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ECONOMIC SHOCKS AND HEALTHCARE CAPITAL INVESTMENTS

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Economic Shocks and Healthcare Capital Investments
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ABSTRACT

Information technology (IT) can enhance firms' long-run performance but is a risky investment with uneven take-up. The drivers of and impediments to IT adoption are also not well-understood. We leverage the healthcare context to empirically examine hospitals' IT investments following three distinct industry shocks. We find novel, consistent, and economically important responses. Recessions restrain investments while insurance expansions stimulate them. A hospital-specific and policy-driven financial shock also spurs IT adoption. The IT margin appears more sensitive to market conditions than other spending decisions. Supplementary analyses further suggest that perceptions of uncertainty about future revenue influence these specific capital investments.

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Information technology (IT) advancements and adoption have been engines of economic and productivity growth for decades and may continue to be with wider use of artificial intelligence and other 21st century computing developments (Jorgenson and Stiroh 1999; Jorgenson 2001; Stiroh 2002; Daly and Valletta 2004; Syverson 2011; Nordhaus 2021). At the firm level, IT investments have been linked to stronger financial performance, improved managerial coordination, and more efficient communication within organizations (Dewan and Min 1997; Brynjolfsson and Hitt 2000; Brynjolfsson, Hitt, and Yang 2002; Anderson, Banker, and Ravindran 2006). Yet, adoption remains uneven, with many firms forgoing investments or delaying until long after new technology is available. Policymakers have responded at times with generous subsidies to accelerate IT adoption,[1] but these programs can rest on implicit and untested assumptions about what restrains firms' willingness to invest in IT.

We examine the drivers of and impediments to IT investments empirically, focusing on three candidate mechanisms. First, *liquidity constraints* could prevent adoption since IT requires significant upfront costs that credit-constrained firms may struggle to finance. Second, *uncertainty* about the future could impede adoption since IT investments are largely irreversible, have limited resale value, and can require complementary organizational changes before generating returns (Pindyck 1991; Schwartz and Zozaya-Gorostiza 2003; Bloom, Bond, and Van Reenen 2007).[2] Third, observed IT adoption patterns could result from heterogeneous *demand* for IT across firms. Incomplete take-up would simply reflect firms' differing private assessments of the returns to adoption, rather than delayed or constrained investment behavior that policy could plausibly address. Distinguishing among these explanations is therefore important for understanding both firm IT investment decisions and the likely effectiveness of policies intended to encourage such investment.

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[1] Examples of such large-scale subsidy programs include the US HITECH Act (2009), the EU Digital Europe Programme (2021-2027), and Germany's Industrie 4.0 initiative (2013-present).

[2] IT capital expenditures ("capex") can be considered even riskier than other capital investments that firms commonly undertake, due to considerable uncertainty around the economic benefits as well as the complexity and implementation costs belonging to a given IT investment (e.g., the common experience of cost overruns). The rate of its eventual obsolescence is another source of uncertainty. Thus, when contemplating the marginal IT investment, greater uncertainty could push managers toward postponement (Schwartz and Zozaya-Gorostiza 2003; Brynjolfsson et al. 2008). See also Bloom (2009, 2014) as well as Caldara and Iacoviello (2022) for discussions of the broader uncertainty-investment relationship. We further describe the conceptual underpinnings for an uncertainty role within our specific analytic context in Section I.

We examine the drivers of IT adoption in the US hospital industry using granular panel data on hospital IT adoption decisions. Our empirical analysis exploits three shocks that substantively impact hospitals' market environments and financial positions. The three shocks each differ in their source, sign, and demand-side implications, but they share the common feature of altering a hospital's revenue stream in a well-defined way. We first study two market-level shocks with opposite effects: the Great Recession and the Affordable Care Act's (ACA) Medicaid expansions. The former increased hospitals' exposure to uncompensated care as patients lost income and insurance coverage, while the latter reduced that burden by extending public insurance to low-income patients (Dranove, Garthwaite, and Ody 2016; Garthwaite, Gross, and Notowidigdo 2018; Blavin and Ramos 2021; Callison et al. 2021; Dranove, Garthwaite, and Ody 2022). However, the recession and Medicaid expansion may also affect the scale or composition of local demand for hospital services.

We therefore study a third, hospital-specific shock: participation in the 340B Drug Pricing Program. Hospitals granted federal 340B status gain access to steep discounts on outpatient drugs from pharmaceutical manufacturers while continuing to bill insurers at standard rates, capturing the spread as additional profits (Robinson, Whaley, and Dhruva 2024; Nikpay, Reinke, and Watts 2026). Over $60 billion worth of 340B drug purchases were made in 2023 alone.[3] Importantly, because 340B narrowly affects acquisition costs for production inputs but has no direct implications for patient demand, it offers a cleaner test of whether IT investments respond to financial circumstances even when local demand for hospital services is largely unchanged.[4]

We consistently find that hospital IT adoption responds strongly to changes in the revenue environment. Hospitals in the areas most severely affected by the Great Recession reduce IT capital investment by 10 to 15 percent within three years. In contrast, hospitals exposed to the 2014 Medicaid expansions adopt nearly 10 percent more IT solutions by 2017, with the trend break

[3] Summary statistics over time as well as a brief 340B description provided by KFF can be found here: https://www.kff.org/health-costs/key-facts-about-hospitals/?entry=hospital-finances-340b-drug-pricing-program.

[4] More specifically, the 340B program involves provider-administered drugs (e.g., cancer therapies), but a local hospital is granted 340B participation independent of local disease prevalence or incidence (e.g., share of population with an existing or new cancer diagnosis) or payer mix (e.g., share of cancer patients that are uninsured). Thus, the potential market size—and hence the perceived returns from hospital-wide IT investments to manage patient demand—should be relatively stable before and after 340B status is granted. Additionally, the 340B program operates at the hospital level, which rules out regional macroeconomic confounders associated with the Great Recession or ACA Medicaid expansions.

beginning when the policy is announced in 2013. Hospitals participating in the 340B program similarly increase adoption, with the trend break beginning in the year before formal participation and reaching approximately 10 to 15 percent more IT solutions by their third year of eligibility. Taken together, negative and positive changes to hospitals' business outlook move IT adoption in opposite directions, and the effects become larger over time. For our two market-level shocks, we also extend the analysis from hospitals to the health IT vendors that serve them and examine vendor entry, exit, and market concentration. The recession's effects propagate up the supply chain, with a reduction in the number of IT vendors and market entry activity within the hardest-hit counties. The ACA Medicaid expansions, by contrast, produce no detectable vendor market response in affected states.

Comparing across shocks, several patterns emerge that point to uncertainty, rather than patient demand or liquidity, as a key influence for hospital managers' decision-making. Our supplementary findings for non-IT investments suggest that the IT response does not simply reflect hospitals scaling inputs in response to fluctuations in patient demand. For the Medicaid and recession shocks, where effects could simultaneously impact patient demand for hospital care, we find no consistent employment response or symmetrical changes in real assets (i.e., beds or operating rooms). Furthermore, the supply-side-focused 340B program generates a substantial IT response with little evidence of comparable investment in capacity-building and only mixed employment effects.

Our results are also inconsistent with liquidity as the sole factor driving adoption. Heterogeneity analyses indicate that the effects are not driven by plausibly more liquidity-constrained hospitals; instead, each economic shock reverberates broadly throughout the industry. The dynamics of the responses additionally suggest hospital managers begin changing behavior even before Medicaid expansion implementation or 340B participation initiates. Thus, our collection of empirical results aligns with the "real-options" logic of investment under uncertainty (Pindyck 1991; Dixit and Pindyck 1994): when hospitals' revenue outlook improves, waiting to invest becomes less valuable, and previously delayed investments proceed. When the outlook deteriorates, hospitals preserve the option to delay.

Our paper ultimately makes several contributions. First, we add to the literature on the economics of IT by providing empirical evidence that uncertainty is a substantive factor in firms' IT investment decisions. There is longstanding academic and policy interest regarding when and why firms adopt IT, but empirical progress has been limited. We advance the literature by leveraging unique industry-wide microdata on firm adoption of IT solutions, situated in a context with multiple economic shocks that originate outside the firm. Our findings provide empirical evidence in support of the largely theoretical literature that applies real-options reasoning to IT adoption (Schwartz and Zozaya-Gorostiza 2003). Doing so also complements other work examining uncertainty effects on investment behavior (Guiso and Parigi 1999; Bloom, Bond, and Van Reenen 2007; Handley and Limão 2015). Second, we contribute to research on technology adoption in healthcare specifically. Existing work has typically emphasized the downstream consequences of health IT rather than providers' upstream decisions to adopt it.[5] Understanding this margin is particularly important because hospitals and other healthcare organizations often lag the rest of the economy in adopting and adapting to new technologies (Litwin 2020; Glaser, Vaezy, and Guptill 2024). Third, we identify a previously understudied effect from three major shocks to the hospital industry. Prior work on the Great Recession documents deterioration in nonprofit hospitals' finances and reductions in aggregate capital spending (Adelino, Lewellen, and Sundaram 2015; Adelino, Lewellen, and McCartney 2022) but not IT, specifically. Studies of supply-side responses to ACA Medicaid expansions generally find limited effects on hospitals' fixed assets (Meille and Post 2023; Duggan, Gupta, and Jackson 2022), but once again, do not investigate the IT investment dimension.[6] And finally, the developing literature on 340B primarily focuses on patient access, care quality, and hospitals' acquisitions of related physician practices (Alpert, Hsi, and Jacobson 2017; Desai and McWilliams 2018, 2021; Knox et al. 2023; Smith et al. 2023), which ignores broader business decisions and productivity enhancements. We therefore provide novel evidence that each of these shocks affects a distinct and increasingly important margin: hospitals' investments in IT.

[5] Recent examples include Miller and Tucker 2011; Lee, McCullough, and Town 2013; Agha 2014; Dranove *et al*. 2014; and Horn, Sacarny, and Zhou 2022. At this time, there is a growing but still quite modest literature on upstream health technology adoption drivers (e.g., Acemoglu and Finkelstein 2008; Miller and Tucker 2009; Richards, Shi, and Whaley 2024). For a comprehensive review of the literature on the effects of health IT adoption on clinical quality, financial metrics, and the healthcare labor market, see Bronsoler, Doyle, and Van Reenen (2022).

[6] Of note, despite Medicaid's potential impact on healthcare providers, supply-side studies are relatively rare, especially those focused on providers' capital investment behavior. There is, however, a voluminous literature of demand-side effects from ACA policy provisions. French *et al*. (2016), Gruber and Sommers (2019), and Soni, Wherry, and Simon (2020) provide extensive ACA literature reviews, especially with respect to healthcare access, utilization, and health outcomes. We also review the modest economics literature examining Medicaid expansion effects on healthcare providers in more detail in Section IVA.

Our paper also has practical implications for policy design and evaluation. Our empirical results support the view that firms underinvest in IT relative to their desired adoption path (i.e., in an uncertainty-free environment), but simultaneously caution that policy efforts narrowly relieving liquidity constraints may not address an influential factor with much wider industry reach: uncertainty. Targeted one-time subsidies—such as those offered through the HITECH Act—may be less effective overall than broader policies that stabilize revenue expectations or reduce downside risk. In this way, the implications from our findings connect to other empirical economics work interested in the linkage between various policy levers and firms' "capex" activity (Bloom 2014; Handley and Limão 2015; Baker, Bloom, and Davis 2016; Gulen and Ion 2016). For Medicaid expansions and the 340B program, specifically, we show that these policy interventions indirectly encouraged greater IT adoption, which could have spillovers across all patient populations and care delivery. Thus, evaluations that focus only on their targeted effects (e.g., Medicaid coverage rates or 340B drug dispensing) could understate their full social return.

The remainder of the paper proceeds as follows. Section I presents a conceptual framework for hospital IT investment under uncertainty, and Section II describes the data. Sections III–V analyze the Great Recession, Medicaid expansions, and the 340B program, respectively. Section VI compares the findings across shocks, and Section VII examines the health IT vendor market. Section VIII concludes.

I. Conceptual Framework

This section describes the economic features that govern the hospital IT adoption decision, which then motivate the three channels we bring to the empirical analysis: patient demand, uncertainty, and liquidity constraints. We define each channel and discuss the empirical patterns that differentiate them. In the main text we discuss the economic features and channels broadly, and in Appendix A, we present a more detailed conceptual model that frames IT adoption as a dynamic decision made under uncertainty.

A. *Economics of Hospital IT Adoption*

First, we conceptualize IT as a production technology with *revenue-amplifying returns*—meaning its payoff grows with the scale of the hospital's underlying operations, rather than generating a fixed dollar return in isolation. This view aligns with the broader productivity literature, which argues that IT benefits firms by improving the efficiency of existing processes and "levering-up" productivity advantages via quicker dispersion across business units (Bartel *et al* 2007; Brynjolfsson *et al*. 2008; Syverson 2011). This impact has a natural mapping to our setting. Hospitals purchase IT solutions that help manage clinical service lines, speed up back-office tasks, and improve communication across units. These systems do not generate new streams of revenue themselves, but rather allow the hospital to carry out its existing operations more efficiently.

Second, IT adoption is an *irreversible investment that can be delayed*. IT investments are irreversible because they require firm-specific organizational changes to operationalize (Brynjolfsson and Hitt 2000; Brynjolfsson, Hitt, and Yang 2002).[7] Furthermore, given the robust IT vendor market, the relevant adoption decision margin is not whether a hospital should adopt at all, but rather *when* to adopt (i.e., invest today or delay). In making this dynamic decision, they consider both current factors and expectations about the future.[8]

Finally, IT adoption requires *large upfront costs*, with reported hospital IT implementations that can range from millions to over a billion dollars in outlays for some large systems.[9] A subset of hospitals may simply be unable to secure funding even for investments that they would otherwise be willing to undertake (Hubbard, 1998). For tractability, the model in Appendix A abstracts from this feature, as embedding financing frictions would complicate the analysis and the intuition is fairly clear.

B. *Channels Driving IT Adoption*

[7] This is consistent with both empirical and anecdotal evidence within healthcare. In the context of nursing homes, Hitt and Tambe (2016) find that the returns to EMR adoption are greater when facilities have better work-organization practices. According to one hospital chief information officer, "The EHR decision wasn't a software decision. It was an operating model decision… The real value comes when you redesign the work." https://www.beckershospitalreview.com/healthcare-information-technology/ehrs/why-this-cio-treated-an-ehr-decision-as-an-operating-model-reset/

[8] For example, ahead of potential Medicaid cuts, one hospital CEO is quoted as saying "There are a lot of unknowns right now, so we're obviously looking at things we can do to tighten our belts ahead of the potential changes." https://www.ems1.com/hospital/rural-calif-hospitals-brace-for-medicaid-cuts-delay-upgrades-amid-uncertainty

[9] See AMA Board of Trustees Report 32-A-19 (2019); e.g., Mass General Brigham's Epic electronic health record implementation was reported at roughly $1.2 billion. Industry reports additionally detail the millions of dollars invested in IT by hospitals each year, e.g., see here: https://www.definitivehc.com/resources/healthcare-insights/average-it-expenses-us-hospitals as well as here: https://www.beckershospitalreview.com/healthcare-information-technology/ehrs/most-expensive-epic-ehrs-ranked/.

These features create three relevant channels through which economic shocks could affect IT adoption. Note that while these channels are conceptually distinct, they are not necessarily mutually exclusive.

The first is *patient demand*. A shock that increases demand for a hospital's services (or shifts patients toward better-reimbursed forms of care) raises the revenue base over which an IT investment can operate. Viewed through the lens of IT as a revenue-amplifying technology, an expansion of the patient base should therefore raise the returns to IT adoption. A negative demand shock works in the opposite direction. If the IT adoption behavior is driven by expansions (or contractions) in patient demand, a hospital's response should not be concentrated on IT alone. Hospitals should also adjust other inputs to patient care, including staffing or physical capacity like beds and operating rooms. A response concentrated on IT, with little movement on other inputs, would therefore be difficult to reconcile with changes to demand as the driving force. Likewise, if hospital revenue changes but patient demand remains largely unchanged, the demand channel predicts little reason for hospitals to change their IT adoption behavior.

The second channel is *uncertainty*. When a hospital's future outlook is uncertain, waiting has value. This logic is central to real-options models of investment under uncertainty (Bernanke 1983; Pindyck 1991; Dixit and Pindyck 1994; Schwartz and Zozaya-Gorostiza 2003). In this framework, a shock affects IT adoption by changing the hospital's expectations about its future revenue environment. A policy that converts uncompensated care into payer-backed reimbursement or creates a new regulated and predictable revenue stream will improve a hospital's outlook and reduce the value of waiting to adopt. A negative macroeconomic shock should have the opposite effect, raising the value of delaying and leading hospitals to postpone adoption.

The third channel is *liquidity*. A hospital may find IT adoption worthwhile but simply be unable to finance the up-front cost. In that case, the binding constraint is not the expected return to IT or the value of waiting, but simply the availability of cash or external financing. Positive revenue shocks should relax this constraint only when they increase realized cash flows or improve current borrowing capacity. Similarly, negative revenue shocks will tighten this constraint by decreasing cash flows or worsening borrowing capacity.

The liquidity and uncertainty mechanisms are both financial channels, but they imply different empirical patterns along two dimensions. The first is through the timing of the adoption response: only the uncertainty channel aligns with anticipatory behavior. If a policy announcement changes the perceived stability of future revenues, the uncertainty channel implies that hospitals will be willing to adjust IT investment even before any new revenue arrives. In contrast, the liquidity channel predicts that investment only occurs once the hospital has the cash on hand. The second implication is heterogeneity across hospitals facing different financial constraints. If the liquidity channel dominates, then we would expect larger responses among the most liquidity-constrained firms. In our setting, these are likely standalone (i.e., non-system-affiliated) hospitals, which will lack internal capital markets (i.e., the ability to unlock funds from the hospital network), and especially those with weak operating margins or limited reserves at baseline.[10]

II. Data

A. *Primary: Hospital Health IT Data*

Our primary data come from the Health Information Management Systems Society (HIMSS) annual survey, which provides detailed information on hospital-level health IT use across a variety of business domains (e.g., clinical care and tracking, revenue cycle management, and back-office functions). We rely on HIMSS survey years 2005 through 2017 and construct a hospital-level measure of aggregate number of software health IT solutions implemented and operational in a given year to reflect overall adoption activity over time. We also benefit from granular information on the purpose of a given health IT investment, which we use to construct a complete set of mutually exclusive categories for IT functionality. To keep the estimation and results reporting tractable, we collapse some health IT purposes into an overarching business function. For example, we have a broader measure of 'Financials' which captures multiple HIMSS reported purposes, including financial decision support, general financials, and revenue cycle management. Likewise, our constructed category of 'Back-office' health IT solutions includes business office software, customer relations management, business intelligence, document management, regulation and standards, and transcription. However, most of our outcome measures map to a single or few

[10] These last two channels could coincide if uncertainty influences the extent to which a hospital is liquidity-constrained. For example, the cost of capital could decrease when lenders have a more positive outlook on a firm's future revenue. However, we view this as still supporting the perspective of uncertainty as the underlying force influencing IT investment, but it is the financial capital provider responding to changes in expectations rather than the hospital itself. In this case, the two empirical patterns that distinguish the uncertainty and liquidity channels—changes in adoption at announcement and differential effects by baseline liquidity constraints—remain the same.

reported specific IT purposes.[11] Another interesting feature of these data is the ability to observe information on health IT vendors. We leverage these data details to construct a measure of total unique vendors a given hospital contracts within a given year, and then in Section VII, shift our analytic perspective to focus on the vendor market, specifically.

As far as we are aware, these data are a novel contribution to the recession-focused literature, the Medicaid expansion-focused literature, and the hospital 340B program literature.[12] For all three sets of our subsequent analyses (Sections III-V), we restrict to hospitals in the HIMSS data that report a valid Medicare identification number (CCN) that we can use to link to our other data sources. This requirement sacrifices approximately 10% of the total hospitals available in the HIMSS data.

B. *Secondary*

To construct the Great Recession shock we use the county-level unemployment rates from the Bureau of Labor Statistics (BLS). To construct the 340B shock, we use data from the Health Resources and Services Administration (HRSA) on hospital 340B participation. We then supplement our health IT (primary) data and shock-specific data with information contained within the American Hospital Association (AHA) annual surveys, the publicly available data from the CMS Hospital Cost Reporting Information System (HCRIS), and IRS 990 Forms submitted by not-for-profit hospitals.

The AHA data provide information on hospital-level real assets (i.e., total number of beds as well as operating rooms) and hiring. For the latter, we focus on measures of full-time and part-time registered nurses (RNs) and licensed practical nurses (LPNs) that belong to a given hospital's workforce in a given year. Nurses of varying skill types are some of the most numerous and vital

[11] Specifically, "Staffing" incorporates human resources, credentialing, and nursing. "Finance" includes financial decision support, general financials, and revenue cycle management. "Clinical Service Line" includes all categories tied to a specific medical area (e.g., cardiology or radiology) as well as clinical systems. And "Information System" (IS) includes all IS systems, IS infrastructure, IS security, along with health information exchange and health information management categories. We also note that the telemedicine outcome is only used in the Medicaid expansion analyses since it was not included as a category in earlier years of the HIMSS data.

[12] We do note that the data do not contain transaction prices or cost estimates for the health IT solutions. While this is one drawback for the HIMSS data, it is also not surprising, given the very detailed information on each hospital, the IT each hospital has invested in, and with whom the hospital contracts for its IT solutions. In other words, reporting on costs (even in ranges) would likely be viewed as information for a given hospital-vendor negotiation that is too proprietary (i.e., "trade secrets") to report in the HIMSS survey.

labor inputs for most hospital operations. We use this supplementary information to compare and contrast findings from our primary outcome of interest, IT adoption.

To facilitate our heterogeneity analyses, we draw on data from several sources. First, we use publicly available data from Cooper *et al*. (2019) to capture hospitals' system affiliations versus standalone status at baseline (i.e., prior to the occurrence of a given shock). Regarding cost reports (i.e., HCRIS), all hospitals participating in the Medicare system are required to annually certify and report information on hospital financial measures. We use this information at the individual hospital level to capture additional baseline characteristics, especially related to a given hospital's financial health tied to operational efficiency and revenues. Additionally, the 990 Forms allow us to construct a broader measure of financial assets as a proxy for capital reserves that not-for-profit hospitals could plausibly use directly or borrow against in order to finance investments.

III. Great Recession Shock

A. *Business Cycles and the Hospital Industry*

Existing economics research spanning more than two decades has examined the impacts of economic downturns on population health, especially with respect to mortality (e.g., Ruhm 2000, 2015; Stevens 2015; Finkelstein *et al*. 2024). A parallel literature has taken interest in the supply-side consequences of negative macroeconomic shocks and tends to find that the healthcare labor market is relatively "recession proof" (e.g., Chen, Lo Sasso, and Richards 2018a; Li, Richards, and Wing 2019; Dillender *et al*. 2021). Yet, this does not mean that the sector is unaffected by recessions. With a high reliance on employer-sponsored health insurance, increases in unemployment following a worsening economy can be associated with lower health insurance coverage and consequently reduced demand for medical services or increased uncompensated care burden for providers (Cawley *et al*. 2015).

Related studies have found that healthcare providers are sensitive to the business cycle to varying degrees, including in how the hospital industry coped with fallout from the Great Recession. For example, empirical work finds strategic shifts in hospitals' clinical care to improve profitability and reduction in overall investments when absorbing the negative income shock (via their investment portfolios) that resulted from the 2008 financial crisis and subsequent stock market crash (Adelino, Lewellen, and Sundaram 2015; Adelino, Lewellen, and McCartney 2022). Earlier work offers more limited evidence of such responses in the aggregate, especially across a wider variety of hospitals (Dranove, Garthwaite, and Ody 2017). Some recent and related research also demonstrates that *ex post* policy responses to the financial crisis (i.e., the Dodd-Frank Act stress tests) raised the cost of borrowing for hospitals, which led them to seek out compensatory efficiencies and lower their care quality (Aghamolla *et al*. 2024).[13] As previously noted, it is currently unknown if the hospital industry's IT capital investments, specifically, are altered by the business cycle. We leverage the financial crisis as a negative shock to hospitals' income as well as a source of greater uncertainty for the industry to better understand hospital decision-making in regards to IT adoption.

B. *Difference-in-Differences Estimation*

While the Great Recession had economy-wide implications, the depth of its impact varied significantly across the country. Our difference-in-differences (DD) strategy exploits the spatial variation in the Great Recession's severity and is similar in spirit to recent work focused on the local economic activity and mortality effects of the downturn (Yagan 2019; Finkelstein *et al*. 2024). Specifically, we focus on the years 2005-2012 and a balanced panel of hospitals present in the HIMSS data for these eight years. Using data from the BLS for 2007 and 2009, we calculate the county-level difference in the unemployment rate for the full US across these two years to use as a proxy measure of the Great Recession's local severity (i.e., a recession 'bite' variable). We narrow our focus to counties that fall in the top and bottom quartiles of the recession bite variable's distribution to define our treatment (top) and control (bottom) group geographies for our DD research design.[14] We then combine this information with our hospitals from the HIMSS data to restrict to hospital-county pairs that satisfy our DD inclusion criteria. Importantly, the average change in the unemployment rate between 2007 and 2009 for counties in the bottom quartile was 2.0 percentage points, while it was 6.9 percentage points for those in the top quartile—i.e., a 245% larger degree of Great Recession severity.

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[13] Unrelated to the Great Recession, Rossi and Yun (2024) likewise find that policy lowering hospitals' borrowing costs leads to greater capital expenditures, especially for new buildings.

[14] In Section IIID, we describe and discuss a sensitivity test that exploits the full variation in the recession bite variable and hence includes the full set of analytically eligible hospitals. Neither the strength of our results nor our subsequent inferences are influenced by this modified estimation when compared to our preferred DD design.

The resulting counties containing our treatment and control hospitals are shown in Figure 1. Areas in the Southeast, parts of the upper Midwest, and the West coast through the Southwest comprise most of the severely affected counties while the central US—ranging from Texas to Montana— and some of the Northeast counties were the least impacted and hence contribute the plurality of our control group areas. The number and baseline summary statistics for the hospitals operating in these two subgroups of counties that make up our first DD analytic sample are displayed in Table 1. Treatment group hospitals have slightly more operational health IT solutions at baseline, on average; however, the mix and average levels of specific IT solution types are comparable across the recession bite divide in Table 1.

Our subsequent estimations are straightforward. We rely on a standard "2x2" DD specification and an event study specification. The respective estimating equations are as follows:

$$Y_{ht} = \alpha_h + \theta_t + \delta(Treated_h \times Post_t) + \varepsilon_{ht} \tag{1}$$

$$Y_{ht} = \alpha_h + \theta_t + \sum_{\substack{j=2005 \\ j\neq 2006}}^{2012} \delta_j \, (Treated_h \times time = j) + \varepsilon_{ht} \tag{2}$$

Equations (1) and (2) each include hospital (α_h) and calendar year (θ_t) fixed effects. *Treated* is equal to one for hospitals operating in the top quartile of Great Recession severity counties and zero otherwise. The *Post* variable is set to one for the 2008-2012 period, which we view as conservative since the Lehman Bros. investment bank collapse did not occur until late 2008, precipitating the full financial crisis and subsequent Great Recession. The event study estimation in Equation (2) allows us to formally examine the parallel trends assumption and capture any dynamic effects from the economic downturn over the 2008-2012 period.

C. *Triple Differences Estimation*

We adapt Equation (1) to formally test for heterogeneous responses in health IT adoption behavior via a DDD design. We posit that system-unaffiliated (i.e., standalone) hospitals, and especially those with weaker financial positions at baseline, would face tighter budget and liquidity constraints following a negative economic shock due to their smaller financial reserves and/or higher borrowing costs and lack of internal lending available to system members. Thus, stronger effects among these subsets of hospitals would be consistent with realized changes in cash flow driving changes in IT investment decisions and point toward the liquidity channel as a key driver.

We first construct an indicator for 'standalone' hospital status that is equal to one for any non-government hospital lacking any system affiliation as of 2007 from Cooper *et al*. (2019). To further home in on hospitals that are most likely to be liquidity-constrained, we next create an indicator that is equal to one for standalone hospitals that are also financially struggling at baseline. For hospital financial performance, we calculate the annual operating margin per hospital and construct an indicator for non-government hospitals that are standalone *and* have on average a negative margin (i.e., lost money from hospital operations on net) over the 2005-2007 period. Finally, we use the not-for-profit hospitals' 990 reporting to create a binary variable equal to one for hospitals above the median in financial assets and zero otherwise. The resulting DDD specification is as follows:

$$\begin{aligned} Y_{ht} = \alpha_h + \theta_t + \lambda_1(Treated_h \times Post_t) + \\ \lambda_2(BaseCharac_h \times Post_t) + \\ \lambda_3(Treated_h \times Post_t \times BaseCharac_h) + \varepsilon_{ht} \end{aligned} \tag{3}$$

The *BaseCharac* variable in Equation (3) represents a general placeholder for any of the third 'D' indicators previously described and used in our DDD estimation. All other features from Equation (1) remain the same.

We then conclude our Great Recession empirics by examining hospitals' real (physical) assets and hiring of nurse labor for HIMSS analytic hospitals that can be matched to the AHA data. The former includes counts of total beds and total operating rooms while the latter captures full-time as well as part-time employees that are registered nurses (RNs) or licensed practical nurses (LPNs). The DD estimations simply rely on Equation (1) and Equation (2) above but replace the health IT outcomes with these supplementary hospital spending outcomes.

D. *Great Recession Effects on Health IT Investments*

The raw average outcomes over time across the treatment and control groups are displayed in Figure 2. Both the number of operational health IT solutions and the total number of vendors are observably and negatively impacted by the Great Recession for hospitals exposed to a more severe local downturn. While both outcomes are trending in parallel across our treatment and control hospitals over the 2005-2007 period, there is a stark divergence soon after the financial crisis, with IT investments slowing down in treated counties while control hospitals continue their upward trend.

The more formal DD event study results are found in Figure 3. The coefficient magnitudes also grow with time, with the largest negative effects present in 2011-2012—three to four years after the onset of the Great Recession (Figure 3). By 2011, health IT adoption has been restrained by roughly 11 percent (i.e., 5 health IT solutions) or more relative to the treatment group's baseline average in Table 1. Given the known difference in the recession bite variable between these two subgroups of hospitals described in Section IIIB (i.e., 4.9 percentage points), the estimates from Figure 3 imply an approximately 2 percent decrease in health IT investments for every one percentage point increase in recession severity. Furthermore, the similar recession effects for both the number IT solutions and the number of vendors suggests that consolidating vendors is not clearly a strategy used by hospital managers when facing a worsening business climate.

As a robustness check, Appendix Figure B1 repeats our event study estimation but includes the full set of analytically eligible hospitals from the HIMSS data (i.e., not restricting to those in the top or bottom quartile for Great Recession bite) and uses a continuous measure of recession bite, rather than the binary variable to dichotomize treatment and control status. The resulting patterns from panel (a) and panel (b) in Appendix Figure B1 are virtually identical to those found in Figure 3, with the exception that the coefficient magnitudes are unsurprisingly smaller than our main analyses, which intentionally capture the differential between the most and the least impacted hospitals.

Table 2 provides our DD and DDD results for the Great Recession. Column 1 shows that hospitals most exposed to the downturn restrain their IT investments by 8 percent when averaged over the full 2008 to 2012 period. Columns 2-4 explore if this finding is driven by standalone hospitals, standalone hospitals with weak financial positions, or (not-for-profit) hospitals with relatively more financial assets, respectively. The corresponding DDD results make clear that the overall negative effect is not driven by standalone or financially struggling hospitals. Instead, the

DDD coefficients are positive and substantive in columns 2 and 3 of Table 2—though lacking precision. Column 4 of Table 2 offers a slightly different picture and implies that hospitals with relatively greater financial reserves have a muted recession response compared to peer hospitals with smaller financial endowments. Taken together, the DDD results show mixed, and not definitive, evidence that the key constraint on IT adoption is liquidity.

Appendix Tables B1 through B3 offer DD estimates for more nuanced vendor outcomes and the use of IT external consultants, as well as each of our mutually exclusive health IT genres of interest. The estimates are uniformly negative and statistically significant at conventional levels for eleven out of thirteen outcomes in Appendix Tables B1-B3. Event study results for each outcome showing statistical significance for the DD estimation are found in Appendix Figure B2.[15] Overall, the event study findings largely mirror those displayed in Figure 3 and reinforce the inferences drawn from Figures 2-3 and Table 2. They also tend to show dynamic effects, with the largest decreases during the 2011 and 2012 years. Relative to baseline adoption levels for hospitals in the top quartile of recession bite (Table 1), these declines reflect changes of roughly 5-60 percent for a given type of health IT solution. A noteworthy exception is the EHR outcome in Appendix Table B2, which shows no effect. The contemporaneous 2009 HITECH Act is known to have generated greater EHR adoption across the US hospital industry during this time period (Gold and McLaughlin 2016; Adler-Milstein and Jha 2017), so our lack of clear effect for this specific type of IT investment is unsurprising.[16]

For comparison, we next capture recession effects using our Equation (1) DD model for our analytic hospitals with supplementary information on physical capital and nurse hiring

[15] In the interest of concision, event study plots are only shown for statistically significant DD results found within each of the relevant Appendix B tables. We maintain this same reporting convention for Appendix C through Appendix E.

[16] The HITECH Act provided financial incentives to expand electronic health record adoption by tying subsidies to "meaningful use" of EHRs for hospitals and physician practices. The HITECH Act is unlikely to confound our estimates for three reasons. First, eligibility was national and determined by hospital type (e.g., acute care or children's hospitals) rather than by region, and our specifications control for hospital fixed effects. Second, the regionally varying components of the rollout—the Medicaid EHR Incentive Program, state privacy policies (Miller and Tucker 2011), and local health information exchange programs—do not track the geographic variation in the three shocks that we study. Third, HITECH incentives targeted patient-facing EHR adoption, whereas our outcomes span the full portfolio of hospital IT, including non-patient-facing systems that the incentives did not directly subsidize. In other words, these incentives were provided nationally, localize to EHR utilization, and were not tied to our three identification strategies: differences in the local business cycle, in state Medicaid expansion decisions, and in hospitals' 340B participation.

available from the AHA data.[17] The DD estimates in Table 3 tend to be small relative to the pre-period mean values, inconsistently signed, and only reaching statistical significance for the number of part-time RNs—implying an approximately 8 percent decline relative to baseline levels. The event study for this statistically significant outcome can be found within Appendix Figure B3. Importantly for full-time nurses (both RNs and LPNs), who make a larger share of total positions and staffing hours, we find no evidence of a staffing reduction. At a minimum, the findings in Table 3 indicate that hospital managers' spending decisions are more sensitive to the business cycle when it comes to health IT, including across the variety of IT subtypes, when compared to other outlays, such as capacity building or clinical workforce size. Moreover, our collection of findings demonstrates that ignoring health IT investments and relying solely on other commonly measured hospital investment and spending behaviors risks underappreciating the broader and longer-lasting impacts of a substantive downturn in the business cycle on the hospital industry.

IV. Medicaid Expansion Shock

A. *Medicaid Insurance and the Hospital Industry*

We now move forward in economic history and turn our attention to the Medicaid public insurance program as our second (*positive)* shock to the hospital industry. This means-tested insurance benefit has been a prominent fixture of the US healthcare system for six decades, but Medicaid's size has also fluctuated over time due to state and federal policymaking. The potential benefits to individuals and households from access to a heavily subsidized insurance program are straightforward. Yet, the downstream benefits to hospitals are not immediately obvious and depend on two important and interdependent aspects of the US healthcare system: comparatively high rates of uninsurance and a high prevalence of unpaid medical bills.[18]

Existing research shows that the uncompensated care burden is largely borne by the hospital industry and that the Medicaid program plays a mitigating role. Estimates from the most recent Medicaid expansions tied to the Affordable Care Act (ACA) suggest an approximately 25-

[17] As previously noted, not all HIMSS hospitals have corresponding AHA information in all years, which accounts for loss of analytic sample size across different estimations.

[18] Both are often lamented features of the US system, with the latter also receiving increased attention by researchers, consumer advocates, and policymakers in recent years (Batty, Gibbs, and Ippolito 2022; Kumar and Adashi 2023; Kluender *et al*. 2024).

50 percent decline in unpaid medical bills for affected hospitals, relative to pre-expansion levels, and improved finances overall (Blavin 2016; Dranove, Garthwaite, and Ody 2016; Kaufman *et al*. 2016; Lindrooth *et al*. 2018; Rhodes *et al*. 2020; Blavin and Ramos 2021; Callison *et al*. 2021; Dunn, Knepper, and Dauda 2021; Duggan, Gupta, and Jackson 2022; Santos, Singh, and Young 2022). Hospitals therefore face considerable financial risk tied to fluctuations in the rate of uninsurance present in their local market, but expanding subsidized coverage can shield healthcare providers from high and hard-to-predict uncompensated care costs in the present and for the foreseeable future.[19]

The ACA became law in 2010 and arguably represented the most substantial health policy reform in the US healthcare system since the founding of the Medicare and Medicaid programs a half-century prior. The legislation included a variety of policy levers to ultimately shrink the share of the US population lacking health insurance. One of the most influential mechanisms to accomplish this policy priority was a national expansion of Medicaid. The expansions were originally intended to take place across the country in January of 2014 (or before in some circumstances), but during the summer of 2012, the US Supreme Court ruled that states must be allowed to opt-out of the proposed ACA Medicaid expansions—an option that many states decided to exercise. Further details of the ACA insurance provisions and subsequent estimates of coverage take-up can be found within Frean, Gruber, and Sommers (2017) and Gruber and Sommers (2019), among others.

An existing empirical literature has tested the effect of the Medicaid expansion on the hospital industry across a variety of dimensions. Lindrooth *et al* (2018) find a lower likelihood of full hospital shutdown following the public insurance expansions, and Nikpay (2022) shows that a post-expansion increase in Medicaid volumes can trigger other Medicaid-linked subsidies for hospitals. Tarazi (2020) and Meille and Post (2023) find evidence of positive impacts of Medicaid expansions on hospitals' nurse retention and/or hiring. The expansion did not, however, forestall

[19] Medicaid is also known to be countercyclical—bolstering medical care demand during economic downturns (Benitez, Perez, and Chen 2021; Benitez, Perez, and Seiber 2021). Relatedly, existing research calculates that a substantive portion of Medicaid spending operates as a transfer from government coffers to the hospital industry (Garthwaite, Gross, and Notowidigdo 2018; Finkelstein, Hendren, and Luttmer 2019). The relative permanence of Medicaid expansions is also important for our purposes. Doubts around policy permanence can lead to weaker investment and encourage further "precautionary delays" (Rodrik 1991). Likewise, other work finds that temporary price shocks have limited impact on provider behavior (Chen *et al*. 2018b; Chen *et al*. 2022). Public insurance expansions are rarely reversed, however.

obstetric unit closures within hospitals, improve circumstances for safety net hospitals, or translate to more community benefit spending (Kanter *et al*. 2020; Stoecker *et al*. 2020; Chatterjee, Qi, and Werner 2021; Chatterjee, Werner, and Joynt Maddox 2021; Carroll *et al*. 2022). As previously noted, only limited empirical work has examined hospitals' capex decisions following Medicaid expansions, with no known work on health IT investments, specifically.[20]

B. *Difference-in-Differences Estimation*

Our primary estimation strategy for identifying Medicaid expansion effects is also a standard DD research design. Our implementation closely follows Brevoort, Grodzicki, and Hackmann (2020). More specifically, the authors consider control comparison states to be those that had not expanded their Medicaid program as of 2017 (19 states) and exclude "early" and "late" adopting states (13 states, plus the District of Columbia)—leaving 19 treatment group states that all implemented their ACA Medicaid expansions on January 1st, 2014. The simultaneous implementation of these policies across states avoids the empirical complications from differential timing in treatment (e.g., see Goodman-Bacon (2021)).

The resulting geographic spread of our treatment and control group states is displayed in Figure 4. We then restrict our analytic sample to a balanced panel of hospitals present in the HIMSS data every year from 2009 through 2017 and operating in one of these policy-relevant states. Within Table 4, we can see the levels of our health IT investment measures averaged over the 2009-2012 period for each subset of analytic hospitals corresponding to their 2014 Medicaid expansion status. At baseline, the average hospital within each group has nearly sixty health IT solutions operational in a given year and contracts with more than a dozen unique IT vendors. The number of solutions tied to a given business purpose ranges from less than one to as many as fourteen, on average (Table 4). Importantly, hospitals' health IT adoption patterns closely mirror each other across the Medicaid expansion divide prior to our 2014 policy shock of interest.

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[20] Other supply-side (i.e., provider-focused) studies of Medicaid effects have tended to focus on clinical practice patterns, earnings, and organization (e.g., Garthwaite 2012; Buchmueller, Miller, and Vujicic 2016; Chen, Lo Sasso, and Richards 2018c; DiNardi 2021; Dillender 2022; Barnes *et al*. 2023; Matta, Chatterjee, and Venkataramani 2024).

Just as before, for our primary outcomes, we conduct a "2x2" DD estimation as well as an event study specification. The respective estimating equations closely follow Equation (1) and Equation (2), with the exception of two variable definitions:

$$Y_{ht} = \alpha_h + \theta_t + \delta(Treated_h \times Post_t) + \varepsilon_{ht} \tag{4}$$

$$Y_{ht} = \alpha_h + \theta_t + \sum_{\substack{j=2009 \\ j\neq 2012}}^{2017} \delta_j \left(Treated_h \times time = j\right) + \varepsilon_{ht} \tag{5}$$

Equations (4) and (5) each include hospital (α_h) and year (θ_t) fixed effects, paralleling what was done in Section III. Now, the treatment indicator (i.e., *Treated*) is equal to one for hospitals operating in 2014 Medicaid expansion states and zero otherwise. Similarly, the *Post* variable is now set to one for the 2014-2017 period. We also believe defining the post-expansion period in this way is conservative since hospitals knew their respective state's policy decision in late 2012– making 2013 a policy announcement year. The event study estimation in Equation (5) allows us to formally examine any anticipatory behavior by hospitals prior to the expansions taking place, along with assessing the validity of the parallel trends assumption. Standard errors are clustered at the state level.

C. *Triple Differences Estimation*

Following the approach in Section III, we adapt Equation (4) to formally test for heterogeneous responses via DDD estimation. The resulting specification is as follows:

$$\begin{aligned} Y_{ht} = \alpha_h + \theta_t + \lambda_1(Treated_h \times Post_t) + \\ \lambda_2(BaseCharac_h \times Post_t) + \\ \lambda_3(Treated_h \times Post_t \times BaseCharac_h) + \varepsilon_{ht} \end{aligned} \tag{6}$$

The *BaseCharac* variable in Equation (6) again represents a general placeholder for any third 'D' indicator used in our DDD estimation. All other features from Equation (4) remain the same. We include the three key sources of potential heterogeneity from before: health system affiliation, baseline hospital financial performance, and the broader measure of financial assets for not-for-profits.[21]

Given that this shock is tied to a specific public insurance expansion, we also follow related studies (e.g., Dranove, Garthwaite, and Ody 2016; Lindrooth *et al*. 2018; Dunn, Knepper, and Dauda 2021) that leverage within-state geographic variation in the likely impact of ACA Medicaid expansions. Specifically, we adapt the Garthwaite, Ody, and Starc (2022) procedure for calculating the predicted payer mix for each hospital based on characteristics of nearby zip codes and create an indicator for whether a hospital is exposed to more uninsured patients.[22] The rationale aligns with the prior DDD explorations insofar as plausibly more shock-exposed hospitals could drive the overall results and consequently help illuminate the underlying mechanisms.

We then conclude our Medicaid expansion empirics by examining hospitals' capacity investments and hiring of nurse labor, just as before. Paralleling what was done for the Great Recession effects in Section III, we simply use Equation (4) and Equation (5) to examine changes in these supplementary outcomes following the public insurance expansions for HIMSS analytic hospitals that have available AHA information in a given year over the 2009-2017 period.

D. *Medicaid Expansion Effects on Health IT Investments*

[21] For hospital financial performance, we calculate the annual operating margin per hospital using the HCRIS information and construct an indicator for non-government hospitals that average a negative margin (i.e., lost money on net) over the 2009-2012 period to create a standalone *and* financially weak indicator, analogous to what was done in Section III.

[22] The rationale for using predicted, rather than realized, payer mix is that a hospital's realized payer mix could be endogenous to the quality investments it makes. To generate the predicted payer measure, we follow the procedure described in Garthwaite, Ody, and Starc (2022) by first estimating a zip-code level multinomial choice model using Medicare inpatient claims data. We then aggregate across nearby zip codes served by a hospital to construct its predicted insurance mix. We adapt their procedure to our setting in two ways. Instead of using the Medicare's 2011 Hospital Service Area File to determine shares, we instead use each year's Medicare inpatient claims data. To measure zip code demographics, we rely solely on the 5-year American Community Survey data.

Figure 5 displays the change in raw outcomes over time across the expansion and non-expansion states, on average. While IT adoption is trending upwards for both treated and control hospitals in this period, a gap emerges around 2013, and treated hospitals appear to accelerate adoption more than control ones. The corresponding event study estimates in Figure 6 reinforce the interpretations from the raw trends in Figure 5. Treatment and control hospitals are trending in parallel over the 2009-2012 period, and then in 2013 (i.e., the policy announcement period), the divergence begins and grows over time. By 2017, hospitals exposed to Medicaid expansions undertake approximately 10 percent more health IT investments than the counterfactual scenario where no Medicaid expansions occur. Using the back-of-the-envelope values from Brevoort, Grodzicki, and Hackmann (2020), which assumes an average increase of 4.4 percentage points in the nonelderly insured population among these 19 expansion states over this post-period, our estimates from Figure 6 imply a roughly 1 percent to 2 percent increase in hospitals' IT capital investments for every one percentage point gain in the nonelderly insured rate.

Table 5 offers the DDD results focused on the Medicaid expansions. Once again, these specific subsets of the affected hospital industry do not drive the overall result. There is no evidence of a greater response by hospitals with disproportionate exposure to the baseline (2012) uninsured population (column 2). The standalone and standalone hospitals with weak financial positions (columns 3 and 4) show negative, large, and statistically significant DDD coefficients. These results imply that hospitals with plausibly tighter budget and liquidity constraints have a smaller health IT purchasing response (in levels) to the expansion shock compared to all other hospitals in the industry. The DDD coefficient is much smaller and noisier for the 'high assets' subgroup in column 5 of Table 5 but does not indicate that presumably better financially endowed hospitals are meaningfully less impacted by the positive policy shock.

Appendix Tables C1-C3, along with Appendix Figure C1, provide additional vendor outcomes as well as a decomposition of the overall Medicaid expansion effect according to the specific health IT purpose—mirroring the approach in Section III. The DD estimates reveal increases in IT focused on clinical service lines (e.g., cardiology care or emergency department care) as well as laboratory services that are statistically significant at conventional levels. An even broader range of IT purposes tied to more administrative—as opposed to clinical—functions increase as well (Appendix Table C3). Back-office management, financial-focused, information systems, and utilization review software solutions all show substantive and statistically significant policy effects. The event studies corresponding to the statistically significant DD results in Appendix Figure C1 also support a causal interpretation for these effects and the trend breaks beginning at policy announcement are consistent with the dynamics in Figure 6. By the end of our study period, the various genres of IT solutions have increased by a range of roughly 5 percent to 30 percent over baseline levels (Table 4).[23]

Table 6 reports the DD estimates for the hospital capacity and nursing workforce outcomes. There are no statistically significant increases for any of the six outcomes. Interestingly, total bed capacity is actually differentially lower by 2% for hospitals experiencing the 2014 Medicaid expansions—though the event study (Appendix Figure C2) is not strongly compelling and cautions against any causal interpretations for this outcome. Taken together, these results largely mirror that of the recession: health IT adoption is much more sensitive to economic shocks than other inputs.

V. 340B Hospital Shock

A. *Federal 340B Program and the Hospital Industry*

The market-level shocks of the Great Recession and ACA Medicaid expansions have potential implications for the demand-side and supply-side of healthcare markets. To better isolate the effects of a hospital's own financial circumstances from the demand channel, we next turn to studying the effect of being granted 340B status on hospitals' IT adoption.

The 340B program debuted in 1992 with the intent of being a narrowly targeted safety-net provider program to facilitate discounted drug access. However, it has grown substantially with time and now involves over 60 percent of not-for-profit hospitals and impacts tens of billions of dollars in annual drug spend. It is also known to generate significant profits for affected hospitals (Nikpay, Reinke, and Quinones 2026; Nikpay, Reinke, and Watts 2026).

A pronounced expansion of 340B hospitals began in 2010. The ACA stipulated that all critical access hospitals would be automatically eligible and that new federal guidance would allow

[23] We also used our DDD estimation to investigate any potential for a 'recession recovery' (or catchup) effect from the 2014 Medicaid expansions. Since some of the areas most exposed to the Great Recession were then exposed to 2014 ACA expansions, it is possible that the positive policy shock allowed them to recover lost ground in terms of health IT adoption. Given the potential overlap of these two shocks, the positive Medicaid expansion effect we estimate could also capture mean reversion of the negative effect from the recession. However, we found no evidence of a stronger policy response or any indication that our overall Medicaid expansion findings were driven by the subset of hospitals previously and most severely exposed to the Great Recession (results available by request).

unlimited contractual arrangements with retail pharmacies in order to secure the supply of discounted drugs (via outsourcing), and hence, made it easier to extract the full financial benefits of 340B classification for hospitals meeting the originally established and modest qualification requirements (Alpert, Hsi, and Jacobson 2017; Desai and McWilliams 2021; Lin *et al*. 2022; Nikpay, Reinke, and Watts 2026). Existing literature typically does not detect clear changes in uncompensated care provision or care quality improvements with 340B participation (e.g., Desai and McWilliams 2021; Smith *et al*. 2023)—though some studies find increases in patient access to care (Knox *et al*. 2023). There is only mixed evidence that 340B creates incentives for hospital-physician consolidation (Alpert, Hsi, and Jacobson 2017; Desai and McWilliams 2018), and we are unaware of any research focused on 340B effects on hospital IT procurement.

B. *Difference-in-Differences Estimation*

Our 340B hospital-level information comes from the HRSA data on all 340B participants and dates of participation (Health Resources and Services Administration, 2026). Figure 7 shows the incidence of new 340B hospitals by year from 1992 through 2025. The pronounced spike of new participants during the post-ACA period is evident. We leverage this rapid increase in participation to test the effects of 340B participation on hospitals' spending decisions.

We first restrict to hospitals in the previously used 19 *non-expansion states* in order to shut down any influence from the ACA Medicaid expansions (Section IV), since these policies are known to interact (Nikpay 2022). We further restrict to those that have been consistently present in the HIMSS data from 2005 through 2017. We then focus on hospitals newly granted 340B status in 2010, 2011, or 2012. We examine these hospitals in particular since the timing of their program entry is arguably more exogenous due to the ACA-related rule changes for 340B participation, as opposed to entries in other periods, when hospitals may have been more strategic in their timing. All other ever-340B hospitals are removed from the analytic sample to ensure that control group hospitals have never financially benefitted from the 340B classification. This leaves us with 121 hospitals as the basis of our treatment group and 723 control hospitals.

Because these hospitals become 340B participants in different years, we wish to avoid the estimation and inference complications due to differential timing in treatment. We therefore follow recent work that utilizes a firm-level "stacked difference-in-differences" research design (e.g., Lin *et al*. 2023; Munnich *et al*. 2026). The design has the advantages of transparency and simplicity.

To implement the design, we first limit the treatment group hospitals to their respective panel data five years before and five years after the year of 340B participation (i.e., the $t = 0$ time point for a given hospital), which yields eleven annual observations per treatment group hospital. Next, we create our comparison hospitals by randomly assigning a placebo treatment date of either 2010, 2011, or 2012 to the previously identified set of potential controls and extracting the same +/– 5-year window around the placebo year. The resulting 723 control hospitals are 'stacked' with the extracted treatment group hospitals to create a balanced eleven-year panel of hospitals—all centered on their true year of 340B participation or their false (placebo) year of participation. The DD estimation is then able to follow the standard approaches for uniform treatment timing:

$$Y_{ht} = \alpha_h + \eta_t + \delta(Treated_h \times Post_t) + \varepsilon_{ht} \tag{7}$$

$$Y_{ht} = \alpha_h + \eta_t + \sum_{\substack{j=-5 \\ j\neq -2}}^{5} \delta_j \, (Treated_h \times time = j) + \varepsilon_{ht} \tag{8}$$

We maintain hospital fixed effects (α_h), just as before, but now have 'stacked time' fixed effects (η_t) in place of our previous calendar year fixed effects in Sections III and IV. *Treated* takes the value of one for true 340B participants and zero for the control group hospitals. The standard errors are clustered at the hospital level throughout.

Table 7 offers summary statistics across the treatment and control group hospitals for the observation year that immediately precedes the true (for treated) or placebo (for control) 340B participation year by two years (e.g., 2010 status for hospitals becoming 340B participants in 2012 or control hospitals receiving 2012 as their randomly assigned placebo start year). Consistent with the treatment-control comparisons for the two prior economic shocks we investigated, the amount and mix of health IT adoption across the various subtypes is reasonably similar between our 340B hospitals and non-340B hospitals. Although, in the aggregate, the average control group hospital has deployed five more IT solutions when compared to the average treatment group hospital.

C. *Triple Differences Estimation*

Our motivations and implementation of the DDD estimation closely align with Sections III and IV. We again focus on hospitals with standalone status in 2009, standalone hospitals with negative operating margin over the period 2007-2009, and not-for-profit hospitals with above-median reported 990 assets in 2009. The estimation is effectively identical as the previous sections, just with the exception of 'stacked time,' rather than calendar year time, so that the *Post* variable takes the value of one for the 6th stacked year through the 11th stacked year for a given hospital in the stacked analytic sample.

$$\begin{aligned} Y_{ht} = \alpha_h + \eta_t + \lambda_1(Treated_h \times Post_t) + \\ \lambda_2(BaseCharac_h \times Post_t) + \\ \lambda_3(Treated_h \times Post_t \times BaseCharac_h) + \varepsilon_{ht} \end{aligned} \tag{9}$$

All other features of Equation (9) are shared with the estimation described by Equation (7).

D. *340B Participation Effects on Health IT Investments*

The raw trends for the average number of health IT solutions and health IT vendors are displayed in Figure 8. Eventual 340B hospitals persistently trailed their control group hospital peers until the year prior to being granted 340B status. The gap continues to shrink in the subsequent years and culminates in the treatment group overtaking the control group by the third year following 340B participation. These patterns are formally tested using the event study DD model and presented in Figure 9. Pre-period trending is stable between the treatment and control hospitals, with suggestive evidence of a differential change beginning in year $t = -1$. During the third to fifth post-period years, 340B participants differentially increase their health IT investments by 5-7 solutions on average, which translates to approximately a 10 percent increase over their prior levels (Table 7).

We can also use known features of the 340B program for a simple back-of-the-envelope exercise to benchmark the IT adoption effects against 340B financial changes in dollar terms. This is an added benefit from our 340B economic shock of interest in comparison to the prior two shocks investigated. To do so, we first note that over the 2010-2012 period (i.e., our treatment initiation years) the Congressional Budget Office calculates approximately \$6 billion in 340B discounted drug acquisitions by hospitals per year (CBO 2025).[24] Medicare payment rules further imply a positive margin of over one-third over acquisition cost for each 340B drug a hospital dispenses (MedPAC 2015; Federal Register 2017). We use one-third for simplicity, which is also likely conservative since markups can be greater in the commercially insured market. Applying this assumed margin to the total annual 340B drug acquisition spend and dividing the resulting profit estimate ($2 billion) by the total number of hospitals in the 340B program in 2011 (1,352 hospitals) implies a lower bound of $1.5 million in financial gain per 340B hospital per year. Recall, we observe newly participating 340B hospitals differentially increasing their health IT investments by five solutions over the first five participation years (Figure 8 and Figure 9). This translates to an additional health IT investment for roughly every $1.5 million dollars of additional net income, on average.[25]

Next, we move to our DDD heterogeneity explorations in Table 8. The estimations for standalone as well as standalone and financially weak DDD versions (columns 2 and 3) once again yield negative coefficients—though lack statistical precision. At the very least, it is clear that they are not solely responsible for the overall effect revealed in Figures 8 and 9 or column 1 of Table 8. Interestingly, when stratifying the treatment group hospitals by 2009 financial assets (among the hospitals with such information available), the effect seems to entirely load on those with relatively *more* financial reserves prior to becoming a 340B hospital. This pattern seems inconsistent with the view that liquidity was the primary hurdle to greater health IT investments—at least among this subgroup of hospitals where we can observe this proxy for baseline access to capital.

Appendix Tables D1-D3, along with Appendix Figure D1, provide the DD and event study results for the additional vendor outcomes, use of IT consultants outcome, as well as the health IT subtype outcomes. For the latter, the 340B participation effects appear more concentrated among the business-oriented IT solutions (Appendix Table D3) rather than clinically-oriented solutions (Appendix Table D2). The lone exception among the care delivery outcomes is laboratory health IT.

[24] The CBO reports approximately $7 billion in 340B drug acquisitions overall, with 87% of spending coming from hospitals.

[25] Of course, we should not conclude or assume that all additional income will be devoted to health IT, specifically. The financial benefits are likely to be spread diffusely throughout the hospital and its business units. This simple exercise is merely describing how a general, non-earmarked (positive) financial shock flows through the average hospital and eventually leads to additional health IT investments.

In Table 9, we again see no clear evidence of hospital capacity-building via total beds or operating rooms following the 340B supply-side profit shock. There is only mixed evidence with respect to the nurse hiring outcomes in columns 3-6 in Table 9. The DD results, and the corresponding event study estimates for statistically significant DD findings in Appendix Figure D2, indicate increased part-time RN and full-time LPN labor inputs but no clear changes for full-time RNs (the most common source of labor).

VI. Summary of Results across Three Shocks

Before concluding our main empirics, we highlight and summarize key findings pertaining to all three economic shocks previously investigated. Each shock caused hospital managers to adjust their health IT purchasing behavior in the expected directions and to a meaningful degree. These are novel findings for the IT adoption literature as well as the literatures individually focused on the Great Recession, ACA Medicaid expansions, and the 340B program, respectively. Our heterogeneity analyses and our exploration of supplementary outcomes then aimed to unpack these overall findings to better understand if a subset of hospitals drive the results, and relatedly, explore the economic considerations influencing managers' decision-making.

Across the three shocks, we do not find that hospitals in weaker financial positions are responsible for the overall effects identified. This finding reveals two important implications: (1) these economic shocks reverberate broadly across the nearly $2 trillion US hospital industry and (2) liquidity constraints are unlikely to solely restrain hospitals' IT investments. Additionally, our event study evidence from Medicaid expansions and 340B participation suggest hospitals responded when their expectations changed (i.e., before substantive changes in cash flows were likely realized). This pattern is more consistent with IT adoption behavior responding to uncertainty about future revenue streams than contemporaneous liquidity constraints.

Furthermore, we find little support for a demand-side channel driving hospitals' IT response to these shocks. Hospitals' patient capacity, as proxied by total beds, operating rooms available, and nursing workforce, do not adjust to these three economic shocks in a consistent way—revealing a stark contrast between the IT adoption effects and other recent studies focused on the Medicare revenue and organizational management effects (e.g., Gross *et al*. 2022; Richards, Shi, and Whaley 2024).[26] Additionally, we find similar IT responses when we examine hospital-level 340B participation, which delivers a financial shock to hospitals but largely leaves patient demand unchanged. Thus, we view these results as more cleanly capturing the direct influence of the hospital industry's financial circumstances on health IT adoption.

VII. Health IT Vendor Market Analyses

A. *Difference-in-Differences Estimation*

Our final set of empirical analyses leverages the HIMSS analytic data to re-examine our macro shocks (i.e., the Great Recession and the ACA Medicaid expansions), but this time focusing on the impact on health IT vendors' geographic entry and exit behavior. The DD research designs parallel Section III and Section IV, but we now collapse the data to the county level and the state level, respectively. Doing so allows us to construct county (state) level measures of unique software vendors with at least one hospital contract in a given county (state), the number of vendors entering a given county (state) in a given year, and the number of vendors exiting a given county (state) in a given year. We then create a proxy measure of market competition prevailing in a given county (state) and year for each of our subtypes of health IT (e.g., laboratory, financials, staffing, etc.). We specifically use a Herfindahl-Hirschman Index (HHI) measure based on the relevant geography-by-time market share belonging to a given vendor selling in a particular health IT market. A vendor's calculated market share is the fraction of all unique vendor-hospital contracts observed in the specific geography and type of health IT in a given year.

The DD and event study estimations closely follow those from Sections III and IV. For the Great Recession analyses, we use:

$$Y_{ct} = \gamma_c + \theta_t + \delta(Treated_c \times Post_t) + \varepsilon_{ct} \tag{10}$$

[26] In additional analyses, we explored proxies for demand changes using overall patient volume measured in two different ways from two different sources for each of our three shocks in Appendix Table D4. None of the three shocks generated an analogous change for these demand-focused outcomes. In fact, the only statistically significant results are for the ACA Medicaid expansions, but these DD estimates are negatively signed, which casts further doubt on changes in patient demand as the key driver of hospitals' health IT purchasing decisions.

$$Y_{ct} = \gamma_c + \theta_t + \sum_{\substack{j=2005 \\ j\neq 2006}}^{2012} \delta_j \, (Treated_c \times time = j) + \varepsilon_{ct} \tag{11}$$

Equations (10) and (11) each include county (γ_c) and calendar year (θ_t) fixed effects. *Treated* is equal to one for counties located in the top quartile of Great Recession severity and zero for counties located in the bottom quartile. The *Post* variable is set to one for the 2008-2012 period, and the standard errors are clustered at the county level.

For the 2014 ACA Medicaid expansion analyses, the estimating equations become:

$$Y_{st} = \pi_s + \theta_t + \delta(Treated_s \times Post_t) + \varepsilon_{st} \tag{12}$$

$$Y_{st} = \pi_s + \theta_t + \sum_{\substack{j=2009 \\ j\neq 2012}}^{2017} \delta_j \, (Treated_s \times time = j) + \varepsilon_{st} \tag{13}$$

Equations (12) and (13) each include state (π_s) and year (θ_t) fixed effects, paralleling what was done in Section IV. Now, the treatment indicator (i.e., *Treated*) is equal to one for the nineteen 2014 Medicaid expansion states and zero for the nineteen non-expansion states. The *Post* variable is set to one for the 2014-2017 period, and the standard errors are clustered at the state level.

B. *Recession and Medicaid Expansion Effects on Vendor Markets*

Tables 10 and 11 provide the vendor market effects from the Great Recession. The DD results show a pattern similar to what was documented for hospital-level IT adoption in Section III. The total number of IT vendors falls by approximately 7 percent for counties most severely impacted by the recession (column 1, Table 10). Most of the net effect is unsurprisingly driven by reduced market entry—approximately 25 percent below baseline levels. The corresponding event study results are in Appendix Figure E1 and support a causal interpretation. With reduced entry and fewer vendors overall, it is also unsurprising that market concentration increases—at least among five of the ten domains of health IT examined (Table 11). The event study patterns in Appendix Figure E2 reinforce this interpretation. However, it should be noted that each of these specific health IT markets at the county level is highly concentrated at baseline. The economic implications of these changes are therefore likely to be limited. Interestingly, the ACA Medicaid expansions did not obviously influence software vendors' willingness to enter or exit an affected state. The DD estimates are modest and fail to reach statistical significance in Table 12. The state-level HHI measures offer no clear pattern either. The DD estimates oscillate in sign and are uniformly noisy in Table 13.

VIII. Conclusions

Information technology is a known opportunity for firms to enhance business functions and improve performance on a host of productivity and financial metrics. However, IT adoption can be costly and risky, with much of the payoff realized over the long-run. How managers balance these tradeoffs when considering an IT investment could be further influenced by economic shocks that affect their bottom lines and market expectations for the future. A better understanding of such investment sensitivities can help explain uneven IT take-up across firms as well as inform directly and indirectly related policy discourse.

Leveraging rich data from the hospital industry and three substantive and well-defined economic shocks, we provide novel evidence that hospital managers' decisions over the marginal health IT investment are highly responsive to fluctuations in financial circumstances. Economic downturns restrain investment while public insurance expansions and hospital-specific (non-IT) subsidies promote it. In other words, hospitals demonstrate consistent and symmetrical actions when facing negative or positive financial shocks. We also find corresponding and dynamic effects across a wide range of health IT types, spanning clinical- as well as business-focused solutions.

The observed changes in IT investment are not closely mirrored along other prominent hospital spending margins: physical capacity building (i.e., beds and operating rooms) or nursing workforce. This contrasts with recent economics work showing that reimbursement changes as well as organizational shifts affect hospitals' short-run spending and investment behavior along these dimensions (e.g., Gross *et al*. 2022; Gupta, La Forgia, and Sacarny 2024; Richards, Shi, and Whaley 2024; Richards and Whaley 2024). At a minimum, the juxtaposition of our findings across hospital spending domains (i.e., IT, patient capacity, and nurse labor) makes clear that hospitals respond on the IT investment margin differently when facing changes in financial and market circumstances. This is a novel empirical insight that can also help explain the uneven adoption patterns within the healthcare sector, despite long-running efforts to stimulate it.

When considering the underlying drivers of the IT investment changes, our heterogeneity analyses do not suggest that the response is confined to the most liquidity-constrained hospitals. The positive effects on these capital investments from Medicaid expansions and 340B participation also suggest some anticipatory behavior change. Similarly, the lack of corresponding responses in physical capacity and staffing, along with the sharp IT effects from a largely financial shock (i.e., 340B), do not align well with changes in patient demand driving IT adoption behavior. Instead, we argue that they are consistent with changes to hospital managers' perceptions of uncertainty playing an influential role over the IT adoption margin. This implies scope for policy to shape IT investment activity by reducing market uncertainty or offering greater revenue stability, which could bolster or even outperform direct subsidies to firms.

Our specific and novel findings for Medicaid expansions and 340B participation also carry substantive policy relevance in their own right. Garthwaite, Gross, and Notowidigdo (2018) calculate that the implied "savings" for states refusing to expand Medicaid through the ACA is smaller in magnitude than the size of the uncompensated care costs imposed on their hospitals by not expanding. We show another, and previously overlooked, indirect consequence of state policymakers' decisions—namely, they are also restraining technological investment among their local healthcare providers. And while Medicaid expansions and 340B subsidized drug availability may directly involve narrow patient populations, the health IT investments we document have the potential to generate positive externalities to much wider patient-payer groups and broader hospital business functioning over time.[27] Ignoring these downstream consequences from these programs could understate their social returns.

[27] Of note, empirical work from Carey *et al*. (2020) and Barkowski, Jun, and Zhang (2025) do not find near-term access to care or utilization spillovers from Medicaid expansions onto other patient groups.

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MAIN RESULTS

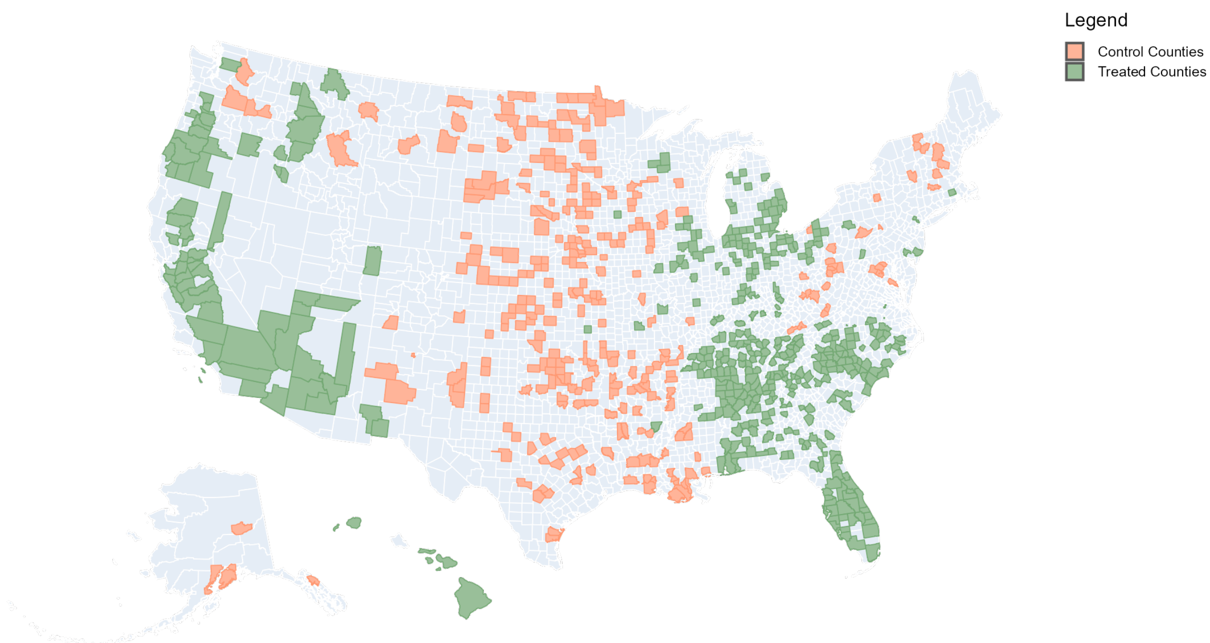


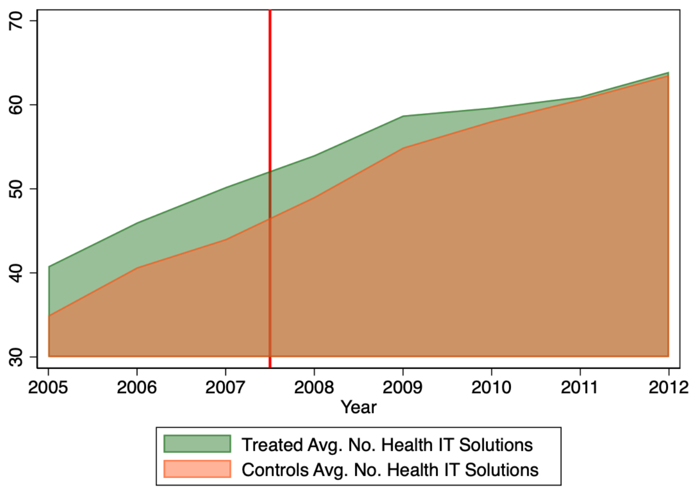
FIG 1. COUNTY LEVEL ANALYTIC SAMPLE INCLUSION STATUS BY INTENSITY OF GREAT RECESSION

Notes: Counties with treatment group hospitals are those in the top quartile of percentage-point change between 2007 and 2009. Counties with control group hospitals are those in the bottom quartile of percentage-point change in the unemployment rate between 2007 and 2009. All other counties are excluded from the analytic sample.

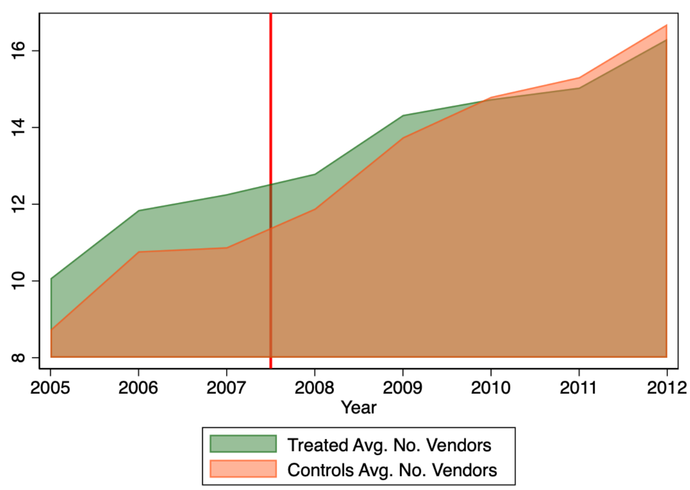
TABLE 1—SUMMARY STATISTICS FOR HEALTH IT SOLUTIONS ADOPTION 2005-2007 STRATIFIED BY GREAT RECESSION INTENSITY

	Top Quartile of Recession Bite	**Bottom Quartile of Recession Bite**
	Mean (SD)	Mean (SD)
Total Health IT Solutions	45.7 (13.9)	39.9 (17.0)
Total Health IT Vendors	11.4 (4.4)	10.2 (4.8)
Care Delivery Health IT Solutions		
Clinical Service Line	9.6 (6.0)	7.9 (6.3)
EHR	2.9 (1.8)	2.5 (1.9)
Laboratory	2.8 (1.4)	2.3 (1.6)
Pharmacy	0.9 (0.4)	0.7 (0.4)
Administrative Health IT Solutions		
Back-Office	0.3 (0.6)	0.4 (0.7)
Financials	10.5 (3.1)	9.2 (3.6)
Info Systems	8.4 (3.2)	7.8 (3.5)
Staffing	7.5 (2.9)	6.6 (3.3)
Supply Chain	1.2 (0.5)	1.0 (0.6)
Utilization Review	1.7 (0.8)	1.5 (0.9)
Hospitals (N)	864	455

Notes: Analytic data are from HIMSS matched to AHA data to recover hospital county location and span 2005 to 2007 for a balanced panel of hospitals used in the main difference-in-differences estimations. "Recession Bite" reflects the county-level change in unemployment rate between 2007 and 2009.



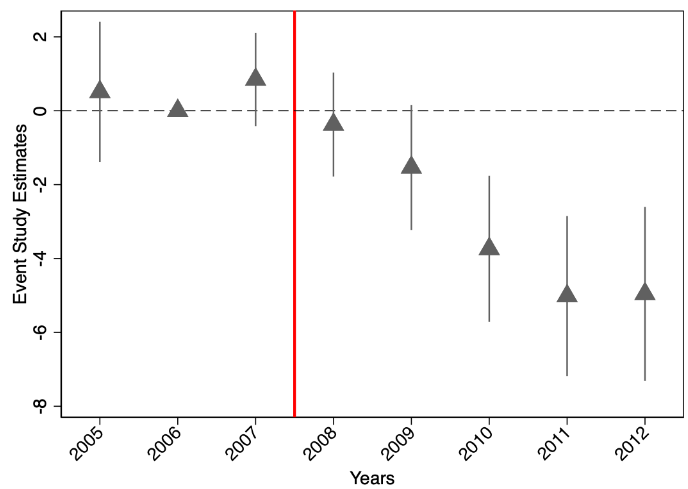
(a) Total Health IT Solutions



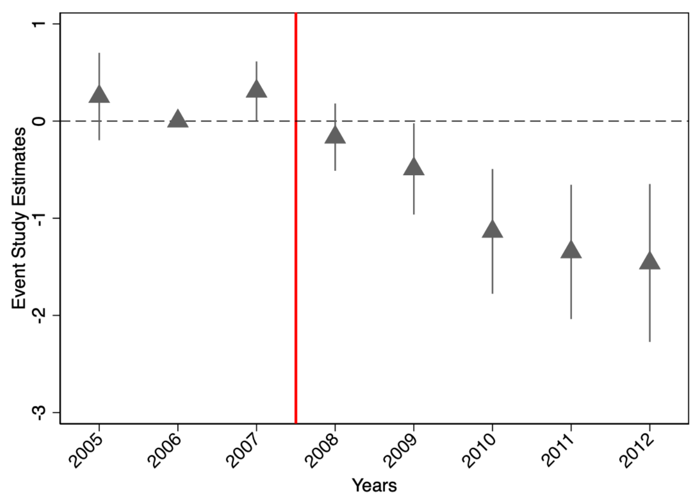
(b) Total Health IT Vendors

FIG. 2. TRENDS IN OUTCOMES FOR GREAT RECESSION SHOCK TREATMENT AND CONTROL HOSPITALS

Notes: Solid vertical bar indicates the start of the Great Recession following the Lehman Brothers investment bank collapse in 2008.



(a) Total Health IT Solutions



(b) Total Health IT Vendors

FIG. 3. EVENT STUDY ESTIMATES FOR GREAT RECESSION EFFECTS ON IT ADOPTION AND CONTRACTING

Notes: Solid vertical bar indicates the start of the Great Recession following the Lehman Brothers investment bank collapse in 2008.

TABLE 2—GREAT RECESSION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) ADOPTION AND HOSPITAL LEVEL HETEROGENEITY

	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions
	(1)	(2)	(3)	(4)
Severe Recession x Post	–3.577*** (0.734)	–4.019*** (0.993)	–3.650*** (0.799)	–6.650*** (1.242)
DDD Estimates				
Severe Recession x Post x Standalone		1.294 (1.412)		
Severe Recession x Post x Standalone & Financially Weak			1.478 (2.029)	
Severe Recession x Post x High Assets				5.934*** (2.240)
Share Treated with Third 'D' = 1	--	0.37	0.15	0.45
Share Controls with Third 'D' = 1	--	0.39	0.14	0.35
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Hospitals	1,319	1,274	1,267	732
Observations	10,552	10,192	10,136	5,856

Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the FIPS level. "Standalone" hospitals are those with no system affiliation as of 2007. "Financially Weak" are hospitals with an average negative operating margin over the 2005-2007 period. "High Assets" are not-for-profit hospitals with above median financial assets reported on IRS 990 forms in 2007. *** P value at 0.01 ** P value at 0.05

TABLE 3—GREAT RECESSION EFFECTS ON HOSPITAL REAL ASSETS AND NURSE HIRING

	Total Beds	Total Operating Rooms	Full-Time RNs	Part-Time RNs	Full-Time LPNs	Part-Time LPNs
	(1)	(2)	(3)	(4)	(5)	(6)
Severe Recession x Post	–2.599 (2.628)	0.018 (0.167)	8.042 (7.041)	–9.016*** (3.065)	–1.131 (0.856)	–0.548 (0.492)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospitals	1,315	1,254	1,315	1,315	1,315	1,315
Observations	10,421	8,325	10,421	10,421	10,421	10,421
Treated Pre-Period Mean	209.5	9.3	242.1	116.1	22.8	8.9
Controls Pre-Period Mean	178.6	8.2	191.9	93.0	26.5	10.6

Notes: Analytic data are derived from merging main sample from Table 2 column 1 with AHA data. Not all HIMSS hospitals are present in AHA surveys for all years or have complete information for all AHA variables in all years. “RN” stands for registered nurse while “LPN” stands for licensed practical nurse. Standard errors clustered at the FIPS level. *** P value at 0.01 ** P value at 0.05

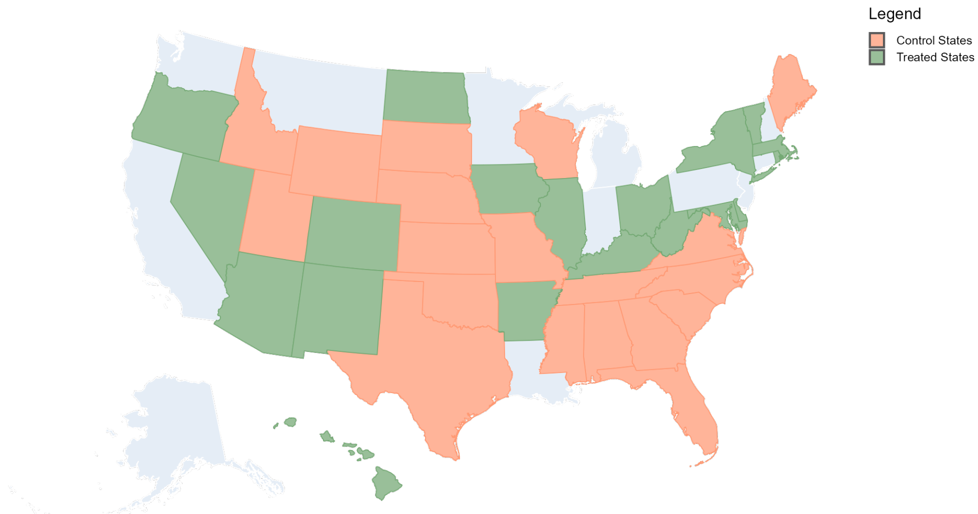


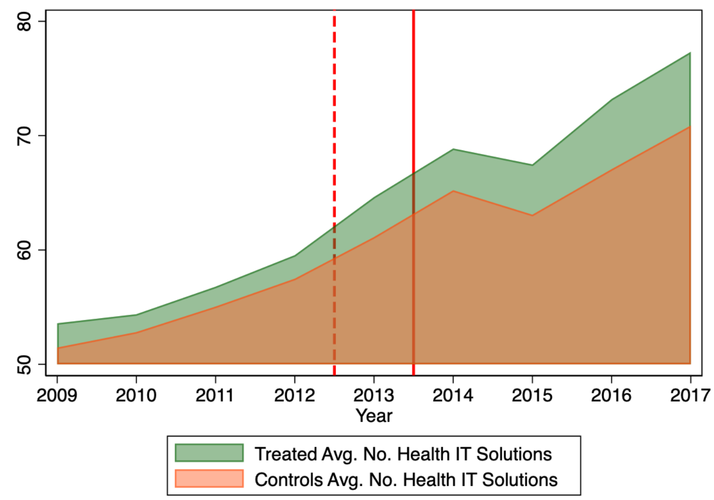
FIG 4. STATE LEVEL ANALYTIC SAMPLE INCLUSION STATUS BY MEDICAID EXPANSION STATUS THROUGH 2017

Notes: Treatment, control, and exclusion criteria follow Brevoort, Grodzicki, and Hackmann (2020). There are 19 treatment states in total and 19 control states in total. Excluded states are a mixture of early and late expansion adopters.

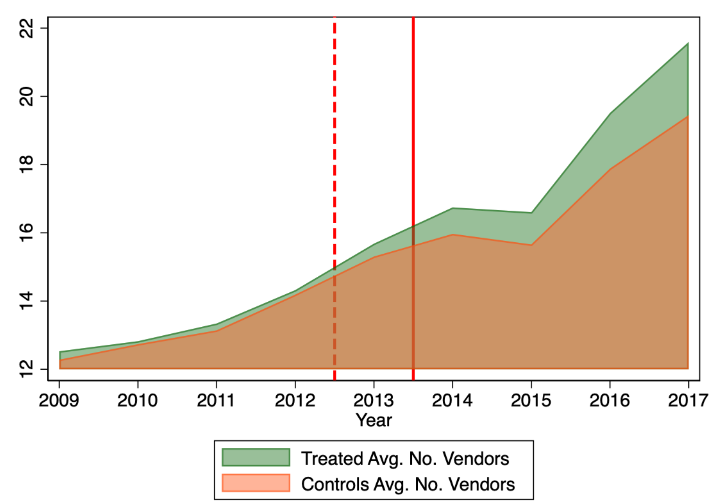
TABLE 4—SUMMARY STATISTICS FOR HEALTH IT SOLUTIONS ADOPTION 2009-2012
STRATIFIED BY ACA MEDICAID EXPANSION STATUS

	2014 Medicaid Expansion States	**Non-Expansion States**
	Mean (SD)	Mean (SD)
Total Health IT Solutions	57.3 (18.1)	55.9 (21.1)
Total Health IT Vendors	13.7 (6.4)	13.6 (7.5)
Care Delivery Health IT Solutions		
Clinical Service Line	14.4 (6.3)	13.3 (7.0)
EHR	4.0 (2.1)	3.9 (2.1)
Laboratory	3.5 (1.6)	3.1 (1.7)
Pharmacy	0.9 (0.3)	0.9 (0.3)
Administrative Health IT Solutions		
Back-Office	2.0 (1.1)	1.9 (1.2)
Financials	11.5 (3.6)	11.7 (4.0)
Info Systems	10.2 (4.0)	10.4 (4.7)
Staffing	7.9 (3.1)	7.7 (3.4)
Supply Chain	1.2 (0.6)	1.2 (0.6)
Utilization Review	1.8 (1.1)	1.8 (1.2)
Hospitals (N)	1,181	1,737

Notes: Analytic data are from HIMSS and span 2009-2012 for a balanced panel of hospitals used in the main difference-in-differences estimations.



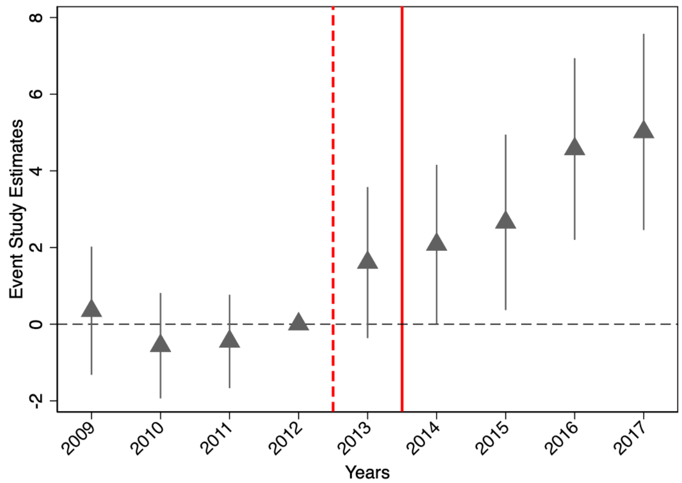
(a) Total Health IT Solutions



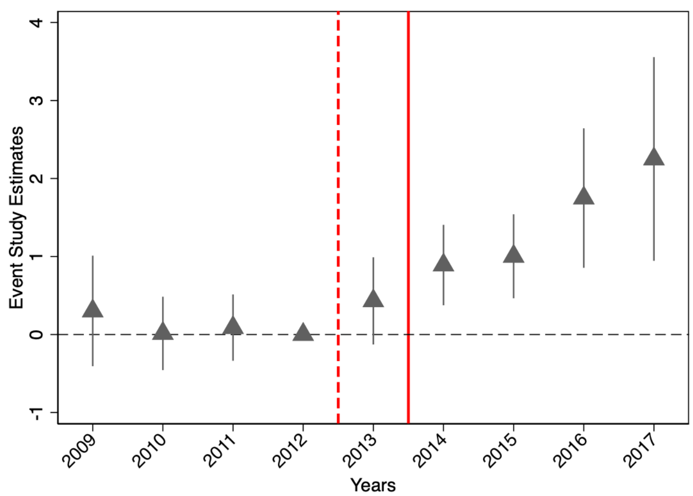
(b) Total Health IT Vendors

FIG. 5. TRENDS IN OUTCOMES FOR ACA MEDICAID EXPANSION SHOCK TREATMENT AND CONTROL HOSPITALS

Notes: Solid vertical bar indicates the start of the Medicaid expansions in 2014. The dashed vertical bar represents the period between the summer 2012 Supreme Court decision and 2014 expansion implementation.



(a) Total Health IT Solutions



(b) Total Health IT Vendors

FIG. 6. EVENT STUDY ESTIMATES FOR ACA MEDICAID EXPANSION EFFECTS ON IT ADOPTION AND CONTRACTING

Notes: Solid vertical bar indicates the start of the Medicaid expansions in 2014. The dashed vertical bar represents the period between the summer 2012 Supreme Court decision and 2014 expansion implementation.

TABLE 5—MEDICAID EXPANSION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) ADOPTION AND HOSPITAL LEVEL HETEROGENEITY

	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions
	(1)	(2)	(3)	(4)	(5)
Medicaid Expansion x Post	3.391*** (0.827)	4.569*** (1.537)	5.281*** (1.352)	4.779*** (1.084)	4.409*** (1.471)
DDD Estimates					
Medicaid Expansion x Post x High Uninsured		–2.412 (1.687)			
Medicaid Expansion x Post x Standalone			–3.902** (1.781)		
Medicaid Expansion x Post x Standalone & Financially Weak				–3.994** (2.000)	
Medicaid Expansion x Post x High Assets					–1.350 (3.173)
Share Treated with Third 'D' = 1	--	0.29	0.36	0.15	0.57
Share Controls with Third 'D' = 1	--	0.70	0.26	0.11	0.38
Hospital FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Hospitals	2,918	1,901	1,993	1,980	1,271
Observations	26,262	17,109	17,925	17,808	11,439

Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the state level. "High Uninsured" represents above median predicted market share of uninsured patients in 2012 (Garthwaite, Ody, and Starc 2022). "Standalone" hospitals are those with no system affiliation as of 2012. "Financially Weak" are hospitals with an average negative operating margin over the 2009-2012 period. "High Assets" is based on not-for-profit hospitals' IRS 990 reporting in 2012 and is equal to one for hospitals above the median. *** P value at 0.01 ** P value at 0.05

TABLE 6—MEDICAID EXPANSION EFFECTS ON HOSPITAL REAL ASSETS AND NURSE HIRING

	Total Beds	Total Operating Rooms	Full-Time RNs	Part-Time RNs	Full-Time LPNs	Part-Time LPNs
	(1)	(2)	(3)	(4)	(5)	(6)
Medicaid Expansion x Post	–4.176**	0.243	8.115	0.018	0.412	–0.360
	(2.075)	(0.254)	(5.639)	(3.076)	(0.755)	(0.309)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospitals	2,887	2,733	2,887	2,887	2,887	2,887
Observations	25,635	20,588	25,635	25,635	25,635	25,635
Treated Pre-Period Mean	188.4	9.6	263.2	121.4	15.7	6.2
Controls Pre-Period Mean	163.1	8.5	217.7	79.6	16.9	5.0

Notes: Analytic data are derived from merging main sample from Table 5 column 1 with AHA data. Not all HIMSS hospitals are present in AHA surveys for all years or have complete information for all AHA variables in all years. "RN" stands for registered nurse while "LPN" stands for licensed practical nurse. Standard errors clustered at the state level. *** P value at 0.01 ** P value at 0.05

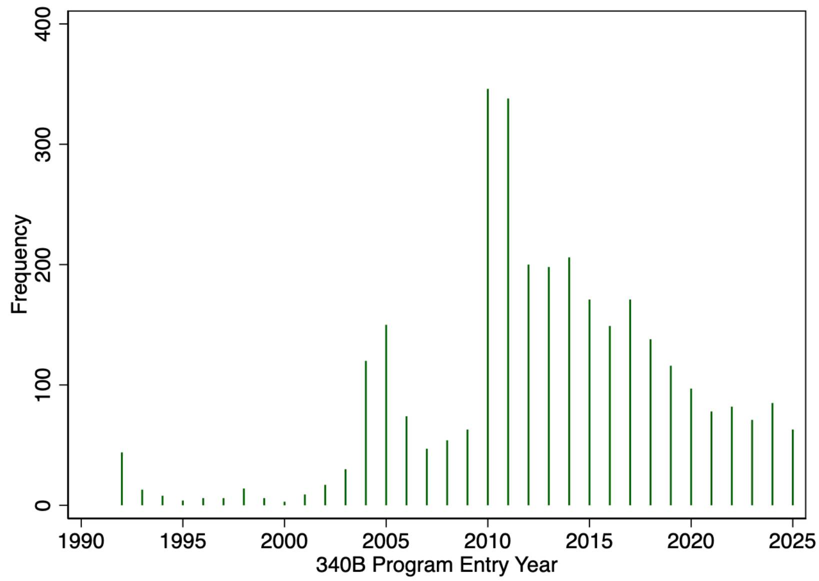


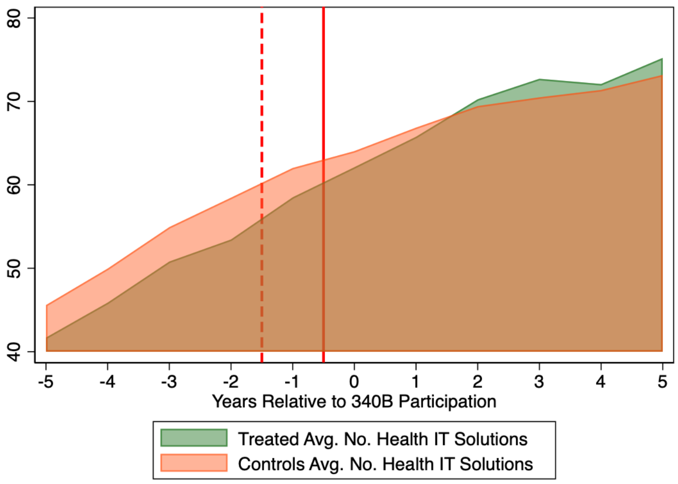
FIG. 7. NEW HOSPITAL 340B PARTICIPATION BY YEAR

Notes: Data capture first year of participation in the federal 340B prescription drug discount program at the hospital level and nationally.

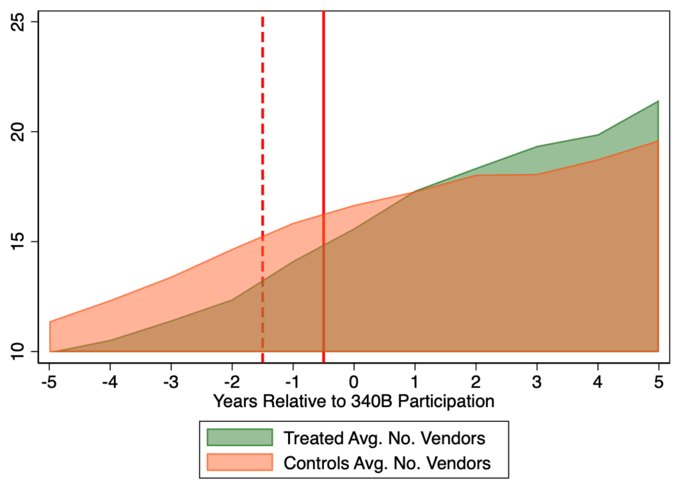
TABLE 7—SUMMARY STATISTICS FOR HEALTH IT SOLUTIONS ADOPTION TWO YEARS PRIOR TO 340B SHOCK STRATIFIED BY TREATMENT VERSUS CONTROL STATUS

	340B Participating Treated Group Hospitals	**Control Group Hospitals**
	Mean (SD)	Mean (SD)
Total Health IT Solutions	53.5 (16.5)	58.5 (16.1)
Total Health IT Vendors	12.4 (5.6)	14.7 (5.9)
Care Delivery Health IT Solutions		
Clinical Service Line	12.2 (6.0)	13.7 (6.2)
EHR	3.4 (1.8)	3.7 (1.7)
Laboratory	2.9 (1.5)	3.3 (1.4)
Pharmacy	0.9 (0.3)	0.9 (0.3)
Administrative Health IT Solutions		
Back-Office	1.9 (1.0)	1.8 (1.1)
Financials	11.1 (3.6)	12.3 (3.4)
Info Systems	10.5 (4.0)	11.3 (3.8)
Staffing	7.6 (3.2)	8.2 (2.8)
Supply Chain	1.2 (0.5)	1.2 (0.5)
Utilization Review	1.8 (1.0)	2.0 (0.9)
Hospitals (N)	121	723

Notes: Analytic data are from HIMSS, and the underlying data are a balanced panel of hospitals 'stacked' around the year of participation for the treatment group hospitals and the randomly assigned placebo year for the control group hospitals. All treatment and control group hospitals are restricted to ACA Medicaid Non-Expansion states (i.e., control states in Figure 4). Summary statistics reflect hospitals' IT adoption patterns two years prior to participating in 340B (treated) or the randomly assigned placebo year (controls).



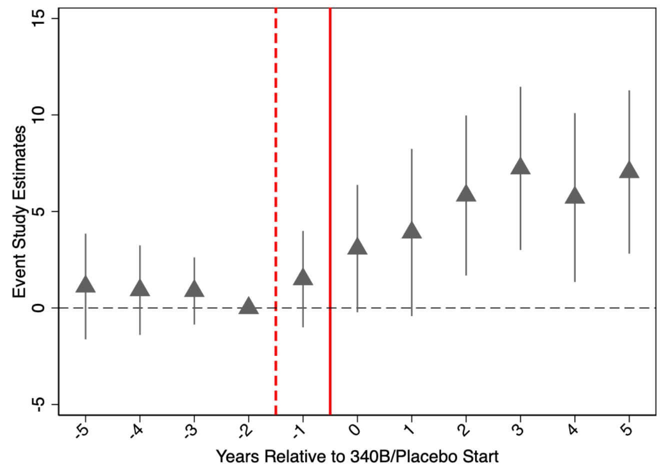
(a) Total Health IT Solutions



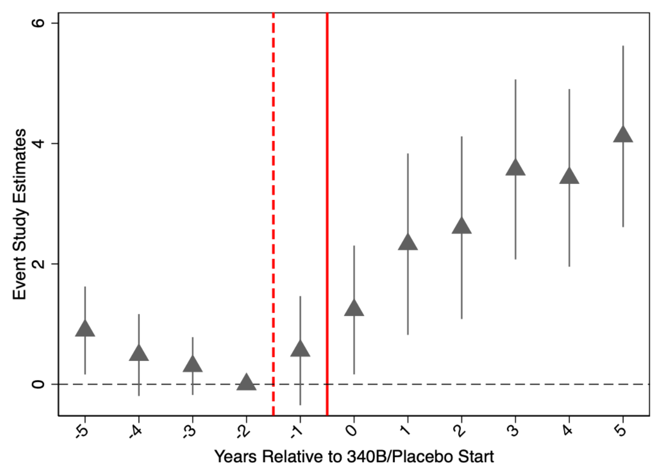
(b) Total Health IT Vendors

FIG. 8. TRENDS IN OUTCOMES FOR 340B PARTICIPATION SHOCK TREATMENT AND CONTROL HOSPITALS

Notes: Solid vertical bar indicates the start of the post-period. The dashed vertical line indicates the presumed program application period. The underlying data are 'stacked' around the year of participation for the treatment group hospitals and the randomly assigned placebo year for the control group hospitals. All treatment and control group hospitals are restricted to ACA Medicaid Non-Expansion states (i.e., control states in Figure 4).



(a) Total Health IT Solutions



(b) Total Health IT Vendors

FIG. 9. EVENT STUDY ESTIMATES FOR 340B PARTICIPATION EFFECTS ON IT ADOPTION AND CONTRACTING

Notes: Solid vertical bar indicates the start of the post-period. The dashed vertical line indicates the presumed program application period. The underlying data are 'stacked' around the year of participation for the treatment group hospitals and the randomly assigned placebo year for the control group hospitals. All treatment and control group hospitals are restricted to ACA Medicaid Non-Expansion states (i.e., control states in Figure 4).

TABLE 8—340B PARTICIPATION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) ADOPTION AND HOSPITAL LEVEL HETEROGENEITY

	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions	Total Health IT Solutions
	(1)	(2)	(3)	(4)
340B Participation x Post	4.587*** (1.472)	5.820*** (2.005)	4.950*** (1.691)	–0.400 (2.328)
DDD Estimates				
340B Participation x Post x Standalone		–4.396 (3.059)		
340B Participation x Post x Standalone & Financially Weak			–4.165 (4.374)	
340B Participation x Post x High Assets				7.542** (3.665)
Share Treated with Third 'D' = 1	--	0.35	0.16	0.37
Share Controls with Third 'D' = 1	--	0.22	0.11	0.38
Hospital FE	Yes	Yes	Yes	Yes
Stacked Year FE	Yes	Yes	Yes	Yes
Hospitals	844	792	788	402
Observations	9,284	8,712	8,668	4,422

Notes: Analytic data are from HIMSS and include a balanced panel of hospitals with 'stacked' analytic data around 340B participation year (treated) or randomly assigned placebo year (controls). Standard errors clustered at the hospital level. "Standalone" hospitals are those with no system affiliation as of 2009. "Financially Weak" are hospitals with an average negative operating margin over the 2007-2009 period. "High Assets" is based on not-for-profit hospitals' IRS 990 reporting in 2009 and is equal to one for hospitals above the median. *** P value at 0.01 ** P value at 0.05

TABLE 9—340B PARTICIPATION EFFECTS ON HOSPITAL REAL ASSETS AND NURSE HIRING

	Total Beds	Total Operating Rooms	Full-Time RNs	Part-Time RNs	Full-Time LPNs	Part-Time LPNs
	(1)	(2)	(3)	(4)	(5)	(6)
340B Participation x Post	8.087 (5.296)	0.425 (0.327)	30.524 (17.822)	16.428** (6.904)	3.253*** (1.161)	0.605 (0.631)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospitals	830	807	830	830	830	830
Observations	8,996	7,119	8,996	8,996	8,996	8,996
Treated 2 Years Prior Mean	175.7	9.5	267.6	115.4	16.8	5.9
Controls 2 Years Prior Mean	180.1	9.0	207.2	85.3	18.9	6.1

Notes: Analytic data are derived from merging main sample from Table 8 column 1 with AHA data. Not all HIMSS hospitals are present in AHA surveys for all years or have complete information for all AHA variables in all years. "RN" stands for registered nurse while "LPN" stands for licensed practical nurse. Standard errors clustered at the hospital level. *** P value at 0.01 ** P value at 0.05

TABLE 10—GREAT RECESSION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) VENDOR BEHAVIOR AT THE COUNTY LEVEL

	Total Health IT Vendors	Total Vendor Entry	Total Vendor Exit
	(1)	(2)	(3)
Severe Recession x Post	–1.053***	–1.129***	–0.362***
	(0.418)	(0.159)	(0.086)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Counties	735	735	735
Observations	5,880	5,880	5,880
Treated Pre-Period Mean	15.4	4.2	2.3
Controls Pre-Period Mean	12.4	3.4	1.9

Notes: Analytic data are from HIMSS and include a balanced panel of counties (unique FIPS). Standard errors clustered at the FIPS level. *** P value at 0.01 ** P value at 0.05

TABLE 11—GREAT RECESSION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) VENDOR MARKET CONCENTRATION (HHI) AT THE COUNTY LEVEL BY TECHNOLOGY PURPOSE

	Clinical Serv. HHI	EHR HHI	Laboratory HHI	Pharmacy HHI	Back-Office HHI	Financials HHI	Info Systems HHI	Staffing HHI	Supply Chain HHI	Util. Rev. HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Severe Recession x Post	123.7 (127.4)	–0.1 (145.6)	138.3 (115.6)	291.2*** (110.5)	126.2 (248.0)	405.3*** (131.5)	207.5*** (81.7)	358.3*** (104.9)	75.1 (110.9)	315.4** (140.4)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Counties	735	730	730	727	718	735	735	735	734	722
Observations	5,645	5,395	5,447	5,253	4,174	5,814	5,873	5,843	5,552	5,365
Treated Pre-Period Mean	5,425	7,813	8,201	8,602	7,932	5,646	2,932	4,349	8,285	7,426
Controls Pre-Period Mean	5,766	8,000	8,264	8,856	7,737	6,406	3,287	4,993	8,378	7,781

Notes: Analytic data are from HIMSS and derived from the county-level analytic sample used in Table 10. Standard errors clustered at the FIPS level. *** P value at 0.01 ** P value at 0.05

TABLE 12—ACA MEDICAID EXPANSION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) VENDOR BEHAVIOR AT THE STATE LEVEL

	Total Health IT Vendors	Total Vendor Entry	Total Vendor Exit
	(1)	(2)	(3)
Medicaid Expansion x Post	5.147 (6.926)	3.500 (3.256)	–0.505 (1.129)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
States	38	38	38
Observations	342	342	304
Treated Pre-Period Mean	156.6	23.0	11.4
Controls Pre-Period Mean	187.9	28.5	13.8

Notes: Analytic data are from HIMSS and aggregated to the state level. Standard errors clustered at the state level. *** P value at 0.01 ** P value at 0.05

TABLE 13—MEDICAID EXPANSION EFFECTS ON HEALTH INFORMATION TECHNOLOGY (IT) VENDOR MARKET CONCENTRATION (HHI) AT THE STATE LEVEL BY TECHNOLOGY PURPOSE

	Clinical Serv. HHI	EHR HHI	Laboratory HHI	Pharmacy HHI	Back-Office HHI	Financials HHI	Info Systems HHI	Staffing HHI	Supply Chain HHI	Util. Rev. HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Medicaid Expansion x Post	–3.9 (43.8)	182.7 (193.5)	–58.9 (171.4)	99.2 (209.3)	63.0 (110.6)	64.3 (133.5)	–10.6 (31.2)	–19.9 (52.1)	–130.9 (157.6)	57.3 (133.5)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States	38	38	38	38	38	38	38	38	38	38
Observations	342	342	342	342	342	342	342	342	342	342
Treated Pre-Period Mean	1,131	1,734	2,275	2,040	916	1,331	720	987	2,059	1,558
Controls Pre-Period Mean	1,112	1,483	1,835	1,742	963	1,229	651	879	1,776	1,442

Notes: Analytic data are from HIMSS and derived from the state-level analytic sample used in Table 12. Standard errors clustered at the state level. *** P value at 0.01 ** P value at 0.05

Appendix A

This appendix presents a simple real-options model of hospital IT adoption, adapted from Pindyck (1991). Its purpose is to formalize the economic logic described in Section I: IT is a sunk investment whose returns amplify the hospital's revenue base, and hospitals can either invest before uncertainty is resolved or delay adoption until they learn more about the revenue environment.

Setup

Time is discrete and the horizon is infinite. The hospital discounts future payoffs at rate $r > 0$. At the beginning of the model, the hospital faces uncertainty over its future revenue state. With probability q, the hospital is in a high-revenue state and receives R_H in each period. With probability $1 - q$, it is in a low-revenue state and receives R_L in each period, where $R_H > R_L > 0$. The revenue state is realized at $t = 0$ and then persists forever.

The hospital decides whether and when to adopt IT. It can adopt immediately, before observing the revenue state, or it can wait one period and make the adoption decision at $t = 1$ after the state has been observed. This timing captures the idea that IT investment opportunities are not one-time offers: hospitals can contract with vendors later, but delaying adoption postpones any potential productivity gains.

Adoption requires a sunk cost $I > 0$. Once adopted, IT raises the hospital's per-period payoff from R_s to $(1 + \alpha)R_s$ in state $s \in \{H, L\}$, with $\alpha > 0$, capturing the revenue-amplifying role of IT. We focus on the nontrivial case in which, once the revenue state is known, adoption is profitable in the high state but not in the low state:

Assumption 1. At $t = 1$, after the revenue state has been observed, the hospital strictly prefers to adopt in the high-revenue state and strictly prefers not to adopt in the low-revenue state:

$$\frac{\alpha R_L(1 + r)}{r} < I < \frac{\alpha R_H(1 + r)}{r}.$$

Assumption 1 ensures that waiting has option value. By waiting, the hospital preserves the ability to adopt if the high-revenue state is realized while avoiding the sunk cost if the low-revenue state is realized.

The hospital compares two strategies: adopting immediately at $t = 0$ or waiting until $t = 1$.

Adopt immediately.

If the hospital adopts at $t = 0$, it pays the sunk cost before observing the revenue state and receives the IT-enhanced payoff in every period thereafter. The net present value (NPV) of immediate adoption is

$$NPV_0 = -I + (1 + \alpha)\frac{1 + r}{r}[qR_H + (1 - q)R_L].$$

Wait to adopt.

If the hospital waits, it receives the unenhanced revenue flow at $t = 0$. At $t = 1$, it has observed the state and adopts only in the high state. Under Assumption 1, the expected present value of waiting is

$$NPV_1 = [qR_H + (1-q)R_L] + q\left[-\frac{I}{1+r} + \frac{(1+\alpha)R_H}{r}\right] + (1-q)\frac{R_L}{r}.$$

The first term is revenue in period $t = 0$ before adoption. The second term is the discounted value of adopting at $t = 1$ in the high-revenue state. The third term is the value of remaining unadopted in the low-revenue state.

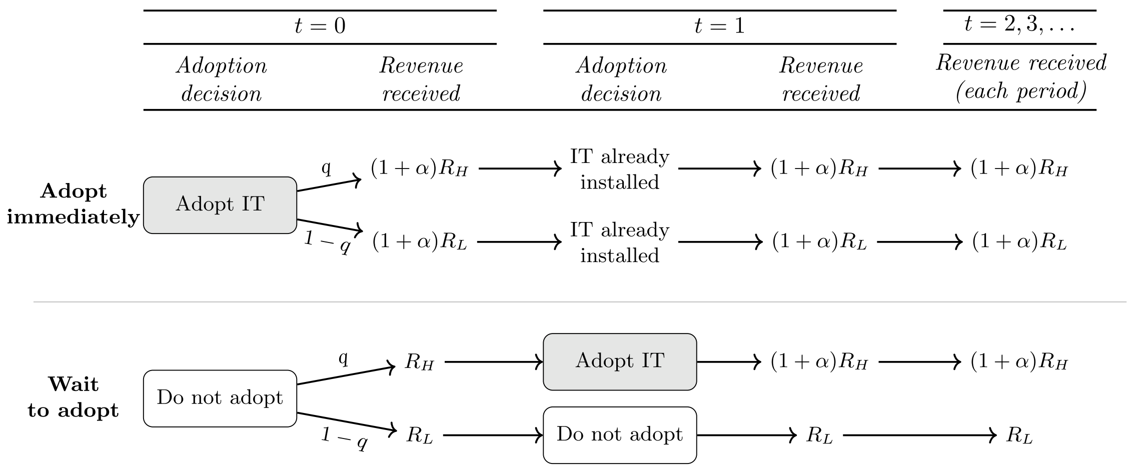


FIG A1. TIMING OF THE IT ADOPTION DECISION.

Notes: Adoption decisions occur at the start of each period, and revenue is received at the end of each period. Under the "adopt immediately" strategy, the hospital adopts at the start of t=0 and therefore receives IT-enhanced revenue beginning in period t=0. Under the "wait to adopt" strategy, the hospital does not adopt at t=0, observes the realized revenue state, and adopts at the start of t=1 only in the high-revenue state.

Adoption Threshold

The hospital adopts immediately when $NPV_0 > NPV_1$. Combining equations (1) and (2), the gain from immediate adoption relative to waiting is

$$NPV_0 - NPV_1 = -I\left(1 - \frac{q}{1+r}\right) + \alpha\left[qR_H + (1-q)R_L\frac{1+r}{r}\right].$$

Equivalently, immediate adoption is optimal when the sunk cost is below the threshold

$$I^*(q) = \frac{(1+r)\alpha[qR_H + (1-q)R_L(1+r)/r]}{1+r-q}.$$

Thus, projects with $I < I^*(q)$ are adopted immediately, while projects with $I > I^*(q)$ are delayed until the revenue state is observed.

Proposition 1. *The immediate-adoption threshold is strictly increasing in the probability of the high-revenue state:* $\frac{\partial I^*(q)}{\partial q} = \frac{(1+r)^2\alpha(R_H - R_L)}{(1+r-q)^2} > 0$.

When the high-revenue state becomes more likely, the value of waiting falls because the hospital is less likely to regret having paid the sunk cost. As a result, the cost threshold for immediate adoption rises: projects that were previously just above the adoption threshold become worth adopting immediately.

Mapping to the Empirical Shocks

Each empirical shock we study can be mapped to a change in q, the probability that the hospital faces a favorable revenue environment.

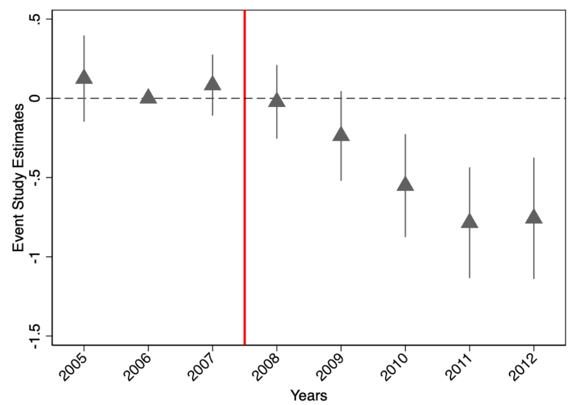
- Medicaid expansion converts uncompensated care into payer-backed reimbursement with more predictable timing, increasing q.
- The 340B program creates a regulated and predictable revenue stream from the spread between discounted drug acquisition costs and standard reimbursement on existing prescriptions, also increasing q.
- The Great Recession increases hospitals' exposure to uncompensated care and less predictable payment, reducing q.

The comparative static $\partial I^*(q)/\,\partial q$ delivers the directional predictions of the revenue-uncertainty channel on our empirical results:. Medicaid expansion and 340B eligibility should increase IT adoption, while a more severe recession should reduce it. Note that a change in q also shifts expected revenue, so these directional predictions are not unique to the uncertainty channel. Thus, distinguishing between these two channels is ultimately an empirical question.

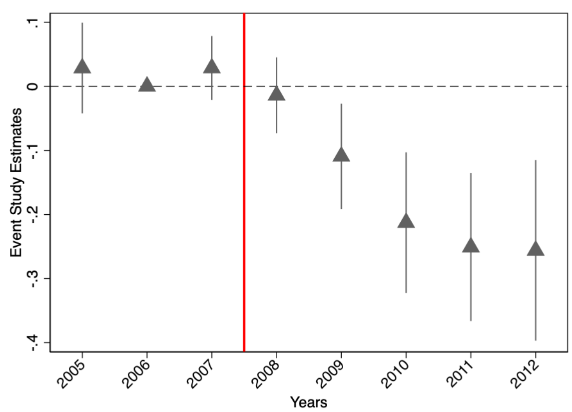
The model also predicts anticipatory responses. Because the adoption threshold depends on the hospital's perceived probability of the high-revenue state, adoption can change when managers' expectations change—for example, at a policy announcement—before realized cash flows have materially changed.

Appendix B

Appendix Figure B1: Event Study Estimates for Great Recession Effects Using Continuous Treatment Measure



(a) Total Health IT Solutions



(b) Total Health IT Vendors

Notes: Solid vertical bar indicates the start of the Great Recession following the Lehman Brothers investment bank collapse in 2008. Analytic sample does not subset to top and bottom quartiles of Great Recession impact; instead, all relevant counties and their percentage-point change in unemployment is used for the DD event study estimation.

Appendix Table B1—Great Recession Effects on Supplementary Health Information Technology (IT) Outcomes

	Total New Vendors	Total Canceled Vendors	Any IT Consultants
	(1)	(2)	(3)
Severe Recession x Post	–0.799***	–0.289***	–0.065***
	(0.120)	(0.063)	(0.018)
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Hospitals	1,319	1,319	1,319
Observations	10,549	10,549	10,549

Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the FIPS level. 20% of treated hospitals and 17% of control hospitals reported use of IT consultants during the 2005-2007 period. *** P value at 0.01 ** P value at 0.05

Appendix Table B2—Great Recession Effects on Care Delivery Health Information Technology (IT) Solutions Adoption

	Clinical Service Line	EHR	Laboratory	Pharmacy
	(1)	(2)	(3)	(4)
Severe Recession x Post	–0.650***	–0.194	–0.267***	–0.062***
	(0.246)	(0.105)	(0.079)	(0.021)
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Hospitals	1,319	1,319	1,319	1,319
Observations	10,549	10,549	10,549	10,549

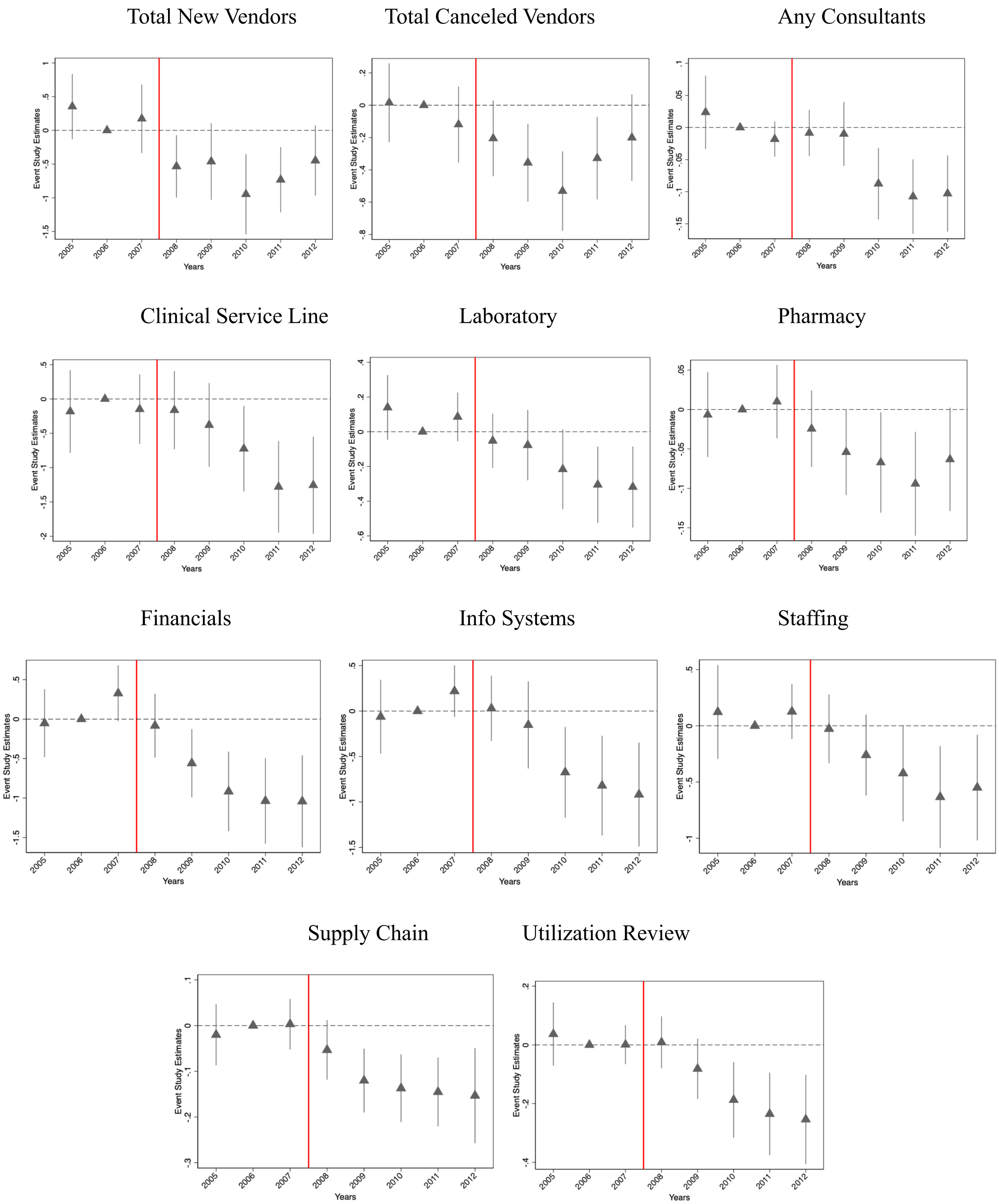
Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the FIPS level. *** P value at 0.01 ** P value at 0.05

Appendix Table B3—Great Recession Effects on Administrative Health Information Technology (IT) Solutions Adoption

	Back-Office	Financials	Info Systems	Staffing	Supply Chain	Utilization Review
	(1)	(2)	(3)	(4)	(5)	(6)
Severe Recession x Post	–0.101	–0.819***	–0.560***	–0.462***	–0.116***	–0.162***
	(0.053)	(0.174)	(0.197)	(0.140)	(0.027)	(0.046)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospitals	1,319	1,319	1,319	1,319	1,319	1,319
Observations	10,549	10,549	10,549	10,549	10,549	10,549

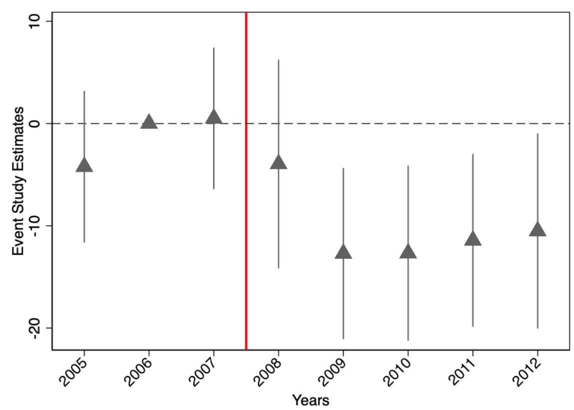
Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the FIPS level. *** P value at 0.01 ** P value at 0.05

Appendix Figure B2: Event Studies for Great Recession Effects Related to Appendix Tables B1-B3



Notes: Correspond to analytic samples and outcomes from Appendix Table B1-B3.

Appendix Figure B3: Event Studies for Great Recession Effects on Hospital Part-Time RN Hiring



Notes: Correspond to analytic sample and outcome definition from Column 4 of Table 3 in main results.

Appendix C

Appendix Table C1—Medicaid Expansion Effects on Supplementary Health Information Technology (IT) Outcomes

	Total New Vendors	Total Canceled Vendors	Any IT Consultants
	(1)	(2)	(3)
Expansion State x Post	0.600***	0.113	–0.022
	(0.188)	(0.100)	(0.015)
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Hospitals	2,918	2,918	2,171
Observations	26,262	23,342	19,533

Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the state level. 20% of treated hospitals and 16% of control hospitals reported use of IT consultants during the 2009-2012 period. *** P value at 0.01 ** P value at 0.05

Appendix Table C2—Medicaid Expansion Effects on Care Delivery Health Information Technology (IT) Solutions Adoption

	Clinical Service Line	EHR	Laboratory	Pharmacy
	(1)	(2)	(3)	(4)
Expansion State x Post		0.037	0.172**	0.037
	0.611***	(0.157)	(0.080)	(0.025)
	(0.183)			
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Hospitals	2,918	2,918	2,918	2,918
Observations	26,262	26,262	26,262	26,262

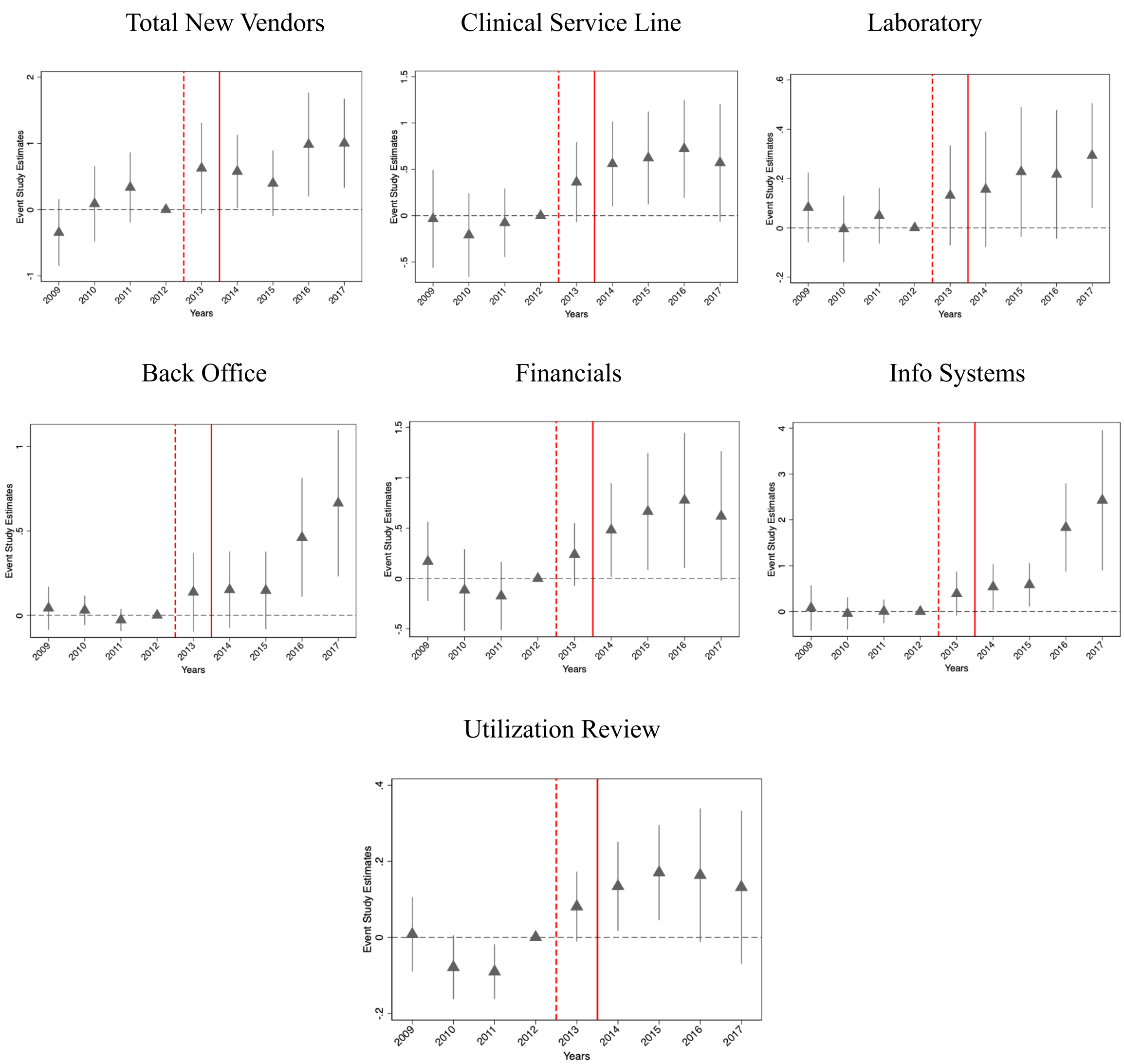
Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the state level. *** P value at 0.01 ** P value at 0.05

Appendix Table C3—Medicaid Expansion Effects on Administrative Health Information Technology (IT) Solutions Adoption

	Back-Office	Financials	Info Systems	Staffing	Supply Chain	Utilization Review
	(1)	(2)	(3)	(4)	(5)	(6)
Expansion	0.320***	0.611***	1.260***	0.049	0.071	0.166***
State x Post	(0.124)	(0.227)	(0.367)	(0.131)	(0.047)	(0.062)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospitals	2,918	2,918	2,918	2,918	2,918	2,918
Observations	26,262	26,262	26,262	26,262	26,262	26,262

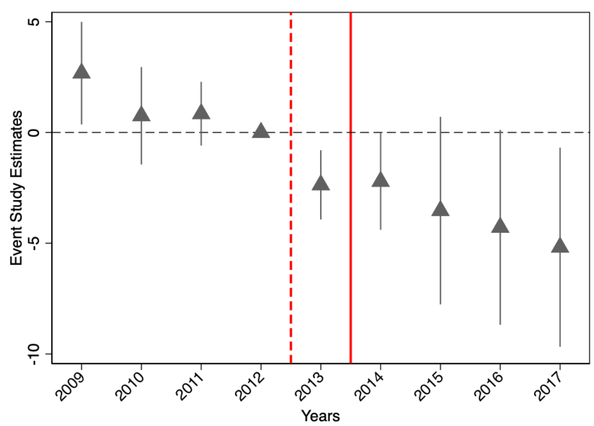
Notes: Analytic data are from HIMSS and include a balanced panel of hospitals. Standard errors clustered at the state level. *** P value at 0.01 ** P value at 0.05

Appendix Figure C1: Event Studies for Medicaid Expansion Effects Related to Appendix Tables C1-C3



Notes: Correspond to analytic samples and outcomes from Appendix Table C1-C3.

Appendix Figure C2: Event Studies for Medicaid Expansion Effects on Hospital Total Beds



Notes: Correspond to analytic sample and outcome definition from Column 1 of Table 6 in main results.

Appendix D

Appendix Table D1—340B Participation Effects on Supplementary Health Information Technology (IT) Outcomes

	Total New Vendors	Total Canceled Vendors	Any IT Consultants
	(1)	(2)	(3)
340B Participation x Post	1.092***	0.404***	0.017
	(0.202)	(0.125)	(0.029)
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Hospitals	844	844	844
Observations	9,284	9,015	9,284

Notes: 'Stacked' analytic data are from HIMSS. Standard errors clustered at the hospital level. 19% of treated hospitals and 15% of control hospitals reported use of IT consultants two years prior to 340B participation (treated) or randomly assigned placebo year (controls). *** P value at 0.01 ** P value at 0.05

Appendix Table D2—340B Participation Effects on Care Delivery Health Information Technology (IT) Solutions Adoption

	Clinical Service Line	EHR	Laboratory	Pharmacy
	(1)	(2)	(3)	(4)
340B Participation x Post	0.196	0.181	0.363**	–0.004
	(0.401)	(0.184)	(0.148)	(0.031)
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Hospitals	844	844	844	844
Observations	9,284	9,284	9,284	9,284

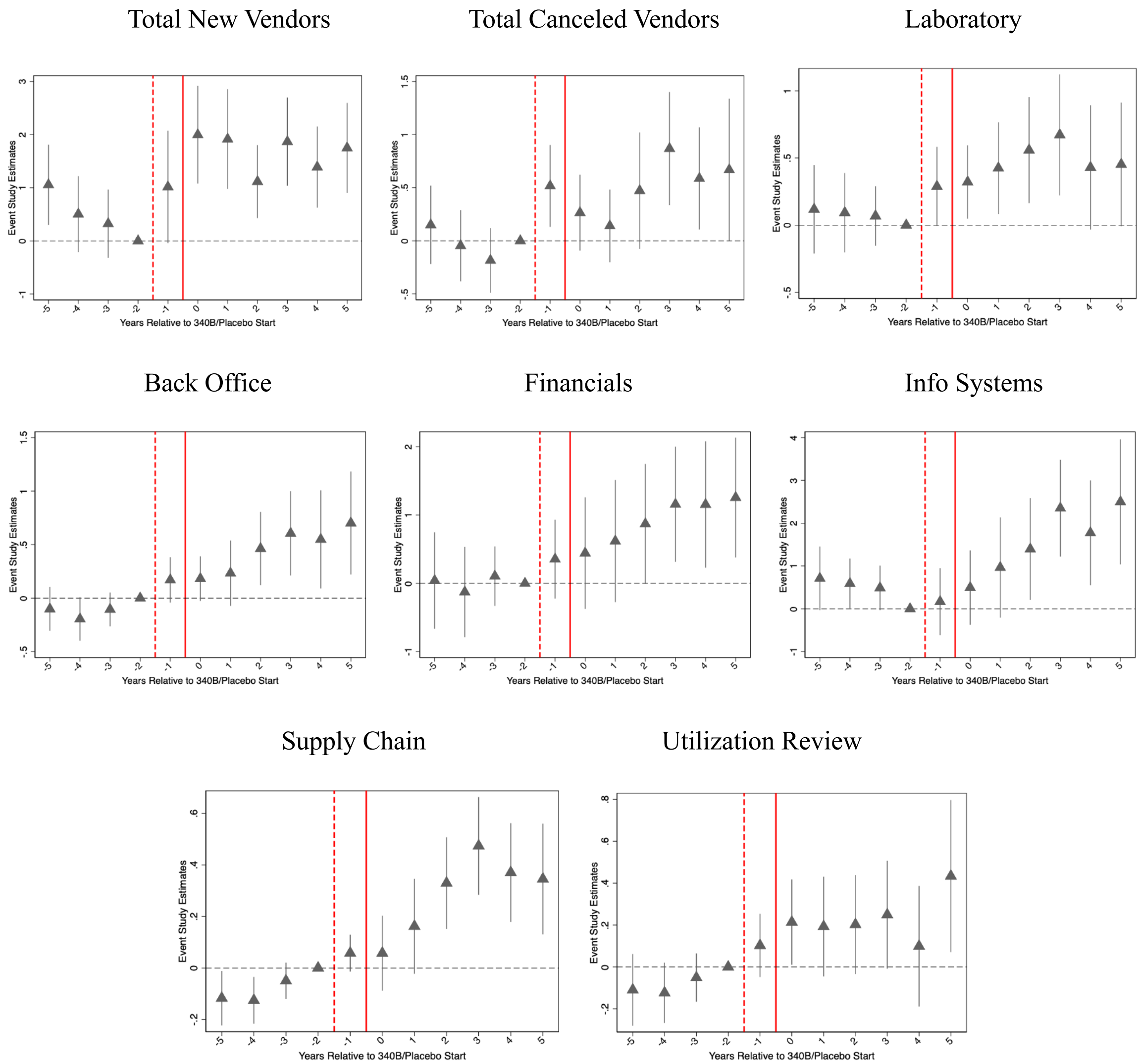
Notes: 'Stacked' analytic data are from HIMSS. Standard errors clustered at the hospital level. 19% of treated hospitals and 15% of control hospitals reported use of IT consultants two years prior to 340B participation (treated) or randomly assigned placebo year (controls). *** P value at 0.01 ** P value at 0.05

Appendix Table D3—340B Participation Effects on Administrative Health Information Technology (IT) Solutions Adoption

	Back-Office	Financials	Info Systems	Staffing	Supply Chain	Utilization Review
	(1)	(2)	(3)	(4)	(5)	(6)
340B Participation x Post	0.502***	0.843***	1.188***	0.461	0.337***	0.268***
	(0.136)	(0.295)	(0.412)	(0.239)	(0.076)	(0.103)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospitals	844	844	844	844	844	844
Observations	9,284	9,284	9,284	9,284	9,284	9,284

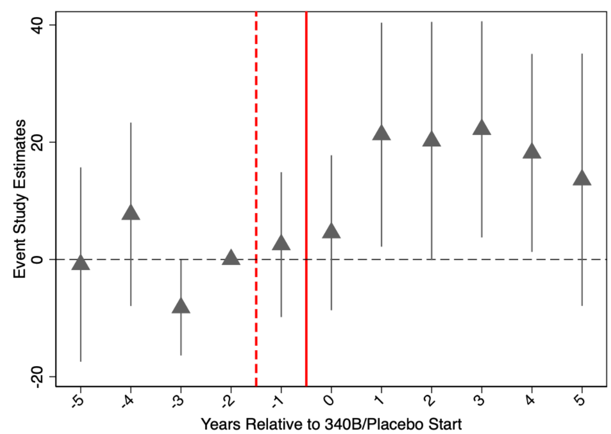
Notes: 'Stacked' analytic data are from HIMSS. Standard errors clustered at the hospital level. 19% of treated hospitals and 15% of control hospitals reported use of IT consultants two years prior to 340B participation (treated) or randomly assigned placebo year (controls). *** P value at 0.01 ** P value at 0.05

Appendix Figure D1: Event Studies for 340B Participation Effects Related to Appendix Table D1-D3

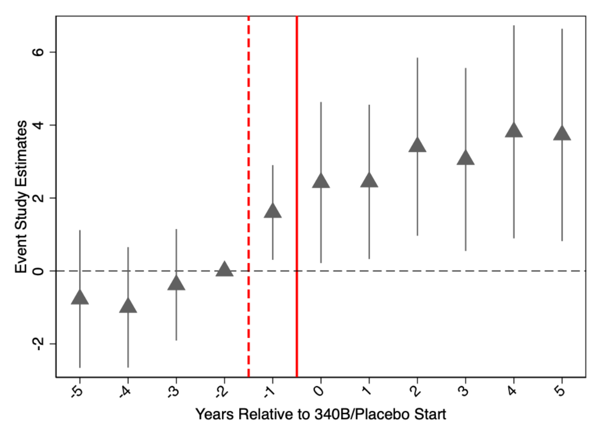


Notes: Correspond to analytic samples and outcomes from Appendix Table D1-D3.

Appendix Figure D2: Event Studies for 340B Participation Effects on Hospital Nursing Hiring



(a) Part-Time RNs



(b) Full-Time LPNs

Notes: Correspond to analytic samples and outcome definitions from Columns 4 and 5 of Table 9 in main results.

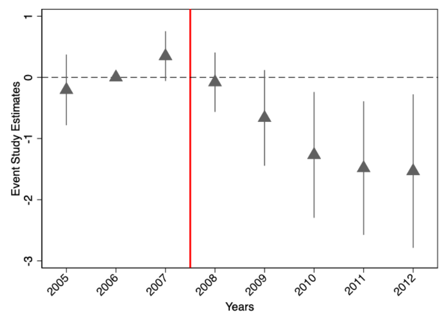
Appendix Table D4—Exploring Hospital-Level Volume Change Measures for Three Economic Shocks from Main Analyses

	Great Recession Shock		Medicaid Expansion Shock		340B Participation Shock	
	Total Admissions (AHA)	Total Inpatient Discharges (HCRIS)	Total Admissions (AHA)	Total Inpatient Discharges (HCRIS)	Total Admissions (AHA)	Total Inpatient Discharges (HCRIS)
	(1)	(2)	(3)	(4)	(5)	(6)
DD Estimate	–105.3	–128.4	–415.3***	–307.1**	246.7	185.3
	(112.3)	(118.0)	(119.5)	(124.7)	(266.6)	(264.9)
Unique Hospitals	1,315	1,277	2,887	2,768	830	806
Observations (N)	10,421	10,127	25,635	24,629	8,996	8,714
Treated Pre-Shock Comparison Outcome Mean	9,765	9,761	8,613	8,379	7,913	7,440

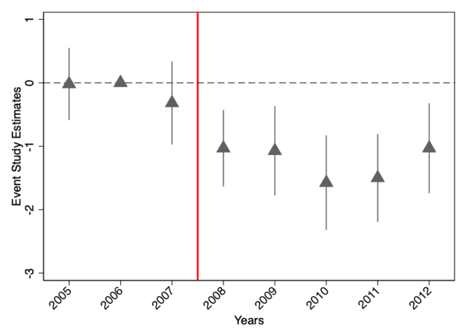
Notes: Analytic samples and diff-in-diff estimations follow those from the main analyses. Only the volume-focused outcomes are different from the prior estimations for each economic shock.

Appendix E

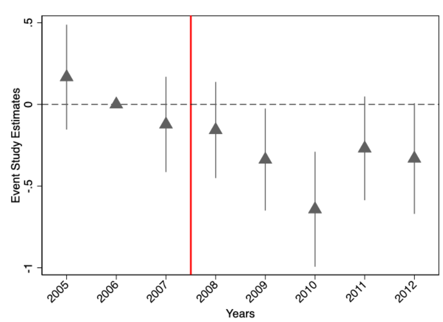
Appendix Figure E1: Event Studies for Great Recession Effects on Vendor Behavior at the County Level



(a) Total Health IT Vendors



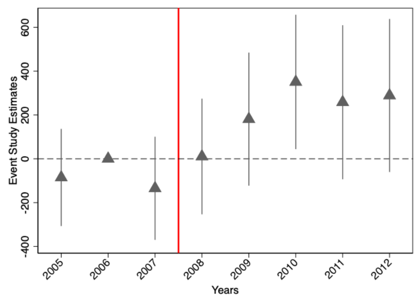
(b) Total Vendor Entry



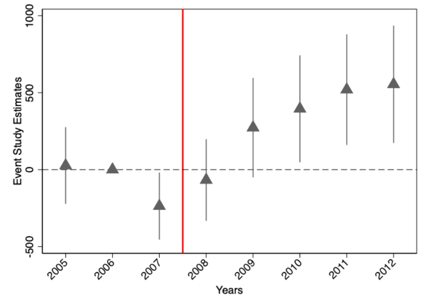
(c) Total Vendor Exit

Notes: Correspond to analytic samples and outcomes from Table 10.

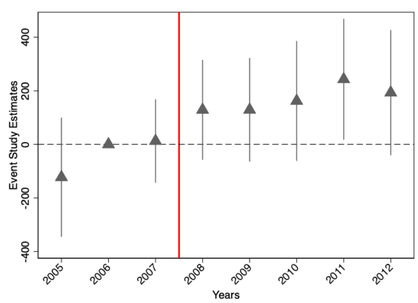
Appendix Figure E2: Great Recession Effects on Vendor Market Concentration (HHI) at the County Level by Technology Purpose



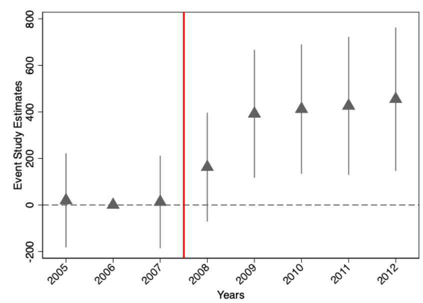
(a) Pharmacy HHI



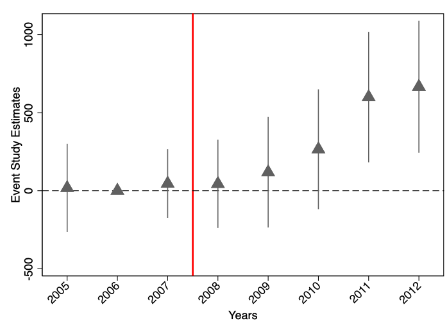
(b) Financials HHI



(c) Info Systems HHI



(d) Staffing HHI



(e) Utilization Review HHI

Notes: Correspond to analytic samples and outcomes from Table 11