Health IT Diffusion and Physician Labor Supply

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Abstract

This paper examines how the diffusion of advanced health information technology (HIT) affects the aggregate supply of hospital-based (HB) physicians, who deliver direct patient care under hospital contracts. Leveraging sharp increases in county-level HIT adoption rates driven by federal incentives, we compare physician supply per 100k population in counties with rapid diffusion (treatment group) to those with slower or no uptake during our sample period (control group). Using an event-study framework, we find that HIT diffusion led to a 10.3% increase in HB physician rate in treated counties relative to control counties, and medical and surgical specialties account for most of the increase. This growth is further concentrated among early-career physicians and in physician shortage areas. Mechanism tests suggest that physicians benefit financially from practicing in treated counties, with higher Medicare reimbursement, more Medicare patients, and increases in hospital profits. Counties with moderate pre-period surgical volumes see the largest increases in physician supply and outpatient surgeries, suggesting greater capacity for demand expansion post-treatment. Various robustness checks support the validity of our results. Our findings suggest that strategic HIT investments can attract physicians, expand care capacity, and reduce geographic disparities in access to health care.

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

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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 aggregate labor supply of physicians—the key players in care provision and primary users of the new technology—remains far less understood. As hospitals and healthcare providers increasingly invest in HIT infrastructure, partly in response to competitive pressures and the "medical arms race" to modernize care environments, understanding these labor market dynamics becomes crucial. This paper aims to fill this gap by examining how the diffusion of hospital HIT affects aggregate physician supply 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 information 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 information in computerized databases and provide clinical treatment recommendations or alerts based on patient data and clinical guidelines (Agha, 2014), but lack CPOE's deeper automation and integration capabilities (Lu et al., 2018). Industry analyses typically consider advanced HIT as representing the final stage of HIT adoption (HIMSS, 2011). While CPOE may affect physician supply on the intensive margin (care volume) and the extensive margin (physician count per 100k population), the latter remains understudied despite its direct relevance to persistent physician shortages.

We examine how hospital-based (HB) physicians—those employed under contract with hospitals to provide direct patient care—respond to CPOE adoption in aggregate labor supply and care provisions. Physicians may be drawn to areas with high HIT adoption, 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 workflow changes associated with HIT adoption, especially during the transitioning phase, could also pose deterrents for some physicians. The net effect of HIT diffusion on the aggregate supply of physicians (extensive margin), 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 HB physician counts per 100k population at the county level, and 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 supply or the timing and level of HIT adoption. To mitigate potential bias from the standard differences-in-differences (DiD) model with two-way fixed effects (TWFE), we use the staggered DiD estimator à la De Chaisemartin and d'Haultfoeuille (2024) as our main approach, and we demonstrate robustness using other recent DiD estimators (à la Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

Using multiple datasets from 2005 to 2017, we find that counties with rapid HIT diffusion experienced an average 10.3% increase in HB physicians per 100k population relative to control counties. Medical and surgical specialties account for most of this growth, likely benefiting from HIT-enabled access to complex diagnostic information, coordinated care, and efficient scheduling. This growth is further concentrated among early-career physicians and in Health Professional Shortage Areas (HPSAs). These results suggest that, given the same increase in HIT adoption, physicians (especially younger ones) may be more likely to consider practicing in underserved areas where greater opportunities and benefits exist. Additional analyses reveal that HB physicians in the treated counties receive higher Medicare-allowed payments and treat more Medicare patients compared to those in the control counties after HIT adoption, potentially due to quicker service provision and easier ordering of additional procedures that result in faster patient throughput. Furthermore, we find that hospitals in areas with rapid HIT diffusion exhibit higher average profits, indicating greater financial stability that may allow more future HB physician hires.

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

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

Another potential concern is that our findings may be driven by large health systems that consolidate and acquire physician practices to attract more patients (Baker et al., 2016). These large health systems, with greater financial and technical capacity, often adopt HIT early (Agha, 2014). If those large systems simultaneously expand the physician workforce through mergers and acquisitions (M&As) or vertical integrations (VIs), our estimates could mistakenly attribute the effects of consolidation-driven physician growth to HIT adoption. To address this concern, we re-estimate our models excluding counties with substantial M&A or VI activities, and the results remain robust, suggesting that consolidation does not drive the observed effects.

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

We conduct extensive robustness checks and placebo tests. Placebo tests show no significant changes in physician supply among groups less likely to be influenced by HIT adoption, such as physicians primarily engaged in research or teaching, those in specialties less HIT-relevant (e.g., dermatology and occupational medicine), and physicians employed by federal agencies. Our results remain robust across multiple subsamples, including counties with limited adoption variability, counties with continuous physician presence, and balanced panels. In addition, alternative model specifications, such as excluding state-specific time trends or county-level controls, and recent staggered DiD estimators yield consistent results. Furthermore, our results are robust to alternative definitions of HIT adoptions, when combining CPOE with physician documentation, another advanced HIT component. All these tests support our main results.

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

Our paper contributes to two strands of literature. First, our paper contributes to the literature on the impact of HIT with new evidence on aggregate physician labor supply and how the effects vary by specialty, career stage, shortage area status, and health care utilization. Prior studies find that HIT positively affects patient health by reducing infant mortality or morbidity, mortality for most complex patients, adverse safety events, and morbidity for those with opioid-related conditions (Miller and Tucker, 2011; McCullough et al., 2016; Freedman et al., 2018; Wang, 2021). Meanwhile, HIT adoption increases the costs for Medicare patients (Agha, 2014) and initial costs to hospitals, which may decrease after 3-6 years depending on local IT intensity (Dranove et al., 2014). These mixed cost results may partly stem from large variations in HIT vendor performance (Lin and Olson, 2024). Recent work finds that hospital HIT adoption can lead to higher exit rates (via retirement) or shifts to office settings among hospitalists, particularly older physicians (Glenn, 2024).[2] Related work on nursing home staff shows HIT reduces nurses in high-end facilities but increases them in low-end ones, with no significant overall change (Lu et al., 2018). We extend this literature by examining how HIT affects *aggregate* physician supply across broader specialties and practice settings, focusing on the local market supply most relevant to patient choices.

Second, our study complements the broad literature on physician labor supply, most of which focuses on changes on the intensive margin. 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 extensive margin, measured in terms of the number of working physicians. A growing literature explores this dimension by studying how physicians select practice locations in response to insurance program expansions, student loan forgiveness programs, or physician subsidies for HPSAs (Falcettoni, 2018; Kulka and McWeeny, 2018; Huh, 2021; Huh and Lin, 2024; Khoury et al., 2024). We contribute to works on local physician labor supply via a technological angle, which combines market-driven incentives and policy-led changes in the past decades. Building on this literature, we exploit variations that are plausibly exogenous to physician labor supply to understand the effects of digital technologies on physicians, hospitals, and patient care provisions.

Our paper has broad policy implications and offers relevant insights for managerial practices.

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

As HIT investment continues to grow globally (Wang and Bloch, 2023), our findings show how these investments can improve IT workforce efficiency and expand access to care while sustaining providers' financial health. HIT investments can ease administrative burdens in cross-department coordination and serve as a competitive strategy for hospitals to attract and retain physicians in areas where they are most needed. Understanding these dynamics between digital technology and labor supply can inform policies on workforce sustainability and equitable care access. Specifically, targeted HIT investments may attract early-career physicians to underserved areas, potentially reducing geographic disparities in health care access and improving local prosperity.

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

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.[3] EHRs enable health care providers to store, access, retrieve, exchange, and manage patient health information electronically, replacing paper records. Initially, hospitals employed a best-of-breed approach, selecting specialized vendors by each department for specific needs. However, this fragmented IT structure led to increased patient safety risks, inefficiencies, and provider frustration. The growing demand for care coordination prompted a shift towards integrated IT systems, linking internal departments to improve efficiency and safety. We focus on HIT adoption in hospital care, which manages patient records on an episode-of-care basis and involves complex tests and treatments. Hospital HIT functions as an integrated enterprise system, connecting internal departments to enhance operational efficiency through various built-in tools. Although ambulatory care HIT also plays an important role, it differs substantially in design and purpose, usually serving simpler, longitudinal patient records within individual practices.[4]

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

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

healthcare providers demonstrating meaningful use (MU) of EHRs (CMS and HHS, 2012). By mid-2018, eligible hospitals received over $21 billion in incentive payments (CMS, 2018a). Since 2015, hospitals failing to adopt HIT and meet MU requirements have faced Medicare reimbursement penalties. Complementing these direct incentives, the Affordable Care Act (ACA), enacted in 2010, reinforced HIT adoption through indirect incentives. The ACA funded comparative effectiveness research using EHR-derived data (Gallego et al., 2013) and introduced initiatives such as care coordination improvements, quality tracking, and outcome-based reimbursements—all dependent on widespread EHR adoption.[5] 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.[6] Unlike other HIT components, CPOE directly structures patient data in ways that align with coding and billing requirements, making it particularly relevant when examining health technology adoption in contexts where payment mechanisms are important considerations (Ganju et al., 2022). As a relatively recent technology, CPOE has been studied as an important automation technology (Lu et al., 2018). Figure A1 shows a CPOE interface.

CPOE can enhance efficiency and care quality in several ways. First, by storing all patient health information in a centralized system, CPOE allows physicians to access critical information when making medical orders. This capability is essential for safe and effective care, given that a large share of non-surgical medical interventions—such as diagnostic tests and medication administration—begin with physician orders. Second, CPOE typically provides pre-programmed, institutionally-approved templates that streamline the ordering process and boost adherence to clinical protocols. By ensuring orders are standardized, legible, and complete, CPOE reduces the risk of lost orders—a common issue in the paper record era. Third, electronic communication through

[5] 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.

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

CPOE accelerates process turnaround times by reducing delays in connecting with relevant departments. For instance, CPOE can significantly reduce the time between ordering a knee X-ray and receiving test results, which previously required manual coordination with the radiology department. Fourth, CPOE reduces clinicians' documentation burden by minimizing the need for future data re-entry. Lastly, when paired with clinical decision support systems, CPOE can detect potential drug–drug interactions and allergies, thus enhancing patient safety at the ordering stage.

These benefits may motivate physicians to work in environments equipped with advanced HIT. However, the learning curve and fixed costs of using HIT can be significant. CPOE adoption can disrupt clinician workflow, especially during the initial implementation phase, requiring substantial adjustments to established routines. Thus, it remains uncertain whether physicians, across varying levels of IT experience and specialties, would be willing to practice in and adapt to an advanced HIT working environment. The trade-offs between potential long-term efficiency gains and short-term adaptation costs may influence which types of physicians are drawn to such environments.

2.3 Aggregate Physician Supply: Conceptual Considerations

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

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

From physicians' perspectives, responses to local HIT diffusion may vary by specialty, career

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

From the patients' perspective, HIT adoption can influence healthcare utilization by making access to services more convenient and timely. By streamlining scheduling, facilitating faster bookings, and improving care coordination, HIT may encourage patients to seek elective procedures earlier and more easily, boosting local demand for physician services. These efficiencies can accelerate care delivery, allowing physicians to serve more patients in less time. 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 supply.

Collectively, these perspectives suggest that HIT diffusion affects physician supply through interconnected channels involving hospital staffing, physician preferences, and patient utilization. In section 5, we first analyze how HIT affects aggregate HB physician supply, 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 Supply Data: Our primary dataset is the Area Health Resources Files (AHRF) (AHRF, 2018), which aggregates information from over 50 sources on health professionals, healthcare utilization, facilities, and demographic characteristics at various geographic levels. We focus on hospital-based (HB) physicians, defined as non-federal doctors of medicine (MDs) employed full-time under contract with hospitals, providing direct patient care focused on physical health.[7]

[7]We focus on physical care where treatment processes and outcomes are more standardized and comparable. We exclude hospital residents. Non-federal physicians are those not employed by federal agencies, such as the Army, Navy, Air Force, Veterans Administration, or the Public Health Service. Given their distinct employment structure,

Our main outcome is the county-year level HB physicians per 100k population.[8] To isolate physicians likely affected by HIT adoption, we exclude specialties with limited HIT relevance: such as Aerospace Medicine, Dermatology, Forensic Pathology, Medical Genetics, Nuclear Medicine, Occupational Medicine, and Public Health/Preventive Medicine. These excluded specialties are grouped and analyzed in a placebo test (Section 5.1).

The AHRF provides data on physician characteristics, including age, self-designated specialty, and professional activity. We categorize physicians into career stages by age: early-career (under 45), mid-career (45–64), and late-career (65+).[9] Specialties fall into four broad categories: medical specialties, surgical specialties, total 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, administration). Since non-patient care roles involve less HIT interaction, these physicians serve as another placebo test.

Finally, the AHRF provides rich county-level demographic and healthcare utilization data, which we use as controls. Demographic variables include the percentage of the population aged 65 and older, percentage Black, population density, income per capita, unemployment rate, Medicare Advantage penetration rate, and educational attainment (percentage with at least a college degree). Due to missing annual data for the last two variables, we use their 2005 values interact with a linear time trend to capture time variation while mitigating potential endogeneity from HIT diffusion à la Dranove et al. (2014). For utilization, we focus on inpatient and outpatient surgical operations at short-term general hospitals, supplemented by outpatient visits and Medicare inpatient discharges.

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

federal physicians are expected not to be influenced by HIT adoption, serving as a falsification test (Section 5.1).

[8] We use physician counts per 100k population à la Chen and Roth (2024), who recommend converting outcomes in per capita units. While Poisson regression could address zero values, the modern DiD estimators are more suitable for models based on linear regressions. As a robustness check, we re-estimate the main specifications excluding counties that ever had zero HB physicians during our sample periods, finding similar results (Section 5.6).

[9] 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%, 52%, and 14% of physicians.

hospital bed size across local facilities.[10] Our one-year lagged CPOE data span 2005–2017, a period marked by rapid US HIT adoption, as shown in Figure 1. The left panel of the figure plots the average county-level adoption rate, starting below 0.5% in 2005 and exceeding 85% by 2017. Table A2 provides year-by-year adoption rates, highlighting the magnitude of this nationwide diffusion.

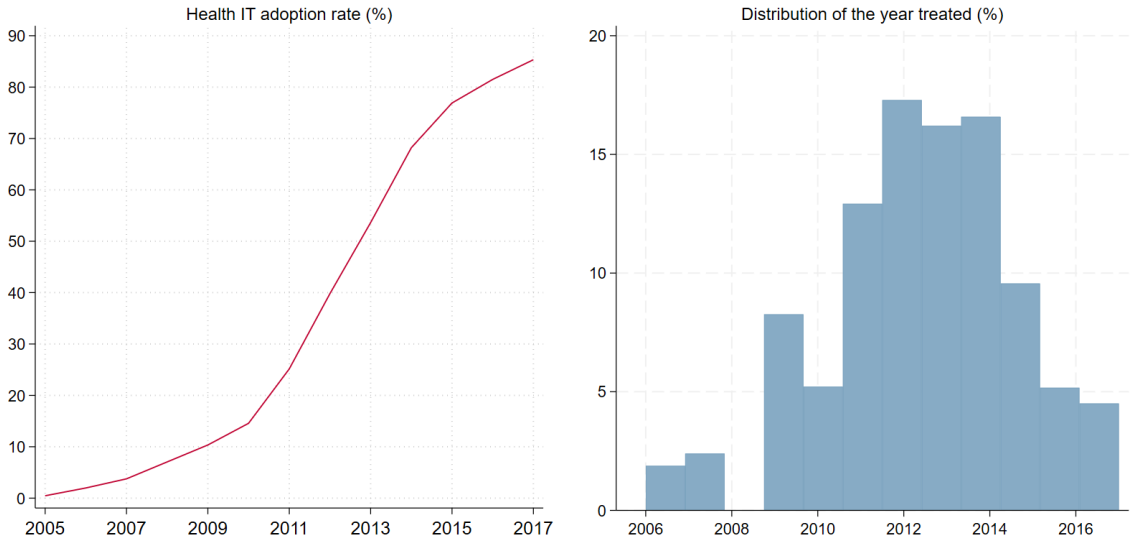


Figure 1: Health IT diffusion pattern

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 the general strategy developed in East et al. (2023), we divide the sample into treatment and control groups based on sharp increases in HIT adoption rates. A county is considered treated in year τ if it experiences a *sharp jump*—the *largest* year-over-year increase in adoption during the sample period—under one of the following conditions: (i) the adoption rate rises from zero to a strictly positive value at τ; or (ii) the adoption rate, already positive at $\tau - 1$, increases by more than 100% at τ.[11] All counties meeting either criterion are classified as treated. This approach ensures that the identified sharp jump reflects a substantial change in HIT adoption—either transitioning from no adoption to some adoption or undergoing a significant expansion—so that pre and post-adoption statuses are meaningfully distinct.

[10] 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.

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

Our classification captures substantial changes in HIT adoption status for most counties (Figure 2). The figure groups counties by the number of distinct positive adoption rates observed during the sample period and plots adoption rates against year relative to treatment for each group.[12] Although adoption trajectories vary across groups, a common pattern emerges: adoption rates remain relatively flat before treatment but rise sharply afterward. We exploit both the variation in HIT 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 supply over time.

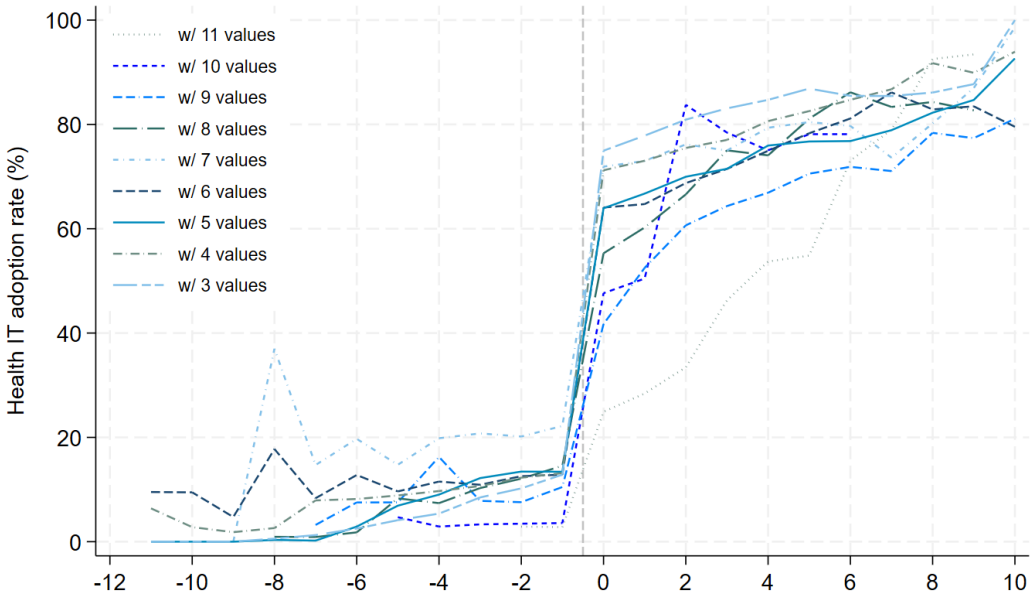


Figure 2: Health IT adoption rate relative to treatment year

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

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

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

Medicare Provider and Service Data: Our third data source is the Medicare Physician & Other Practitioners by Provider and Service dataset (CMS). From this dataset, we extract two key physician-level measures: the total allowed amounts a physician receives for treating Medicare beneficiaries and the number of distinct Medicare beneficiaries treated by each physician. The total allowed amount includes Medicare payments, patient deductibles and coinsurance, and any third-party contributions. These measures assess whether physicians benefit financially from practicing in areas with higher HIT adoption. Since this dataset starts in 2013, the analysis using these two measures is limited to a shorter time frame. We aggregate each measure to the county level by summing values across all HB physicians within the same county.

Market Structure and Profit Data: We supplement the above datasets with the Healthcare Cost Report Information System (HCRIS), which provides additional county-level controls and alternative outcome measures. The Centers for Medicare & Medicaid Services (CMS) require Medicare-certified institutional providers to submit annual cost reports detailing provider characteristics, utilization, and financial statements. To capture market concentration in hospital care at the county level, we construct the Herfindahl-Hirschman Index (HHI), calculated as the sum of the squared market shares of all local hospitals, where each hospital's market share is defined by its proportion of total hospital beds in the county. A higher HHI indicates a more concentrated hospital market. We also calculate average hospital profit per county by averaging profits across all local hospitals, where profit is defined as the difference between total patient revenue and total cost.

Sample Construction. The AHRF includes approximately 3,230 counties. After merging all datasets, our final analytical sample consists of approximately 2,380 counties during the years 2006-2018, excluding 2009 due to missing AHRF data. When merging datasets, we apply a one-year lag between HIT adoption and physician supply outcomes to account for physician response time, which ties 2008 adoption to the 2009 outcomes. The reduction in our merged sample size primarily results from missing data from HIMSS. To ensure the validity of the county-level HIT adoption rate derived from HIMSS, we compare the number of hospitals recorded in HIMSS with those in HCRIS. On average, HIMSS covers 95% of the hospitals listed in HCRIS. Given that over 96% of US hospitals participate in Medicare, we believe that the HIT adoption rates derived from the HIMSS data accurately represent the overall HIT adoption status across most counties.[13]

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

3.2 Summary Statistics

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

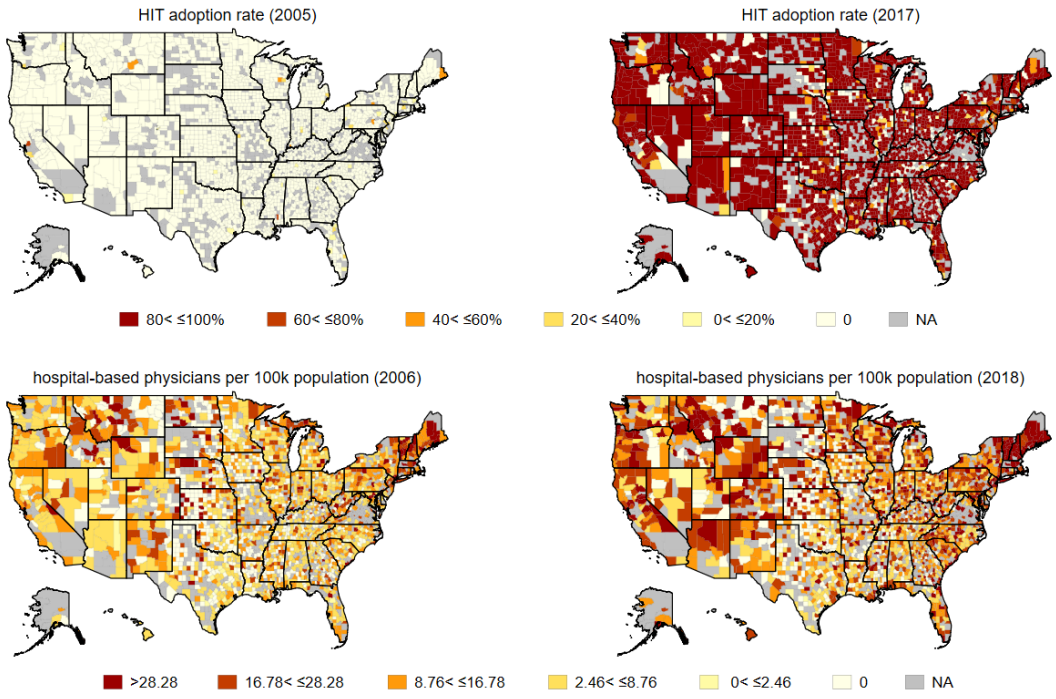


Figure 3: Geographic distribution of HIT adoption and hospital-based physician density

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

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

	Overall	Never-treated	Ever-treated
HB physician counts per 100k population	10.27	10.30	10.27
	(11.6)	(12.8)	(11.5)
Health IT adoption rate (%)	1.46	0	1.64
	(5.39)	(0)	(5.69)
% 65+ population	15.7	17.2	15.5
	(4.07)	(4.35)	(4.00)
% black	9.10	9.44	9.05
	(14.4)	(15.6)	(14.2)
Population density	239	107	256
	(1,722)	(520)	(1,815)
Income per capita	32,356	34,872	32,046
	(8,325)	(10,304)	(7,996)
Unemployment rate (%)	6.65	6.65	6.65
	(2.29)	(2.35)	(2.28)
Hospital HHI	0.80	0.92	0.78
	(0.27)	(0.15)	(0.27)
Medicare Advantage penetration rate (%)	4.06	2.87	4.21
	(7.73)	(5.58)	(7.95)
% above college degree	12.6	11.4	12.8
	(5.7)	(5.1)	(5.7)
# 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. Table A2 provides year-by-year statistics. Standard deviations are in parentheses.

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 10 HB physicians per 100k population. Before treatment, the average HIT adoption rate was below 1.5% across all counties, with only a small set of counties showing positive pre-treatment adoption rate. The statistics by treatment status reveal that HB physician supply per county was nearly identical between treated and control counties prior to HIT adoption. Both groups were similar across most county-level observable characteristics, except that ever-treated counties were more densely populated, had less concentrated hospital

markets, smaller aging populations, and higher Medicare Advantage penetration rates before HIT adoption. The sample includes 2,394 counties, with 2,129 classified as ever adopters. Among these, over 70% transitioned from 0 to 100% adoption, and 92% exhibited no more than three distinct adoption rate values over time. This distribution supports our approach of defining treatment and control groups based on discrete changes in HIT adoption rates.[14]

4 Empirical Strategy

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

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

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

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

[14] Table A2 reports yearly summary statistics, showing that most county-level controls remain stable except for increases in the population aged 65 and older, income per capita, and some fluctuations in the unemployment rate. Table A3 provides summary statistics for variables used in additional analyses.

X_{it} includes a rich set of county-year level variables, as described in Section 3.1. 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.[15] δ_i denotes county fixed effects, controlling for time-invariant county characteristics that might simultaneously affect physician supply and HIT diffusion. Our key coefficient of interest, β_1, measures the effect of HIT adoption on HB physician supply at the county level. A positive β_1 would indicate that more physicians are willing to practice in areas with greater HIT adoption, whereas a negative β_1 would suggest physician reluctance to work in HIT-intensive environments.

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

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

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

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

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

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

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

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

Mechanism and Robustness Tests: To further understand how HIT diffusion affects physician location choices, we examine its impact on provider financial performance. Specifically, we analyze three key financial metrics described in Section 3.1, assessing whether practicing in HIT-intensive environments yields measurable financial benefits for physicians. Additionally, we ex-

plore heterogeneity in these effects across counties with varying levels of existing healthcare utilization and assess how HIT diffusion may influence subsequent patient care utilization. Finally, we perform a series of sensitivity checks to evaluate the robustness of our main findings, ensuring that the results are not driven by specific sample compositions or model specifications.

5 Results

5.1 Main Results: HIT and Aggregate HB Physician Supply

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

As a falsification test, we re-estimate the main specifications using the following outcome measures: (i) HB federal physicians, (ii) physicians in other categories, and (iii) physicians in placebo specialties—all of which are expected to exhibit limited job mobility in response to HIT diffusion. For example, federal physicians are generally less likely to change jobs or practice locations due to the unique benefits associated with their positions, such as job security, subsidized health insurance, and generous pension plans. 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 in comparison to the main outcome variable. As expected, we find no significant effects of HIT adoption on the supply of any of these groups, reinforcing the validity of our main findings.

Table A4, Panel A, Column (1) reports the estimated average treatment effect from Equation (1). The results show that treated counties experienced an average increase of 1.28 HB physicians

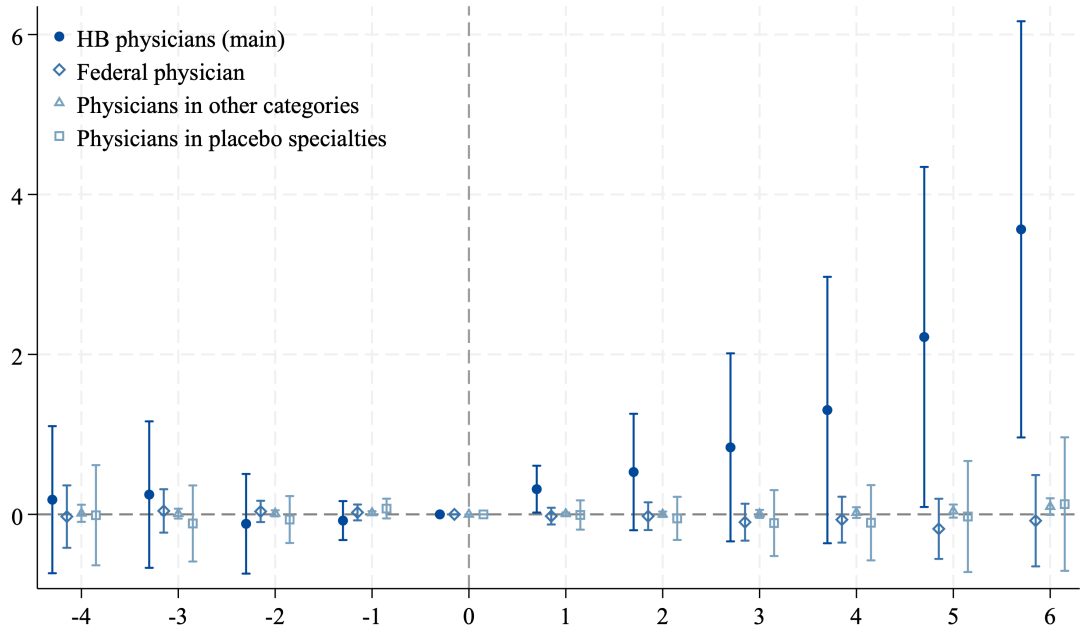


Figure 4: Effect of HIT diffusion on HB physician supply, main results and falsification tests

Notes: The figure presents the main result, comparing them with effects on 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, 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, per-capita income, unemployment rate, the fraction of population aged 65 or older, the fraction of the Black population, population density, HHI for the county-level hospital market. Additional controls include 2005 values of the Medicare Advantage penetration rate and the fraction of college-educated or above, each interacting with linear time trends. The whiskers correspond to 95% confidence intervals, with standard errors clustered at the state level.

per 100k population, representing a 10.3% gain ($= 1.28 \div 12.5 \times 100\%$) relative to the control group. The p-value from the joint significance test of the pre-treatment interaction terms indicates that we cannot reject the hypothesis that these coefficients are jointly zero, supporting the parallel trends assumption. These results suggest that local HIT adoption affects aggregate physician location choices, *ceteris paribus*. Areas with higher HIT adoption may attract HB physicians by offering comprehensive, real-time patient data that enhances clinical decision-making. In addition, HIT streamlines ordering and documentation, reducing administrative burdens and potentially boosting workflow efficiency and revenues. Although adopting HIT may be difficult for some physicians,

the aggregate effect of county-level HIT adoption on HB physician supply remains positive.

We further explore heterogeneous effects across categories within HB physicians: medical specialties, surgical specialties, total general practice (GP), and other specialties. Common medical specialties include Internal Medicine, Pediatrics, and Cardiovascular Disease, while surgical specialties include Obstetrics and Gynecology, General Surgery, and Orthopedic Surgery. Total GP comprises General Practice and Family Medicine. Figure A2 presents the event-study estimates for these specialty groups. The results reveal a post-treatment increase in the number of HB physicians per 100k population in treated counties relative to control counties for both medical and surgical specialties. In contrast, the effects on total GP and other specialties are insignificant. Table A4 Columns (2)–(5) report the regression estimates. On average, the post-treatment interaction terms indicate a relative increase of 0.709 (19.1%) in medical specialties and 0.303 (14.2%) in surgical specialties. These results suggest that the observed overall increase in HB physician supply is primarily driven by medical and surgical specialties.

This pattern likely arises because medical specialties depend on complex diagnostic data and coordinated chronic disease management, while surgical specialties rely on efficient scheduling, preoperative evaluations, and postoperative monitoring. All are processes that local HIT adoption can help enhance. In contrast, hospital-based general practitioners typically provide broader, less specialized care that requires fewer advanced HIT functionalities. The "other specialties" category shows noisy estimates, likely reflecting the diverse HIT dependencies among these specialties. Importantly, our results reflect aggregate physician supply rather than individual physician choices. For example, if a senior physician retires or shifts to office-based settings, hospitals can reallocate resources to hire multiple early-career, HIT-savvy physicians, leading to a net increase in supply.[16]

5.2 HIT Diffusion or Physician Practice Consolidation?

We next examine whether the observed increase in HB physician supply is influenced by health care consolidation, a growing trend that could also shape local HIT diffusion. Consolidation activities, such as M&As and VIs, may simultaneously expand physician networks and accelerate HIT

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

adoption within health systems. For example, a large health care system acquiring local physician practices might integrate them into hospital outpatient departments while adopting advanced HIT to streamline care management across the entire network. In such cases, the effect of HIT diffusion on physician supply could be confounded by consolidation.

To address this concern, we re-estimate the main specifications after excluding counties that experienced substantial M&A or VI activities. The HIMSS data contain information on system affiliation for hospitals and affiliated non-hospital care facilities. A health *system* is defined as either an independent hospital *per se* or an integrated health care delivery network comprising multiple hospitals and affiliated non-hospital facilities. We consider a hospital system to have experienced an M&A (VI) in a given year if the number of hospitals (ambulatory care units) within the system increased compared to the previous year. At the aggregate level, a county is classified as experiencing substantial M&A (VI) activity in a given year if the share of local systems undergoing such changes exceeds the median across the sample (i.e., 0.167 for M&As and 0.25 for VIs). In our sample period, VIs are more common than M&As.

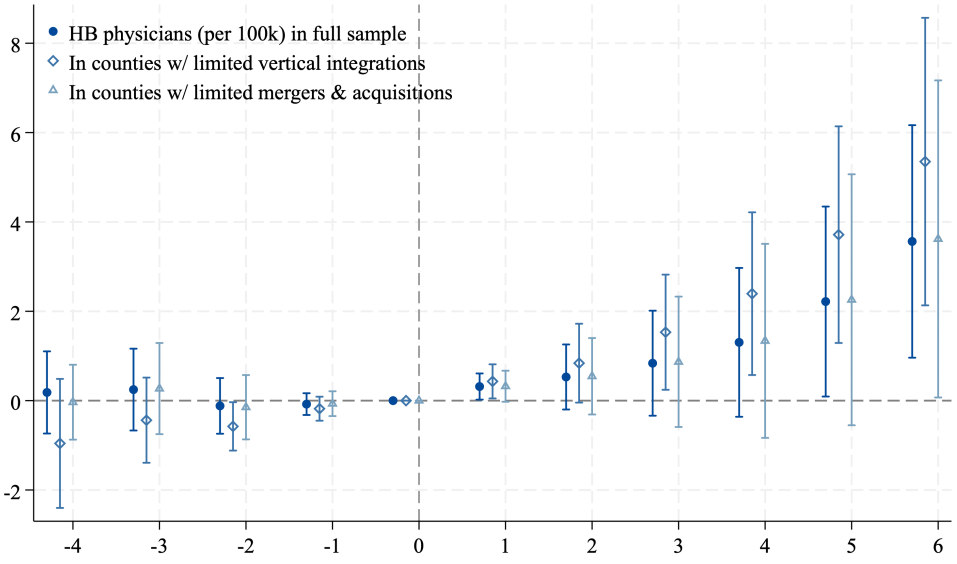


Figure 5: Effect of HIT diffusion on HB physician supply in counties with less consolidation

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

Figure 5 presents the event-study estimates, and Table A5 (last two columns) reports the corresponding regression results. The results indicate that even after excluding counties with substantial

VI activities (diamonds), treated counties still exhibit a significant increase in HB physician supply relative to controls, suggesting that HIT diffusion independently drives physician supply changes. For counties without substantial M&A activities (triangles), the event-study estimates closely mirror the main results in magnitude and pattern, though the confidence intervals are notably wider, likely due to reduced sample size. This test addresses the concern that large health systems may drive the observed results by consolidating to acquire physicians and expand their patient base while simultaneously adopting advanced HIT. However, our findings indicate that HIT adoption itself remains an independent driver of increased HB physician supply. The persistence of positive effects in the absence of major consolidation activities underscores the role of HIT in shaping physician location decisions, independent of broader structural changes in the health care market.

5.3 Heterogeneity by Physician Career Stage and by Shortage Status

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

Heterogeneity by Career Stage: We first examine heterogeneity by physicians' career stage.[17] Figure 6 shows event-study estimates separately for early-career (under 45), mid-career (45–64), and late-career (65+) physicians. Table A5 presents corresponding estimates in Columns (1)–(3). We observe a significant post-treatment increase in early-career physicians (diamonds) in treated counties relative to controls, but the effects for mid- and late-career physicians are insignificant. This result suggests that the overall increase in physician supply is primarily driven by younger physicians. The finding aligns with previous research showing that early-career physicians are more likely to (re)consider practice locations in response to external changes (Polsky et al., 2000; Kessler et al., 2005; Huh, 2021; Khoury et al., 2024; Huh and Lin, 2024). In terms of HIT adoption, younger physicians may face fewer barriers to navigating complex IT systems and may value faster access to patient information and streamlined workflows enabled by HIT. As a result, they appear more willing to practice in HIT-intensive environments, driving the observed aggregate effects.

Heterogeneity by Physician Shortage Area Status: Next, we assess how the effects of HIT diffusion vary by Health Professional Shortage Area (HPSA) designation. We classify a county as

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

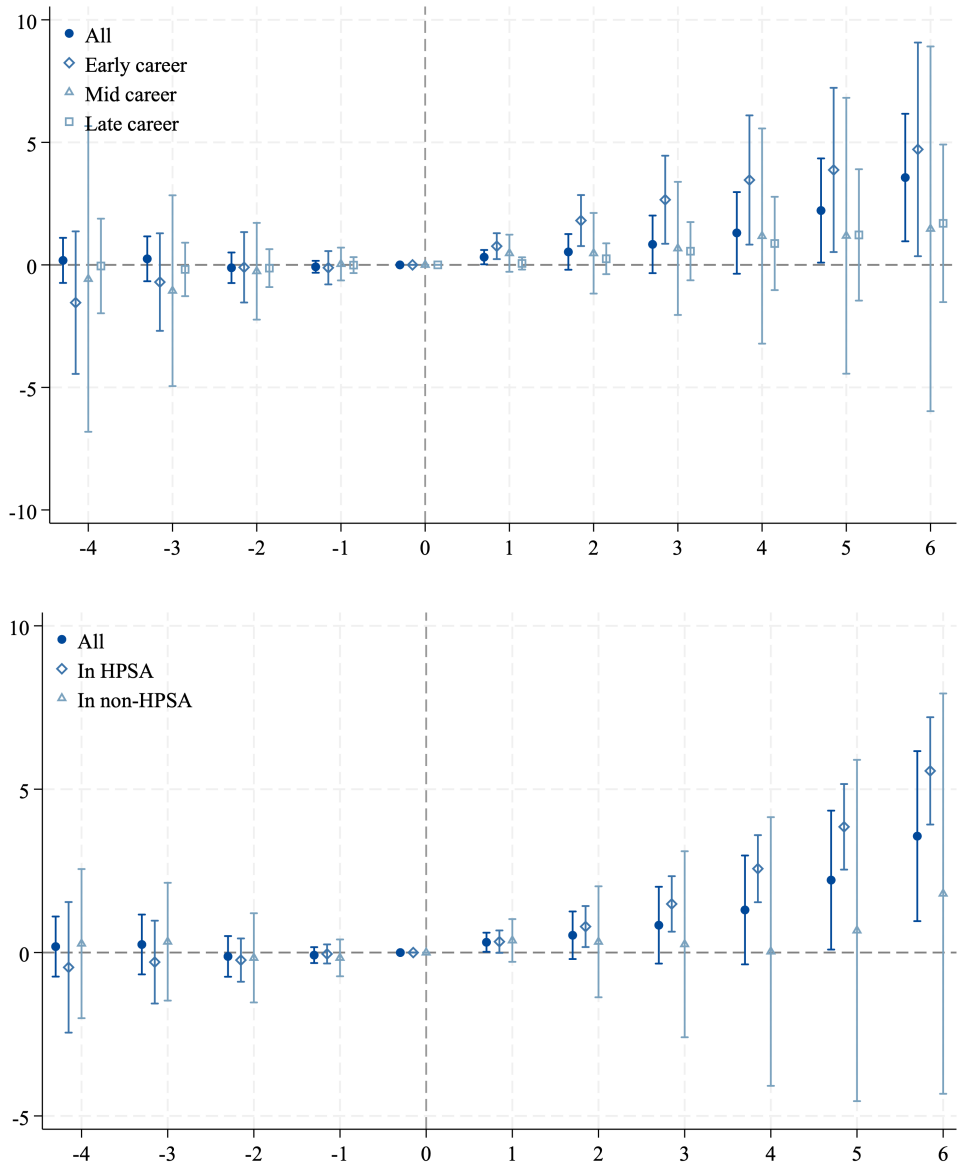


Figure 6: Effect of HIT diffusion on physician supply, by career stage and HPSA status

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.

ever-HPSA if at least part of the county was ever designated as having a shortage of primary care practitioners.[18] We re-estimate the main specifications for ever-HPSA counties and the remaining counties. Figure 6 (bottom panel) and Table A5 (Columns (4)–(5)) show that the treatment effect

[18]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.

is significant among ever-HPSA counties, meaning a significant increase in HB physicians per 100k in treated HPSA-counties relative to the control HPSA-counties. In contrast, HB physicians do not appear to change significantly post-treatment in never-HPSA counties. This indicates that the overall effects of HIT adoption on HB physician supply are largely driven by improvements in shortage areas. One plausible explanation is that HIT adoption enhances the ability to provide high-quality care in resource-limited settings, making HPSA counties more attractive by improving clinical efficiency and offering better practice opportunities where physician demand remains high.

Heterogeneity by Career Stage and HPSA Interaction: To explore the nuanced heterogeneity arising from the interaction between career stage and shortage status, we conduct subsample analyses by physician career stage within HPSA and non-HPSA counties. Figure A3 and Table A6 report the results. We find that early-career physicians in ever-HPSA counties experience a significant relative increase following HIT adoption. In contrast, there are no significant changes for early-career physicians in non-HPSA counties or for mid- and late-career physicians in either setting. A plausible explanation is that early-career physicians, being more HIT-savvy, may prefer less competitive areas (HPSA) where advanced HIT systems are installed to reduce operational burdens, especially when combined with financial incentives in the form of physician subsidies. Notably, the Medicare Physician Bonus Program offers a 10% bonus for physicians providing services in HPSAs, potentially making these areas more attractive when paired with advanced HIT infrastructure.[19] By reducing administrative burdens and streamlining clinical workflows, HIT may enable physicians to serve more patients, potentially boosting hospital revenues and physician earnings.

5.4 Potential Mechanism: The Financial Impact of HIT Adoption

We now examine whether HB physicians benefit financially from practicing in areas with more rapid HIT diffusion. Specifically, we use three proxies for financial performance: (i) average Medicare-allowed amounts per HB physician, (ii) average number of distinct Medicare beneficiaries per HB physician, and (iii) average hospital profits.[20] These metrics capture both direct physician-level financial gains and broader institutional financial performance.

To construct the first two measures, we identify HB physicians as those furnishing at least 90%

[19] Medicare pays a 10% quarterly bonus to eligible providers serving in HPSAs, based on service location rather than patients' residence or physicians' primary location. See https://www.cms.gov/medicare/payment/fee-for-service-providers/physician-bonuses-health-professional-shortage-areas-hpsas.

[20] The first two financial measures are analyzed over a shorter period due to data availability starting in 2013.

of their services in hospital inpatient or emergency room settings.[21] We then compute county-level averages by averaging (i) and (ii) across all HB physicians by county. Figure 7 presents the event-study estimates, with results in Table A7 (Columns (1)–(2)). The results show that HB physicians in treated counties receive significantly higher Medicare-allowed payments following sharp HIT adoption, compared to those in control counties. These positive effects remain statistically significant up to four years post-adoption. A similar pattern emerges for the average number of distinct Medicare beneficiaries per physician, suggesting that HIT adoption not only increases physicians' reimbursement but also expands their capacity to serve more patients. This likely reflects how HIT enables quicker service provision and easier ordering of additional procedures, leading to faster patient throughput and enabling physicians to deliver care more efficiently while increasing revenue.

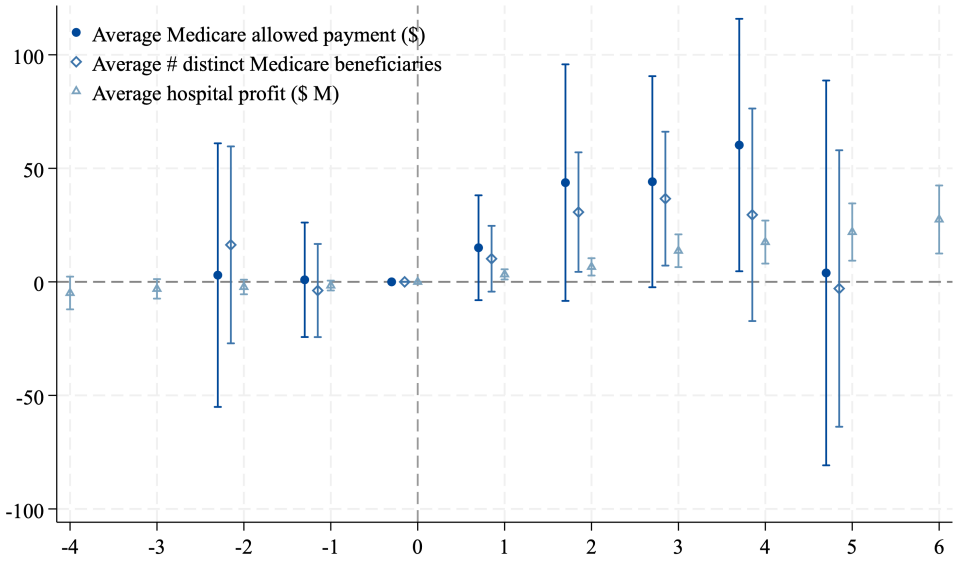


Figure 7: Effect of HIT diffusion on financial metrics

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

Next, we consider average hospital profits, calculated as the difference between total patient revenues and costs based on the HCRIS data. As shown in Figure 7 and Table A7 (Column 3), hospitals in treated counties experience sustained profit gains following HIT adoption relative to control counties. This result suggests that the increased physician capacity to provide more ser-

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

vices, combined with streamlined clinical operations enabled by HIT, most likely contributes to higher hospital profitability. Enhanced profitability may, in turn, enable hospitals to expand physician staffing, contributing to the observed continued increase in HB physician supply.

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

5.5 Heterogeneity by Utilization: Physician Supply and Patient Utilization

Building on the results that HIT diffusion boosts physician and hospital financial performance, we now examine the changes in patient care utilization, recognizing the interplay between service demand and provider capacity. Specifically, we examine whether physician responses to HIT diffusion vary with pre-period local health care utilization levels and how this, in turn, influences subsequent service use, shedding light on potential demand-supply dynamics affected by HIT.

We focus on two main utilization measures: outpatient and inpatient surgical operations at short-term general hospitals, measured per 100k population at the county level using AHRF data.[22] To capture heterogeneity, we categorize counties into tertiles based on pre-treatment surgery volume, using the 2000–2004 average (before our sample period) to ensure consistent baseline comparisons and avoid biases from utilization growth before advanced HIT diffusion. We also report alternative utilization measures, including outpatient visits and Medicare hospital inpatient discharges, and discuss why and how these utilization measures may respond differently.

Outpatient Surgery Volume: The top panels of Figure 8 and Table A8 (Columns (1)–(3)) present the results for outpatient surgical operations. We find a significant increase in HB physician supply in mid-tertile counties, while effects remain insignificant in both top- and bottom-tertile counties. This pattern suggests that physicians are more responsive to HIT adoption in areas with moderate patient demand, where the benefits of streamlined workflows can be maximized without the challenges associated with oversaturated markets or high case complexity. In contrast, high-utilization areas may have poorer patient populations or complex chronic conditions that reduce the attractiveness of practicing (Cooper et al., 2012; Hayes et al., 2016), while low-utilization areas may

[22] Short-term general hospitals provide acute care to patients with short-term medical conditions (e.g., surgeries, infections, injuries). They typically offer a broad range of services (e.g., emergency care, surgical procedures, maternity services, general medicine), focusing on treatments that require relatively short hospital stays (less than 30 days).

simply lack sufficient demand. Mid-tertile counties likely represent an optimal balance, offering enough patient volume without excessive competition or complex caseloads.

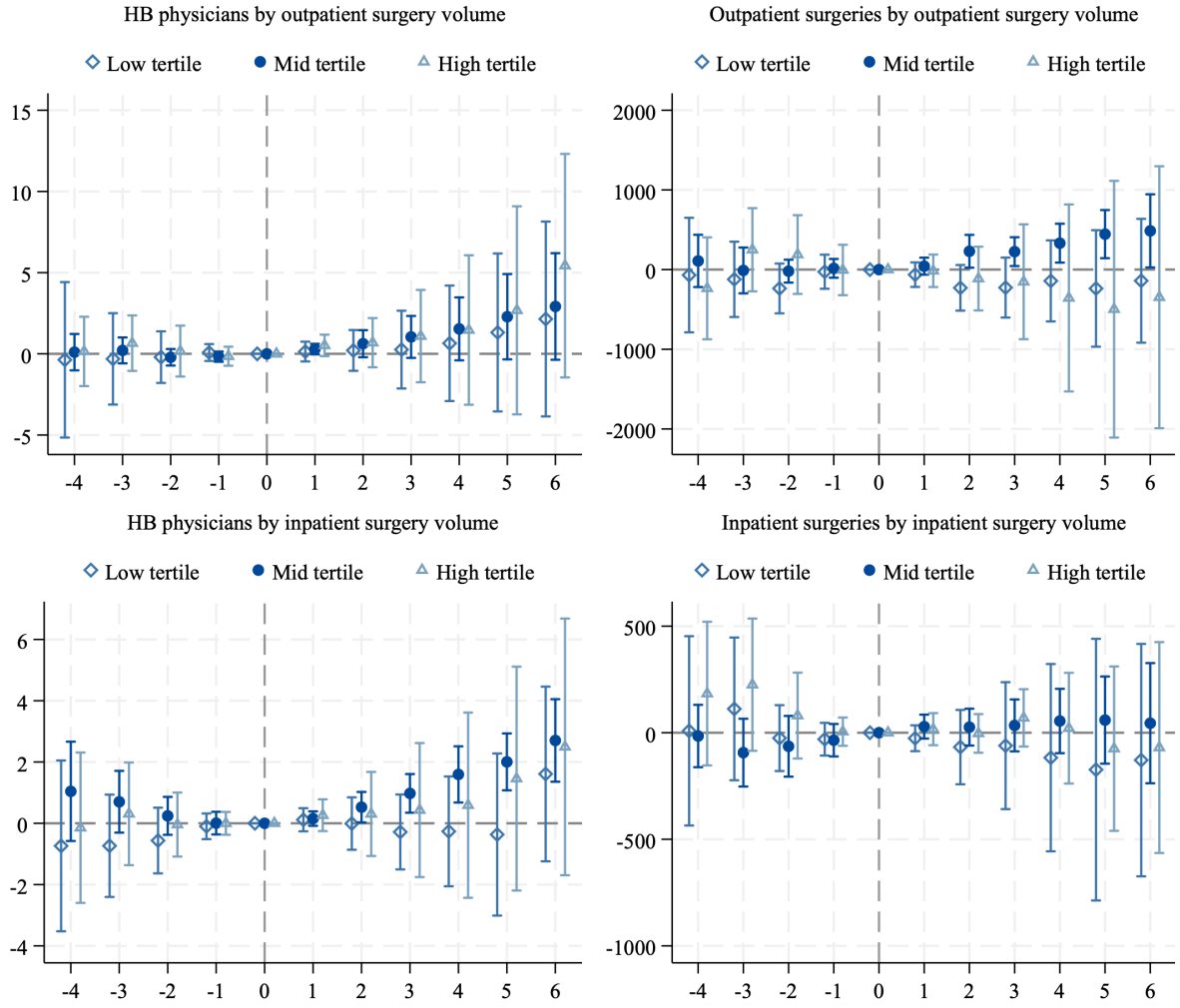


Figure 8: Heterogeneity by pre-treatment outpatient/inpatient surgery volume

Notes: The upper panels show results by tertiles of outpatient surgery volume, and the bottom panels show results by tertiles of inpatient surgery volume, based on pre-treatment counts. 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.

We further assess whether HIT diffusion affects subsequent patient utilization by examining outpatient surgeries per 100k population at short-term general hospitals. The top-right panel of Figure 8 and Table A8 (Columns (4)–(6)) show that only mid-tertile counties exhibit a significant post-HIT increase in outpatient surgical procedures, consistent with the physician supply results. Since outpatient surgeries often involve elective or less complex procedures that can be more easily

scheduled and scaled when HIT streamlines administrative tasks such as scheduling, documentation, and care coordination, this increase in high-margin outpatient surgeries aligns with our earlier finding of greater average hospital profits in treated counties.

Inpatient Surgery Volume: We then repeat this analysis for inpatient surgical operations (bottom panels of Figure 8 and Table A9). While HB physician supply still increases in mid-tertile counties post-treatment, there is no corresponding rise in inpatient surgeries across any tertile. This slight divergence suggests that the value of HIT may be less pronounced in inpatient settings, where surgeries are often more invasive, urgent, or involve higher-risk patients, making volumes less responsive to operational efficiencies. Inpatient procedures also typically require longer recovery periods and greater resource commitments, limiting hospitals' ability to scale up volumes quickly, even with improved HIT infrastructure. The observed increase in HB physicians in these mid-tertile areas may reflect a growing need for specialized inpatient care teams, where additional physicians support complex surgical cases, manage comorbidities, and ensure care quality—improvements not easily captured by inpatient surgery volume alone. Given that outpatient services generally represent a higher-margin revenue stream, this difference complements our earlier finding of greater hospital profits in treated counties, highlighting that HIT-driven efficiencies may have stronger financial impacts in outpatient settings where service expansion is more flexible.[23]

Outpatient Visits and Medicare Discharges: Figure A4 examines heterogeneity by outpatient visits and Medicare inpatient discharges. Figures in the top panel show that outpatient visits significantly increased only in mid-tertile counties post-treatment. HB physician supply remains unchanged across all tertiles, potentially because outpatient visits are typically shorter, less complex, and generate lower revenue per encounter compared to surgical procedures. Physicians may find outpatient visit-driven demand insufficiently attractive, even with HIT improvements. Figures in the bottom panel show that HB physician supply increases significantly in low- and mid-tertile counties, with a stronger effect in the mid-tertile group, while inpatient discharges remain unaffected. This suggests that HIT adoption may attract physicians to areas with lower to moderate inpatient demand, with more room to expand services. The lack of Medicare inpatient discharge growth may reflect capacity limits or the less flexible nature of inpatient care.

Compared to the clear patterns in surgical operations, these utilization measures show more noise, likely due to factors such as varying case complexity and preferences for less invasive treat-

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

ments. Overall, our utilization results suggest that HIT's impact is more pronounced in complex surgical procedures, where operational efficiencies and scheduling improvements play a larger role.

5.6 Robustness Checks

We conduct several analyses to assess the robustness of our results. First, we rerun the main specifications using different subsamples. Specifically, we restrict the sample to counties with no more than five distinct HIT adoption rates, as counties with more gradual adoption patterns may have fewer discrete changes. Results for this subsample are presented in Figure A5 (diamonds). We also exclude counties that ever recorded zero per-capita HB physicians during the sample period to ensure that our findings are not driven by these counties (Figure A5, triangles). Additionally, we perform a balanced event study, limiting the analysis to counties with at least four periods before and after the treatment (Figure A5, squares).[24] Across all these subsample analyses, our main findings remain consistent (Table A10, Columns (1)–(3)).

Second, we explore alternative model specifications. Removing state-specific time trends yields estimates similar to the main results (Figure A6, diamonds). The findings remain robust when we further exclude county-year level controls (Figure A6, triangles). Third, we apply alternative staggered DiD estimators from recent Econometric literature (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). As shown in Figure A7, the results are generally consistent across estimators, with all showing similar trends and magnitudes of treatment effects. The estimates from the conventional two-way fixed effects (TWFE) specification are slightly less precise but follow the same overall pattern as the alternative methods.

Finally, we incorporate an alternative definition of advanced HIT adoption based on the adoption of either CPOE or physician documentation (PD) systems, as used in a prior study (e.g., Dranove et al. (2014). Our results remain robust though slightly less precise (Figure A8), as most of the key variation and advanced automation features are driven by CPOE, as discussed in section 2.2.[25] In summary, these robustness checks demonstrate that our main results are generally robust to variations in sample composition, model specifications, and alternative measurements.

[24] The threshold of four periods considers the tradeoff between the availability of pre-treatment observations and sample size retention. Observations beyond the fourth period before and after treatment are excluded.

[25] PD allows physicians to transition from paper-written to electronic (unstructured) notes (Dranove et al., 2014). In contrast to CPOE, PD is not a core component of the meaningful use criteria under the HITECH Act, but rather an optional menu item. The correlation coefficient between CPOE adoption rate and COPE/PD adoption rate is 0.94.

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 changes at the physician level. For example, a net increase in HB physicians could reflect compositional changes, such as replacing retiring senior physicians with junior ones, variations in the mix of primary care providers and specialists, or changes in physician roles and responsibilities. Second, our focus on HIT adoption could be enriched by examining how digital and physical medical technologies jointly affect physician supply, but data limitations prevent such analysis. Nevertheless, our comprehensive controls mitigate concerns that other technological investments drive the results. Third, we lack data to distinguish whether physician supply responses stem from domestic or international medical practitioners making initial or lateral practice location choices, which could be policy-relevant. 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, it is challenging to isolate its impact, let alone distinguish between direct effects and indirect effects through physician labor supply. These remain promising directions for future research.

6 Conclusion

This study examines how the rapid diffusion of advanced HIT influences HB physician supply across US counties. Leveraging sharp local HIT adoption, we find that treated counties experienced a 10.3% increase in HB physicians per 100k population relative to control counties, with growth primarily driven by early-career physicians and concentrated in areas that faced physician shortages. HIT adoption leads to higher Medicare-allowed payment per physician, more Medicare patients treated, and increases in average hospital profits. In addition, we find increases in outpatient surgical volumes, particularly in counties with moderate pre-treatment utilization levels, suggesting that HIT-enabled efficiencies in outpatient settings enhance patient throughput and revenue generation. These findings remain robust after accounting for market concentration, healthcare consolidation, various model specifications, alternative DiD estimators, and analyses across multiple subsamples.

Our results have implications for health policy and management. For policymakers, investing in HIT may help attract and retain physicians, particularly in areas with physician shortages and, thus, excess demand for medical care. Such investments could complement existing incentive pro-

grams by making HIT-enabled environments more appealing to early-career physicians, who may be more comfortable with advanced HIT. For hospital managers, aligning digital investments with workforce strategies is essential for improving physician productivity and retention. Recognizing the role of HIT in affecting physician supply can help hospitals align digital investments with hiring strategies to sustain growth and meet evolving patient care demands.

Our findings contribute to the broader discussion on automation and the future of work in health care. Advanced HIT adoption over an extended period has laid the groundwork for the data-rich environments that modern digital tools rely on. At the aggregate county level, we find that advanced HIT appears to complement physician labor, enhancing productivity and patient access rather than displacing physician jobs. Future research could explore how burgeoning digital innovations, such as AI tools and interoperable systems, can be optimally integrated within HIT to further support physicians in delivering better patient care.

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A Figures and Tables

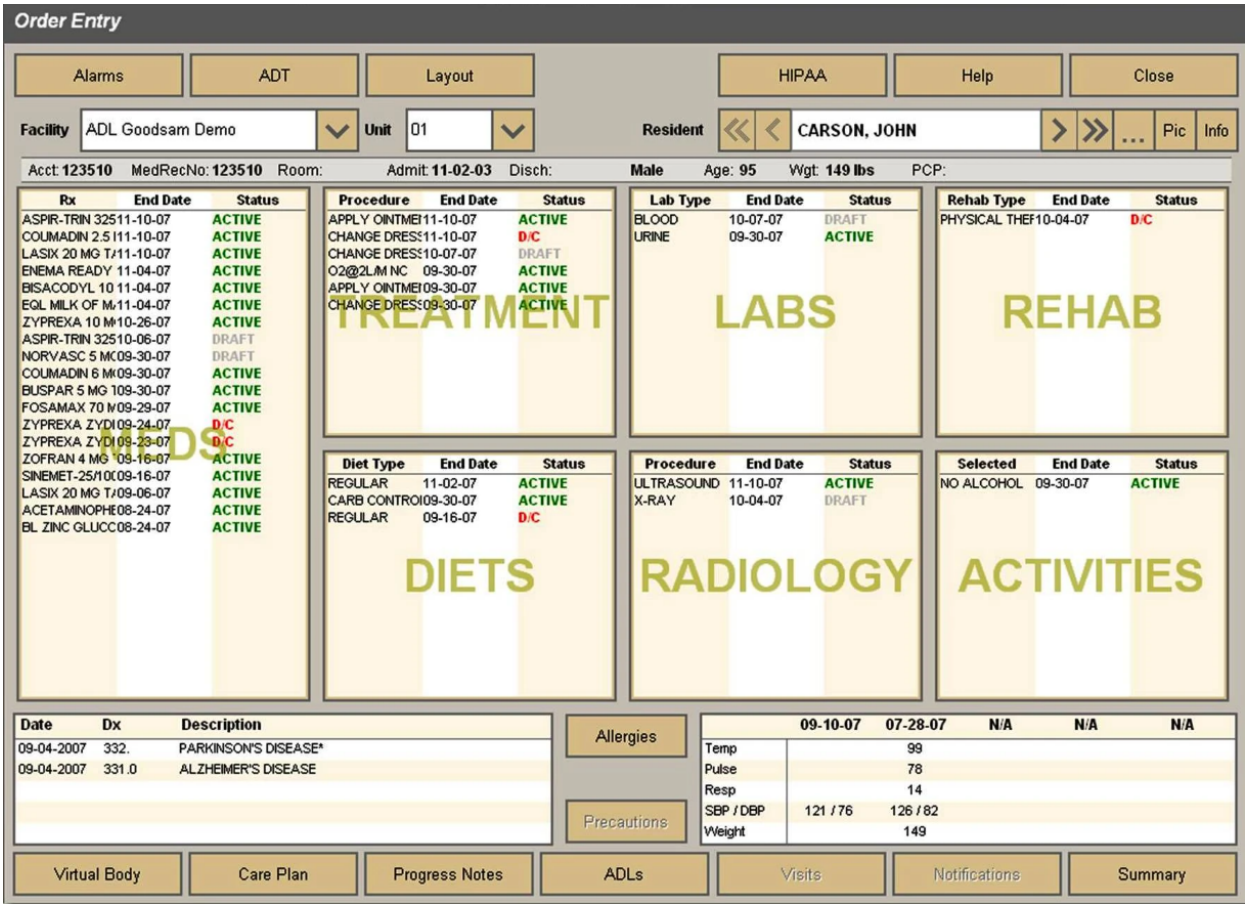


Figure A1: Example of a Computerized Physician Order Entry (CPOE) Interface

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

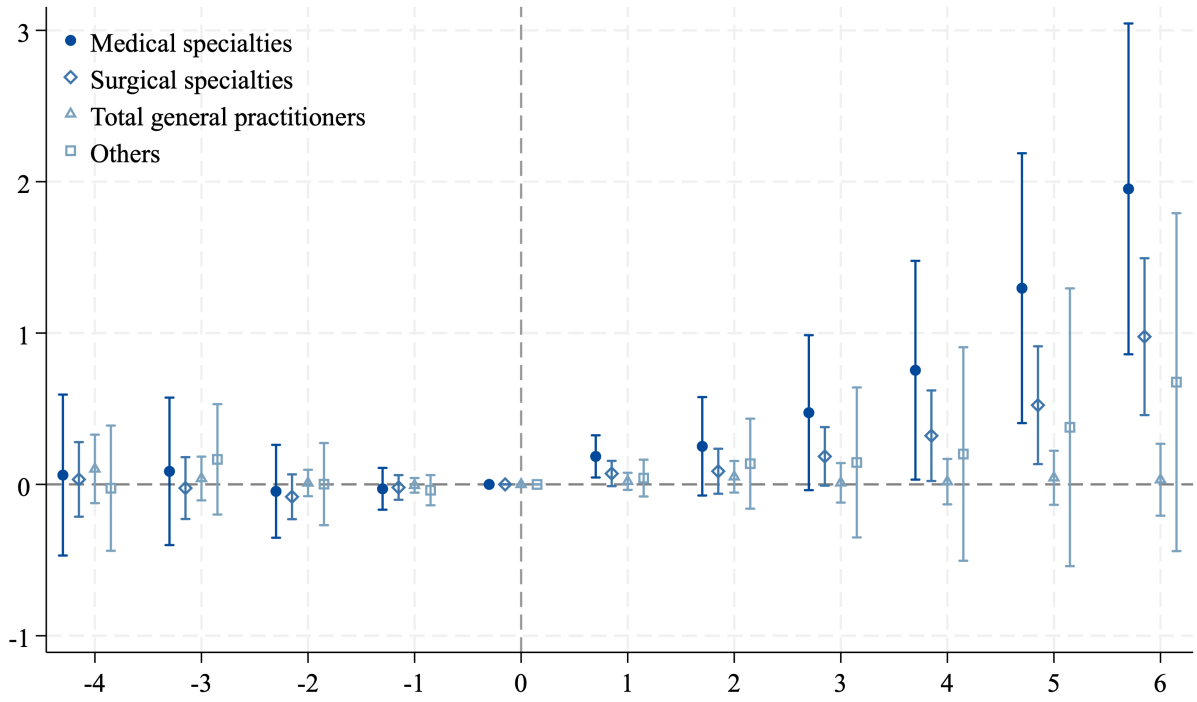


Figure A2: Effect of HIT diffusion on HB physician supply, by main specialty

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

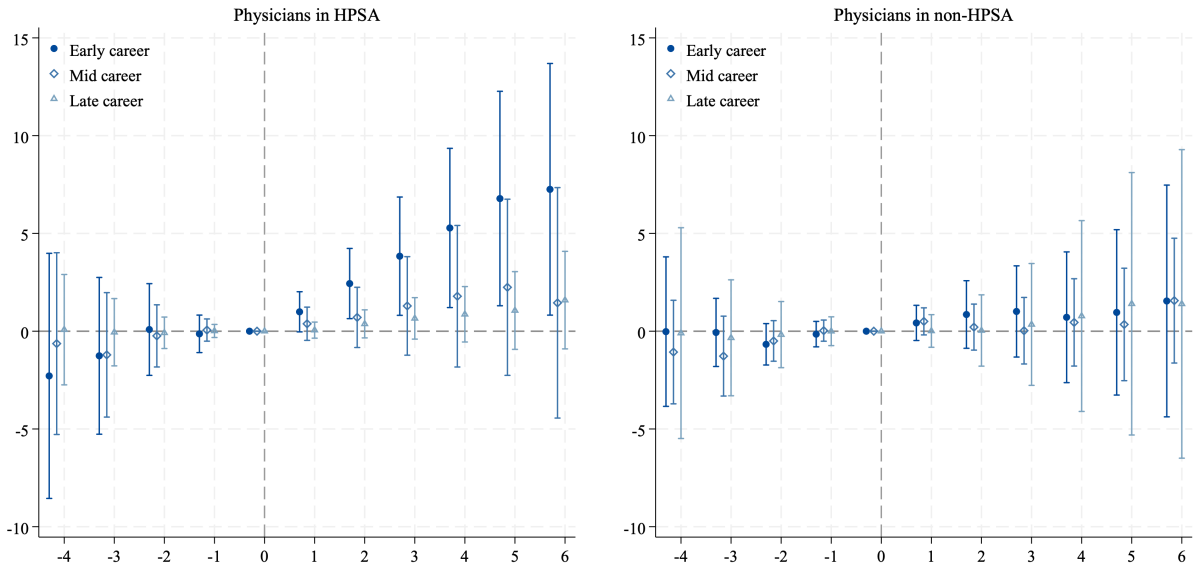


Figure A3: Effect of HIT adoption on physician supply: by career stage and HPSA

Notes: The figures show event-study estimates from subsample analyses defined by the interaction of physician career stage and HPSA status. 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.

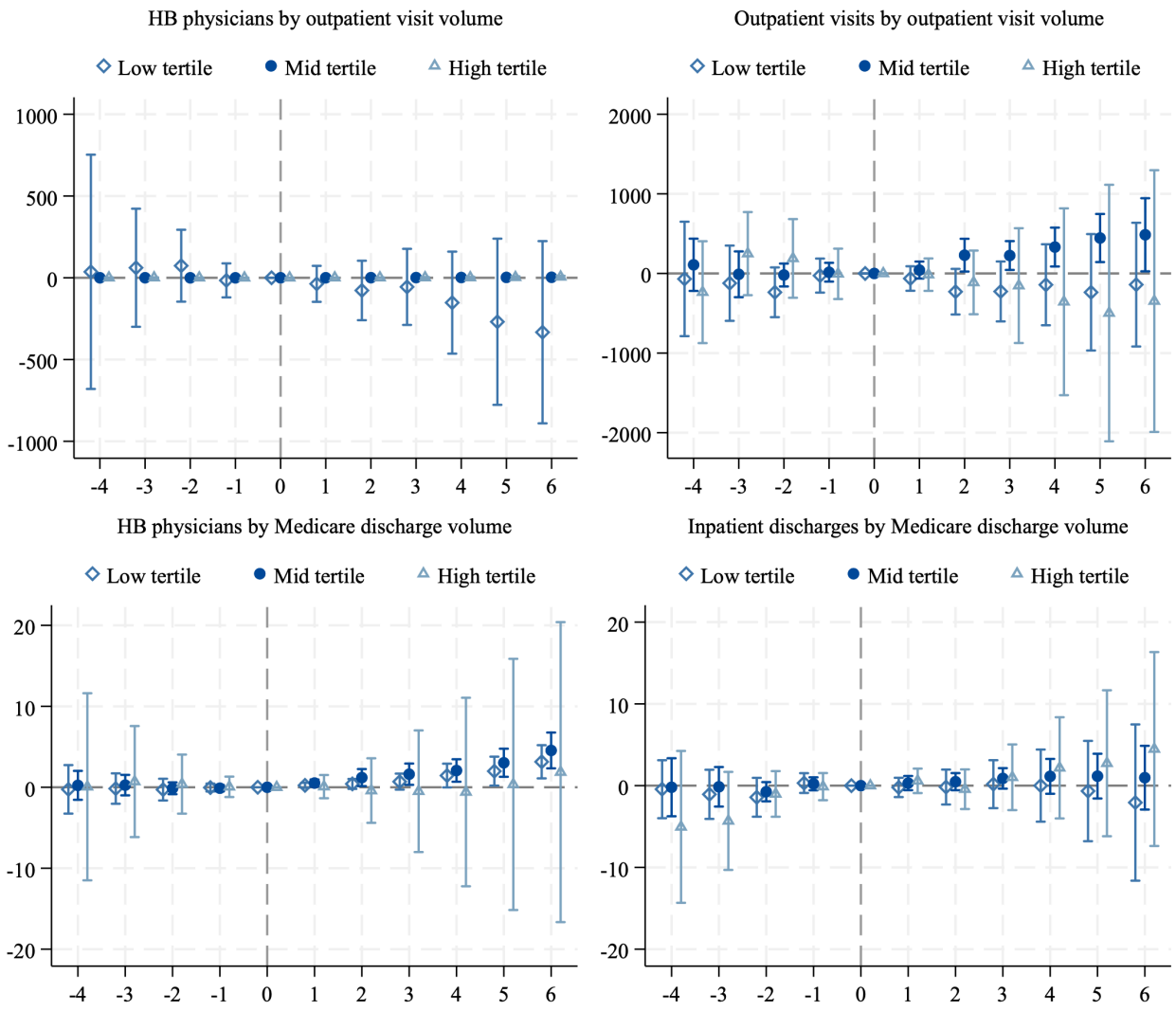


Figure A4: Effect of HIT diffusion by pre-treatment outpatient visit or inpatient discharge tertile

Notes: The upper panels show results by tertiles of outpatient visit volume, and the bottom panels show results by tertiles of Medicare inpatient discharge volume, based on pre-treatment counts. 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.

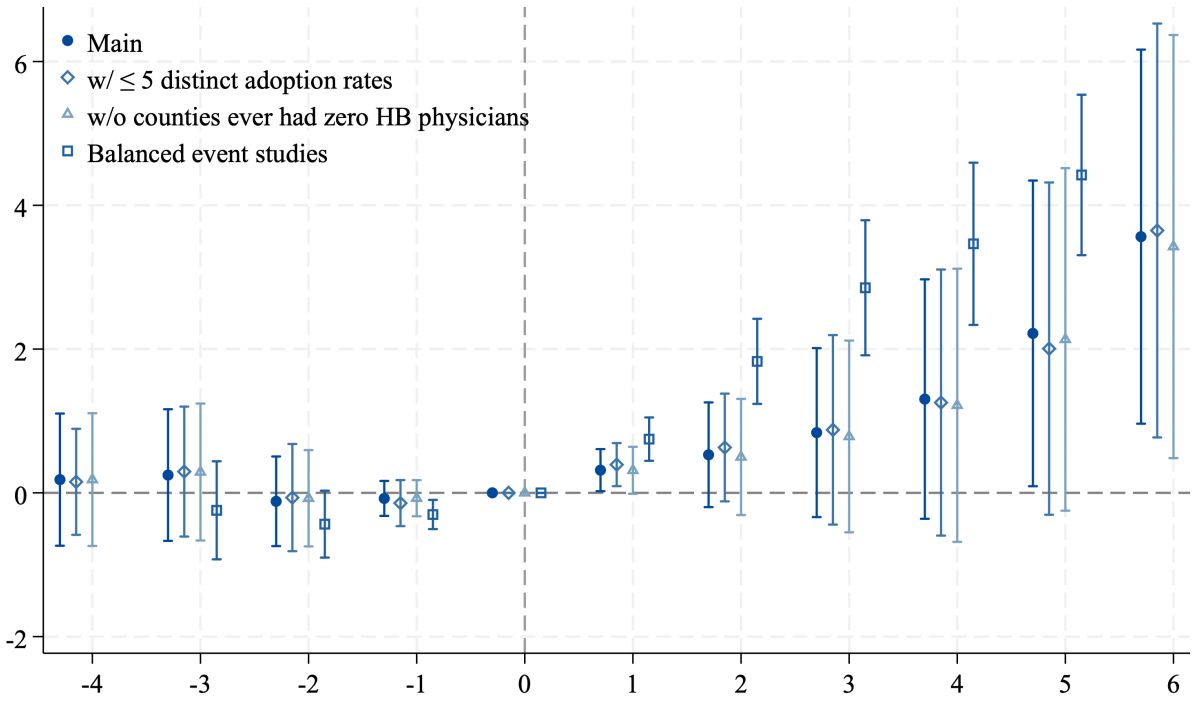


Figure A5: Effect of HIT diffusion on HB physician supply: robustness checks

Notes: For "w/ $\leq$ 5 distinct adoption rates," we include only counties with no more than five distinct HIT adoption rates. For "w/o counties ever had zero HB physicians," we exclude counties that ever had zero HB physicians during the study period. For "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.

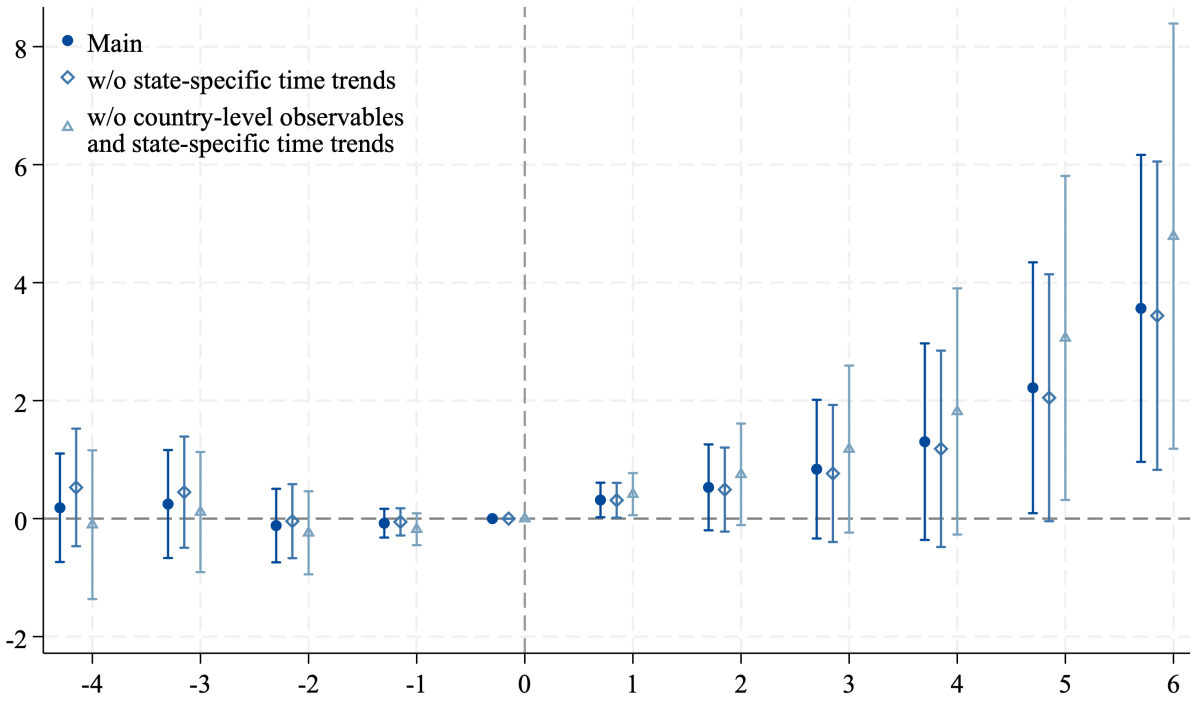


Figure A6: Effect of HIT diffusion on HB physician supply: specification checks

Notes: We conduct specification checks by (a) excluding state-specific time trends and (b) excluding both state-specific time trends and county-level or county-year observables. 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.

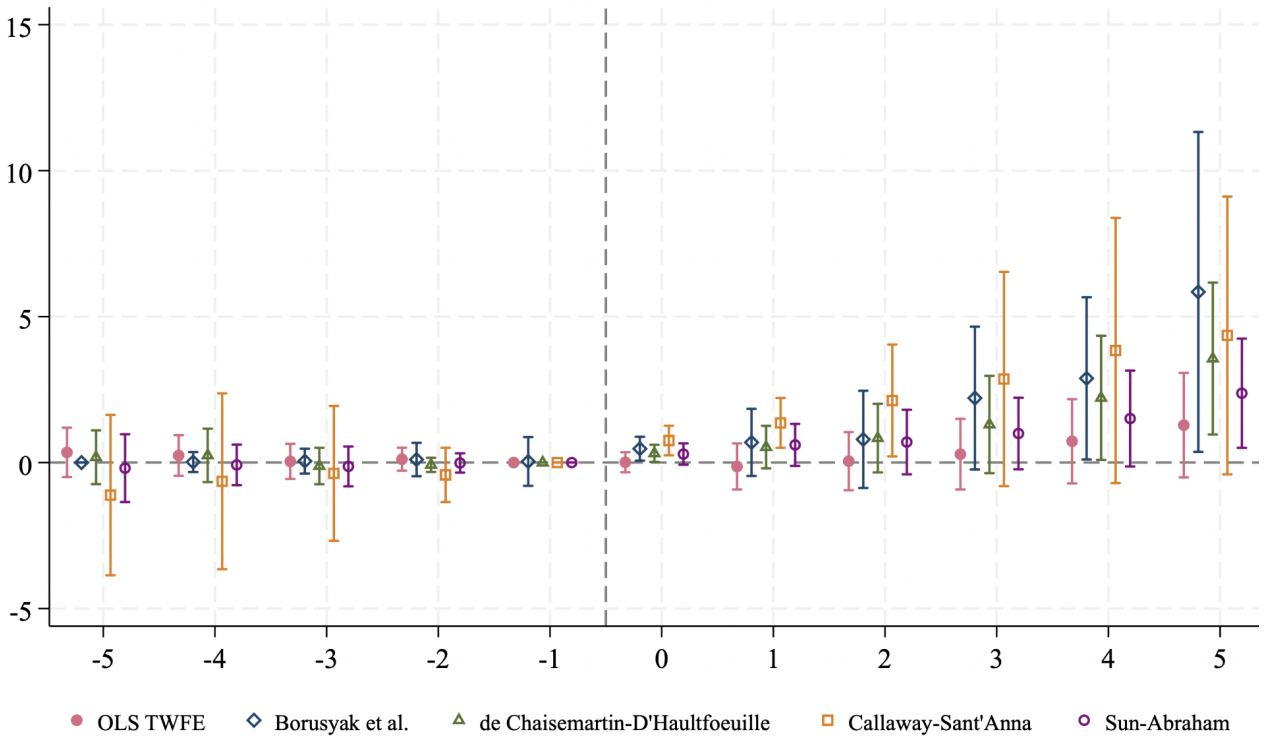


Figure A7: Effect of HIT diffusion on HB physician supply: alternative DiD estimators

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.

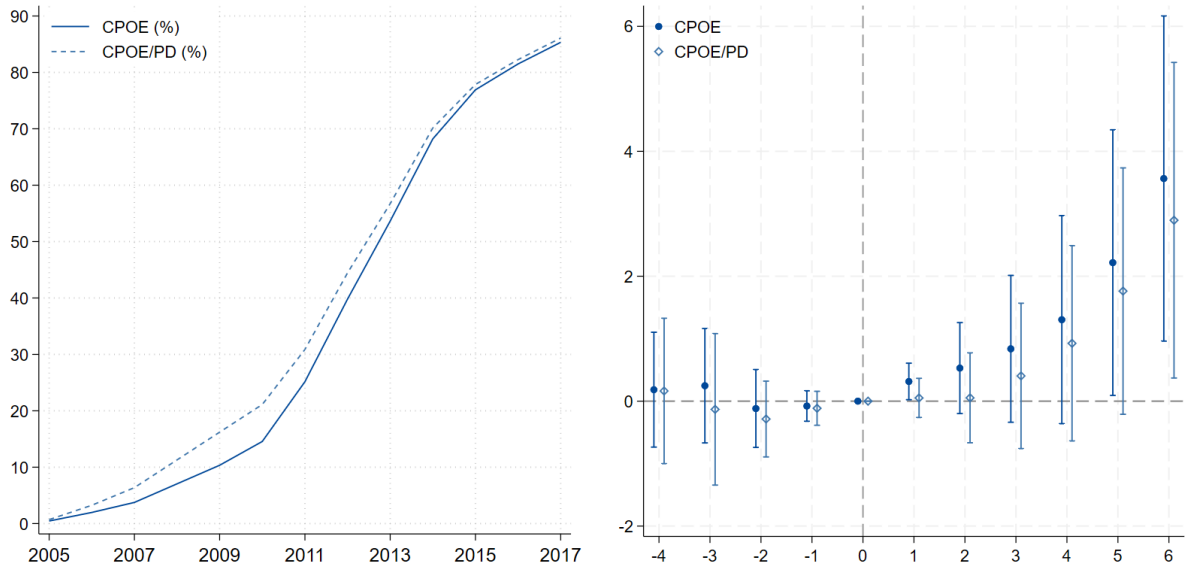


Figure A8: Effect of HIT diffusion on HB physician supply: alternative HIT measures

Notes: The figures present 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). 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.

Table A2: Summary statistics for main variables over time

Year	2006	2007	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
HB physician counts per 100k population	8.64 (10.32)	9.09 (11.11)	9.76 (11.68)	10.29 (12.19)	10.36 (12.44)	11.05 (13.27)	12.46 (15.40)	13.95 (17.43)	15.39 (20.13)	15.07 (19.97)	15.72 (21.01)	16.71 (22.42)
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)
% 65+ population	15.0 (4.02)	15.1 (4.00)	15.2 (4.01)	15.6 (4.04)	15.8 (4.05)	16.0 (4.05)	16.5 (4.11)	16.9 (4.16)	17.3 (4.22)	17.7 (4.27)	18.1 (4.32)	18.5 (4.37)
% black	8.95 (14.30	9.01 (14.34)	9.05 (14.37)	8.98 (14.26)	9.04 (14.25)	9.09 (14.24)	9.15 (14.23)	9.16 (14.17)	9.20 (14.17)	9.17 (14.07)	9.19 (14.02)	9.23 (14.03)
Population density	234 (1,710)	236 (1,713)	237 (1,718)	230 (1,730)	233 (1,746)	235 (1,768)	237 (1,788)	239 (1,797)	240 (1,803)	242 (1,814)	243 (1,818)	244 (1,815)
Income per capita	27,447 (6,751	28,739 (7,439	30,404 (8,151)	33,412 (7,541)	33,849 (7,481)	35,697 (8,593)	38,003 (9,400)	38,714 (10,509)	39,875 (10,935)	40,843 (11,004)	40,983 (10,984)	42,130 (11,289)
Unemployment rate (%)	5.41 (1.78)	4.91 (1.65)	4.86 (1.67)	9.00 (3.21)	9.16 (3.11)	8.55 (2.96)	7.66 (2.75)	7.21 (2.61)	6.20 (2.23)	5.48 (1.94)	5.21 (1.78)	4.55 (1.56)
Hospital HHI	0.787 (0.280)	0.789 (0.280)	0.798 (0.277)	0.796 (0.277)	0.798 (0.277)	0.801 (0.276)	0.800 (0.277)	0.798 (0.278)	0.797 (0.278)	0.796 (0.277)	0.798 (0.278)	0.799 (0.278)
# 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 for the key dependent, independent, and control variables by year over our sample period. Standard deviations are in parentheses.

Table A3: Summary statistics for additional variables over time

Year	2006	2007	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Medical HB physicians per 100k population	2.40 (4.42)	2.44 (4.52)	2.65 (4.76)	2.88 (5.09)	2.92 (5.14)	3.17 (5.47)	3.69 (6.49)	4.21 (7.32)	4.75 (8.48)	4.71 (8.36)	4.95 (8.90)	5.20 (9.42)
Surgical HB physicians per 100k population	1.25 (2.54)	1.36 (2.77)	1.49 (2.93)	1.66 (3.16)	1.77 (3.52)	1.93 (3.72)	2.28 (4.28)	2.54 (4.68)	2.83 (5.13)	2.72 (4.91)	2.72 (4.95)	2.81 (5.13)
Total GPs per 100k population	2.50 (5.95)	2.48 (5.84)	2.63 (5.89)	2.62 (5.59)	2.54 (5.36)	2.66 (5.29)	2.78 (5.14)	3.04 (5.33)	3.29 (6.22)	3.11 (6.11)	3.15 (6.08)	3.38 (6.84)
Other HB physicians per 100k population	2.49 (4.01)	2.81 (4.41)	2.99 (4.58)	3.13 (4.79)	3.13 (4.87)	3.29 (5.37)	3.71 (6.11)	4.16 (6.64)	4.52 (7.23)	4.53 (7.31)	4.90 (7.83)	5.32 (8.41)
Federal physicians per 100k population	3.48 (7.14)	3.55 (6.91)	3.83 (7.33)	3.55 (6.39)	3.49 (6.22)	3.33 (5.80)	3.35 (5.78)	3.57 (5.79)	3.61 (5.80)	3.29 (5.52)	3.16 (5.42)	3.00 (5.14)
Placebo specialties per 100k population	0.11 (0.63)	0.11 (0.63)	0.12 (0.68)	0.13 (0.82)	0.12 (0.78)	0.14 (0.81)	0.15 (0.84)	0.15 (0.74)	0.17 (0.83)	0.17 (0.80)	0.16 (0.80)	0.17 (0.84)
Physicians in other catego--ries 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)
Early-career physicians per 100k population	47.38 (65.42)	45.73 (70.45)	44.25 (70.69)	41.25 (61.70)	41.18 (62.66)	41.34 (63.27)	41.10 (63.76)	40.46 (64.01)	39.81 (64.70)	39.41 (66.09)	39.52 (66.87)	38.63 (67.14)
Mid-career physicians per 100k population	64.72 (56.67)	64.89 (57.34)	64.80 (57.20)	64.38 (55.33)	63.92 (55.17)	63.83 (55.05)	63.39 (55.20)	62.93 (55.44)	62.35 (55.89)	61.95 (56.20)	60.96 (56.19)	60.01 (55.94)
Late-career physicians per 100k population	13.70 (13.38)	14.38 (14.48)	14.32 (14.61)	15.30 (14.32)	15.12 (13.79)	15.87 (14.30)	16.89 (15.02)	18.08 (15.91)	18.77 (16.35)	19.90 (17.25)	21.29 (18.25)	22.49 (19.19)
Avg. Medicare allowed payments per physician	– –	– –	– –	– –	– –	– –	72,015 (47,048)	72,168 (45,977)	72,859 (44,794)	73,020 (45,196)	73,480 (53,794)	72,161 (45,840)
Avg. # Medicare benefi--ciaries per physician	– –	– –	– –	– –	– –	– –	485 (449)	472 (421)	470 (406)	467 (406)	461 (414)	449 (431)
Avg. profits per hospital	7.18E+07 (1.16E+08)	7.92E+07 (1.27E+08)	8.67E+07 (1.36E+08)	1.08E+08 (1.70E+08)	1.17E+08 (1.84E+08)	1.28E+08 (2.00E+08)	1.38E+08 (2.14E+08)	1.51E+08 (2.33E+08)	1.66E+08 (2.57E+08)	1.83E+08 (2.84E+08)	2.00E+08 (3.15E+08)	2.18E+08 (3.48E+08)
Outpatient surgeries per 100k population	6,197 (6,342)	6,145 (6,396)	6,214 (6,297)	6,126 (5,311)	6,192 (5,419)	6,149 (5,355)	6,075 (5,367)	6,075 (5,491)	6,167 (5,544)	6,450 (5,805)	6,444 (5,698)	6,510 (5,843)
Inpatient surgeries per 100k population	2,402 (2,861)	2,388 (3,008)	2,309 (2,738)	2,142 (2,225)	2,055 (2,160)	2,011 (2,296)	1,926 (2,085)	1,840 (2,027)	1,784 (1,901)	1,810 (1,953)	1,794 (1,915)	1,767 (1,956)
# 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 outcome measures for additional analyses by year over our sample period. Standard deviations are in parentheses.

Table A4: Treatment effects 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	1.282**	0.709***	0.303***	0.031	0.240	-0.052	0.014	0.023
	(0.644)	(0.299)	(0.114)	(0.067)	(0.273)	(0.110)	(0.132)	(0.027)
Panel B								
Event time −4	0.184	0.083	0.034	0.105	-0.039	-0.076	-0.132	0.011
	(0.469)	(0.256)	(0.129)	(0.123)	(0.193)	(0.186)	(0.228)	(0.055)
Event time −3	0.247	0.090	-0.029	0.037	0.148	0.007	-0.221	0.008
	(0.467)	(0.241)	(0.104)	(0.079)	(0.184)	(0.140)	(0.215)	(0.032)
Event time −2	-0.118	-0.038	-0.081	0.006	-0.004	0.017	-0.127	0.012
	(0.318)	(0.153)	(0.075)	(0.046)	(0.136)	(0.071)	(0.118)	(0.020)
Event time −1	-0.078	-0.019	-0.017	-0.009	-0.033	0.022	0.063	0.018
	(0.124)	(0.069)	(0.040)	(0.025)	(0.050)	(0.051)	(0.056)	(0.011)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	0.315**	0.183***	0.070	0.020	0.042	-0.020	-0.004	0.006
	(0.149)	(0.075)	(0.043)	(0.030)	(0.062)	(0.049)	(0.086)	(0.009)
Event time 2	0.529	0.249	0.085	0.050	0.146	-0.011	-0.023	0.001
	(0.371)	(0.178)	(0.079)	(0.056)	(0.152)	(0.080)	(0.109)	(0.018)
Event time 3	0.838	0.475*	0.186*	0.012	0.165	-0.072	-0.038	0.005
	(0.600)	(0.284)	(0.101)	(0.070)	(0.252)	(0.105)	(0.159)	(0.026)
Event time 4	1.304	0.747*	0.316**	0.023	0.218	-0.037	-0.024	0.022
	(0.850)	(0.402)	(0.152)	(0.081)	(0.358)	(0.128)	(0.140)	(0.036)
Event time 5	2.218**	1.272***	0.505***	0.049	0.392	-0.142	0.063	0.041
	(1.085)	(0.498)	(0.195)	(0.096)	(0.465)	(0.163)	(0.249)	(0.044)
Event time 6	3.564***	1.913***	0.943***	0.035	0.673	-0.047	0.177	0.096*
	(1.328)	((0.600)	(0.259)	(0.130)	(0.555)	(0.255)	(0.228)	(0.056)
Mean DV	12.5	3.71	2.14	2.88	3.79	3.47	3.94	0.142
N	27,506	27,506	27,506	27,506	27,506	27,506	27,506	27,506
P-value of testing joint significance of pre trends	0.361	0.631	0.533	0.859	0.128	0.935	0.353	0.446

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

Table A5: Treatment effects by physician or county characteristic

	By career stage			By HPSA		Excluding VIs/MAs	
	Early-career	Mid-career	Late-career	Ever HPSA	Never HPSA	Excluding VIs	Excluding MAs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Treatment Effect	2.693***	0.854	0.690	2.155***	0.493	2.137***	1.315
	(0.974)	(1.701)	(0.738)	(0.421)	(1.571)	(0.755)	(0.842)
Panel B							
Event time −4	-1.542	-0.574	-0.045	-0.453	0.274	-0.958	-0.035
	(1.484)	(3.182))	(0.985)	(1.020)	(1.164)	(0.737)	(0.427)
Event time −3	-0.701	-1.054	-0.185	-0.292	0.333	-0.438	0.270
	(1.016)	(1.986)	(0.557)	(0.647)	(0.920)	(0.487)	(0.521)
Event time −2	-0.099	-0.260	-0.132	-0.231	-0.162	-0.576**	-0.147
	(0.733)	(1.007)	(0.395)	(0.338)	(0.697)	(0.276)	(0.367)
Event time −1	-0.117	0.035	-0.009	-0.042	-0.163	-0.180	-0.068
	(0.347)	(0.342)	(0.166)	(0.149)	(0.288)	(0.137)	(0.142)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	0.764***	0.476	0.059	0.334*	0.371	0.432**	0.323*
	(0.270)	(0.387)	(0.127)	(0.175)	(0.334)	(0.195)	(0.177)
Event time 2	1.809***	0.474	0.250	0.796***	0.330	0.839*	0.546
	(0.531))	(0.839)	(0.321)	(0.320)	(0.867)	(0.450)	(0.436)
Event time 3	2.659***	0.673	0.559	1.488***	0.255	1.532***	0.869
	(0.917)	(1.386)	(0.606)	(0.433)	(1.452)	(0.658)	(0.745)
Event time 4	3.464***	1.176	0.874	2.568***	0.032	2.394***	1.338
	(1.346)	(2.240)	(0.971)	(0.524)	(2.098)	(0.929)	(1.108)
Event time 5	3.874**	1.188	1.223	3.849***	0.675	3.715***	2.258
	(1.709)	(2.872)	(1.368)	(0.668)	(2.665)	(1.237)	(1.433)
Event time 6	4.713**	1.472	1.695	5.561***	1.804	5.350***	3.619**
	(2.225)	(3.797)	(1.641)	(0.838)	(3.126)	(1.642)	(1.811)
Mean DV	42.24	63.88	17.31	11.68	13.35	14.55	13.26
N	27,506	27,506	27,506	13,788	13,710	10,229	18,887
P-value of testing joint significance of pre trends	0.798	0.567	0.848	0.953	0.757	0.139	0.204

Notes: 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 and 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 by career stage×HPSA interaction

	Ever HPSA			Never HPSA		
	Early-career	Mid-career	Late-career	Early-career	Mid-career	Late-career
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Treatment Effect	4.120***	1.253	0.694	0.870	0.448	0.573
	(1.580	1.410	0.611	1.360	0.871	1.889)
Panel B						
Event time −4	-2.285	-0.634	0.079	-0.022	-1.068	-0.099
	(3.198	(2.372	(1.440	(1.950	(1.351	(2.750)
Event time −3	-1.506	-1.344	-0.176	-0.242	-0.873	-0.439
	(2.046)	(1.624)	(0.878)	(0.889)	(1.04)2	(1.512)
Event time −2	0.086	-0.240	-0.081	-0.670	-0.499	-0.174
	(1.197)	(0.811)	(0.411)	(0.540)	(0.530)	(0.863)
Event time −1	-0.135	0.058	0.012	-0.150	0.030	-0.001
	(0.490)	(0.290)	(0.170)	(0.332)	(0.276)	(0.376)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	0.992*	0.380	0.054	0.424	0.502	0.012
	(0.523)	(0.434)	(0.210)	(0.459)	(0.353)	(0.425)
Event time 2	2.437***	0.706	0.374	0.854	0.209	0.036
	(0.916)	(0.786)	(0.366)	(0.882)	(0.600))	(0.930)
Event time 3	3.836***	1.292	0.655	1.010	0.025	0.345
	(1.543)	(1.285)	(0.541)	(1.190)	(0.868)	(1.590)
Event time 4	5.280***	1.788	0.865	0.712	0.450	0.776
	(2.077)	(1.847)	(0.723)	(1.706)	(1.139))	(2.490)
Event time 5	6.784***	2.246	1.059	0.962	0.345	1.403
	(2.798)	(2.298)	(1.014)	(2.158)	(1.467)	(3.424)
Event time 6	7.256**	1.450	1.589	1.545	1.563	1.396
	(3.283)	(3.007)	(1.273)	(3.024)	(1.629)	(4.025)
Mean DV	38.22	59.12	16.75	46.28	68.65	17.89
N	13,788	13,788	13,788	13,710	13,710	13,710
P-value of testing joint significance of pre trends	0.678	0.490	0.987	0.481	0.709	0.975

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 and 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 above. "Mean DV" refers to the mean of the dependent variable. Standard errors, clustered at the state level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Treatment effects on financial metrics

	Avg. Medicare allowed payments (1)	Avg. Medicare beneficiaries (2)	Avg. hospital profit (3)
Panel A			
Treatment Effect	3514**	23*	1.32E+07***
	(1580)	(13)	(3557217)
Panel B			
Event time −4	–	–	-4901395
			(3677232)
Event time −3	–	–	-3083856
			(2190022)
Event time −2	296	16	-2256629
	(2962)	(22)	(1639003)
Event time −1	91	-4	-1625724
	(1286)	(10)	(1105948)
Event time 0	omitted	omitted	omitted
Event time 1	1502	10	3301234***
	(1178)	(7)	(1144993)
Event time 2	4370*	31**	6604654***
	(2658)	(13)	(1943887)
Event time 3	4411*	37***	1.37E+07***
	(2371)	(15)	(3682233)
Event time 4	6025**	30	1.75E+07***
	(2836)	(24)	(4832508)
Event time 5	393	-3	2.19E+07***
	(4323)	(31)	(6434445)
Event time 6	–	–	2.75E+07***
			(7644333)
Mean DV	72,880	471	1.37E+08
N	10,617	10,617	27,417
P-value of testing joint significance of pre trends	0.994	0.638	0.590

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

Table A8: Treatment effects by pre-treatment outpatient surgery volume tertile

	DV: HB physician rate			DV: Outpatient surgeries		
	Low tertile	Mid tertile	Top tertile	Low tertile	Mid tertile	Top tertile
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Treatment Effect	0.632	1.314*	1.742	-172.254	273.133***	-228.840
	(1.326)	(0.773)	(1.724)	(201.178)	(95.479)	(439.817)
Panel B						
Event time −4	-0.370	0.102	0.148	-68.653	109.039	-235.033
	(2.442)	(0.572)	(1.089)	(366.652)	(167.424)	(326.383)
Event time −3	-0.312	0.211	0.656	-122.381	-10.582	249.334
	(1.436)	(0.407)	(0.871)	(241.151)	(146.802)	(266.319)
Event time −2	-0.204	-0.213	0.169	-236.638	-19.552	188.698
	(0.810)	(0.260)	(0.799)	(159.483)	(73.441)	(252.076)
Event time −1	0.080	-0.175	-0.148	-26.660	15.494	-4.828
	(0.265)	(0.161)	(0.299)	(109.143)	(60.183)	((161.398)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	0.140	0.292*	0.519	-63.618	42.867	-15.108
	(0.311)	(0.166)	(0.337)	(78.539)	(54.394)	(103.934)
Event time 2	0.209	0.624	0.686	-228.903	229.640**	-112.634
	(0.640)	(0.425)	(0.773)	(146.076)	(105.140)	(203.941)
Event time 3	0.261	1.041	1.091	-225.882	225.241***	-152.661
	(1.221)	(0.659)	(1.450)	(192.112)	(92.348)	(367.839)
Event time 4	0.649	1.537	1.467	-142.042	331.722***	-355.647
	(1.813)	(0.989)	(2.348)	(259.432)	(124.551)	(598.703)
Event time 5	1.316	2.287*	2.678	-236.722	445.142***	-497.233
	(2.482)	(1.340)	(3.269)	(373.028)	(154.187)	(821.950)
Event time 6	2.146	2.916*	5.429	-140.263	486.076**	-347.053
	(3.061)	(1.675)	(3.512)	(396.513)	(234.176)	(838.845)
Mean DV	7.21	11.62	18.63	2850.60	5564.86	10383.69
N	9,035	9,233	9,238	9,035	9,233	9,238
P-value of testing joint significance of pre trends	0.929	0.353	0.577	0.288	0.812	0.577

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

Table A9: Treatment effects pre-treatment inpatient surgery volume tertile

	DV: HB physician rate			DV: Inpatient surgeries		
	Low tertile	Mid tertile	Top tertile	Low tertile	Mid tertile	Top tertile
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Treatment Effect	0.031	1.184***	0.807	-87.112	40.096	-0.819
	(0.679)	(0.313)	(1.146)	(156.426)	(64.967)	(101.920)
Panel B						
Event time −4	-0.737	1.042	-0.144	8.862	-15.435	183.558
	(1.422)	(0.827)	(1.252)	(226.574)	(74.673)	(171.942)
Event time −3	-0.734	0.702	0.308	111.830	-93.415	225.421
	(0.852)	(0.514)	(0.855)	(170.833)	(81.131)	(158.337)
Event time −2	-0.563	0.242	-0.041	-25.231	-63.748	80.476
	(0.547)	((0.315)	(0.533)	(78.820)	(72.740)	(102.792)
Event time −1	-0.098	0.006	-0.002	-30.424	-35.030	4.917
	(0.214)	(0.189)	(0.190)	(39.190)	(38.847)	(33.840)
Event time 0	omitted	omitted	omitted	omitted	omitted	omitted
Event time 1	0.116	0.154	0.264	-25.854	28.670	16.653
	(0.193)	(0.120)	(0.264)	(30.899)	(28.661)	(38.391)
Event time 2	-0.009	0.526**	0.305	-67.404	26.307	-3.236
	(0.437)	(0.253)	(0.700)	(89.002)	(44.062)	(46.221)
Event time 3	-0.283	0.975***	0.431	-60.618	34.324	69.555
	(0.624)	(0.322)	(1.116)	(151.874)	(62.123)	(68.595)
Event time 4	-0.264	1.595***	0.590	-117.036	55.011	21.342
	(0.915)	(0.468)	(1.542)	(224.241)	(77.007)	(132.490)
Event time 5	-0.366	2.004***	1.459	-173.252	59.346	-74.672
	(1.349)	(0.473)	(1.864)	(313.208)	(104.342)	(196.717)
Event time 6	1.610	2.703***	2.494	-128.577	44.697	-69.627
	(1.455)	(0.687)	(2.137)	(278.175)	(143.847)	(252.477)
Mean DV	7.08	11.11	19.34	575.29	1541.33	4006.54
N	9,068	9,254	9,184	9,068	9,254	9,184
P-value of testing joint significance of pre trends	0.826	0.420	0.516	0.684	0.760	0.585

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

Table A10: Treatment effects on HB physician supply: robustness checks

	≤5 adopt--ion rates	Counties w/o zero HB physicians	Balanced eve--nt studies	No state--year trends	No state/cou--nty controls
	(1)	(2)	(3)	(4)	(5)
Panel A					
Treatment Effect	1.245*	1.233*	2.672***	1.200*	1.761**
	(0.690)	(0.732)	(0.393)	(0.639)	(0.834)
Panel B					
Event time −4	0.153	0.184	–	0.528	-0.103
	(0.376)	(0.471)	–	(0.508)	(0.643)
Event time −3	0.296	0.289	-0.243	0.449	0.112
	(0.461)	(0.486)	(0.348)	(0.481)	(0.520)
Event time −2	-0.066	-0.075	-0.435*	-0.044	-0.241
	(0.380)	(0.342)	(0.237)	(0.320)	(0.359)
Event time −1	-0.143	-0.075	-0.302***	-0.055	-0.181
	(0.163)	(0.128)	(0.104)	(0.118)	(0.138)
Event time 0	omitted	omitted	omitted	omitted	omitted
Event time 1	0.392***	0.314*	0.747***	0.311**	0.415**
	(0.153)	(0.167)	(0.154)	(0.150)	(0.182)
Event time 2	0.631*	0.499	1.829***	0.492	0.751*
	(0.382)	(0.412)	(0.302)	(0.363)	(0.439)
Event time 3	0.876	0.784	2.853***	0.765	1.179
	(0.673)	(0.681)	(0.479)	(0.593)	(0.722)
Event time 4	1.256	1.218	3.464***	1.183	1.816*
	(0.944)	(0.970)	(0.576)	(0.849)	(1.064)
Event time 5	2.006*	2.134*	4.422***	2.049*	3.062**
	(1.179)	(1.216)	(0.569)	(1.068)	(1.401)
Event time 6	3.650***	3.426**	–	3.440***	4.788***
	(1.469)	(1.502)	–	(1.333)	(1.839)
Mean DV	12.0	17.9	12.4	12.5	12.4
N	26,690	15,950	12,549	27,506	28,426
P-value of testing joint significance of pre trends	0.311	0.425	0.0083	0.302	0.246

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