (0.13)
Hospital HHI	0.91 (0.19)	0.92 (0.18)	0.78 (0.28)	0.79 (0.28)	-0.0010 (0.01)
Population size	35790.46 (37006.14)	38154.47 (41841.94)	91844.85 (201929.36)	101128.98 (229263.44)	-6920.11** (2289.41)
Population density	100.48 (460.43)	111.84 (568.82)	250.77 (1803.74)	271.49 (1905.60)	-9.37 (8.31)
# counties	265		2,129		–

Notes: This table reports summary statistics for the dependent and control variables at the start/end of the sample period separately by treatment status. We also report the "difference-in-differences" value, equal to the difference in the change from the start to end of the sample period between ever-treated and never-treated counties. Standard deviations are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: 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 A5: Treatment effects on HB physician density: IV estimation

	Main specifications (main results)	Main specifications on IV sample	IV estimation
	(1)	(2)	(3)
Panel A			
Treatment Effect	2.162**	2.603**	2.313*
	(1.043)	(1.293)	(1.347)
Panel B			
Event time −4	-0.649	-1.478	
	(0.842)	(1.028)	
Event time −3	0.008	-0.424	
	(0.628)	(0.748)	
Event time −2	-0.040	0.232	2.824
	(0.418)	(0.522)	(3.067)
Event time −1	-0.331	-0.319	0.474
	(0.327)	(0.450)	(0.332)
Event time 0	omitted	omitted	omitted
Event time 1	0.821**	0.987**	1.552*
	(0.345)	(0.443)	(0.925)
Event time 2	1.442**	1.593**	0.565
	(0.662)	(0.799)	(2.450)
Event time 3	1.661*	1.970*	2.476
	(0.917)	(1.038)	(2.889)
Event time 4	2.420*	2.681*	2.155
	(1.283)	(1.523)	(2.641)
Event time 5	3.236*	4.328*	4.815
	(1.688)	(2.295)	(4.815)
Event time 6	4.744**	6.052**	
	(2.177)	(2.930)	
Mean DV	19.43		
N	28,426		
P-value of testing joint significance of pre trends	0.125	0.330	0.297

Notes: Panel A reports estimates from Equation (1), and Panel B from Equation (2). Some pre- and post-treatment effects cannot be estimated due to a lack of variation in treatment during those periods in the continuous DiD framework. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: 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 A7: Potential Bias under 50% and 80% Power, à la Roth (2022)

	(1)	(2)	(3)	(4)	(5)
Panel A: different types of physicians					
		by specialty category			
Variables	total HB	medical	surgical	general prac.	others
ATT	2.162**	1.136*	0.641**	0.132	0.252
Bias, 80% power	0.219	0.040	0.035	0.011	0.155
Bias, 50% power	0.153	0.028	0.025	0.007	0.108
	total physicians	high-HB physicians	by age group		
			Under 45	45 – 64	65+
ATT	4.717***	1.561**	2.263**	0.523	0.375
Bias, 80% power	0.335	0.113	0.192	0.214	0.103
Bias, 50% power	0.234	0.079	0.134	0.149	0.071
Panel B: subsample analyses results					
	low vertical integration	low mergers & acquisitions	primary care shortage area		
			yes	no	
ATT	2.743	2.463**	2.401**	1.588	
Bias, 80% power	0.562	0.205	0.335	0.065	
Bias, 50% power	0.391	0.143	0.234	0.045	
Panel C: mechanism / financial analyses results					
	physician level		hospital level finances (unit: $M)		
	Medicare $	# services	profit	revenue	cost
ATT	40.855**	57.82*	14.959***	17.846***	2.886**
Bias, 80% power	0.012	0.148	0.645	0.796	0.150
Bias, 50% power	0.008	0.103	0.450	0.554	0.105

Note: This table shows estimates of largest potential biases from under-powered pre-trends using Roth (2022). Biases are calculated under linear violations of parallel trends with slopes against which conventional pre-tests have 50% or 80% power, respectively. Robust standard errors are clustered at the state levels. Robust p-values: *** p<0.01, ** p<0.05, * p<0.1

Table A8: 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 A9: 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 A10: Treatment effects on surgery volumes, overall

	Outpatient surgeries	Inpatient surgeries	Outpatient visits	Medicare discharges	ED visits
	(1)	(2)	(3)	(4)	(5)
Panel A					
Treatment Effect	168.291	35.76	-.333	7.696	11.65
	(125.776)	(59.592)	(57.117)	(7.263)	(7.88)
Panel B					
Event time −4	-65.141	107.734*	-7.423	-10.415	27.55
	(106.28)	(56.422)	(67.229)	(18.393)	(6.65)
Event time −3	-10.32	54.659	7.575	-14.328	6.71
	(107.578)	(48.343)	(51.784)	(12.194)	(5.33)
Event time −2	-28.412	25.081	-9.052	-14.022*	-5.02
	(81.085)	(41.883)	(38.434)	(8.182)	(3.78)
Event time −1	-21.087	-5.307	-13.248	-3.191	1.79
	(58.351)	(19.262)	(16.048)	(3.776)	(2.59)
Event time 0	omitted	omitted	omitted	omitted	omitted
Event time 1	43.227	28.169	.113	1.184	1.08
	(57.422)	(29.343)	(21.913)	(3.289)	(3.21)
Event time 2	106.198	19.053	-31.41	1.014	6.64
	(91.882)	(32.229)	(40.961)	(4.321)	(5.11)
Event time 3	114.503	49.122	43.783	8.483	12.59
	(114.801)	(48.479)	(62.101)	(6.338)	(8.15)
Event time 4	173.252	66.76	2.382	11.796	22.79**
	(166.162)	(83.436)	(72.501)	(10.522)	(10.93)
Event time 5	292.448	5.97	-30.715	14.883	13.23
	(215.14)	(98.852)	(107.542)	(12.62)	(12.66)
Event time 6	410.545	46.515	14.399	13.441	17.86
	(250.691)	(129.479)	(111.023)	(15.832)	(16.82)
Mean DV	6360.508	2053.855	2898.191	438.283	484.73
N	28426	28426	28426	28426	28426
P-value of testing joint significance of pre trends	.883	.355	.831	.184	< 0.01

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 utilization measure 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 A11: Treatment effects on surgery volumes by pre-treatment care utilization

	DV: Outpatient surgeries		
	Low tertile	Mid tertile	Top tertile
	(1)	(2)	(3)
Panel A			
Treatment Effect	-23.725	426.589**	232.16
	(259.234)	(197.06)	(211.63)
Panel B			
Event time -4	-368.85	636.305***	156.09
	(358.431)	(179.923)	(158.97)
Event time -3	-11.058	30.703	151.48
	(259.234)	(122.305)	(143.83)
Event time -2	68.628	26.415	22.41
	(181.639)	(98.102)	(105.72)
Event time -1	87.556	-42.97	-45.45
	(135.455)	(53.763)	(122.45)
Event time 0	omitted	omitted	omitted
Event time 1	-78.916	146.033*	67.504
	(133.736)	(87.287)	(120.163)
Event time 2	56.782	386.231*	26.956
	(206.062)	(208.722)	(136.36)
Event time 3	-25.104	473.345**	195.305
	(236.061)	(209.971)	(187.89)
Event time 4	-187.505	599.446**	330.814
	(336.614)	(296.253)	(294.74)
Event time 5	-7.416	374.203	567.65
	(422.19)	(312.161)	(382.58)
Event time 6	165.869	745.631**	347.125
	(495.296)	(331.336)	(478.042)
Mean DV	7075.771	6179.145	5838.662
N	9,371	9,519	9,536
P-value of testing joint significance of pre trends	.447	< 0.01	.368

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 A12: 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							
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.