Hedging or Healing: How Business Cycle Exposure Affects the Safety Net

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Abstract

Tax exemption and government support are intended to insulate non-profit hospitals from business cycles, who are expected to provide stable community benefits. This paper documents erosion in the stability of this social safety net. The rising popularity of high-deductible health plans (HDHPs) reduces insurance risk sharing and increases the cyclicality of hospital operations. Realized income shocks induce more ex post procyclical responses in hospital revenues and utilization in markets with higher pre-shock HDHP penetration. Claims data confirm that HDHP enrollees reduce inpatient visits in downturns. Ex ante, hospitals hedge this exposure by cutting staff, investment, and uncompensated care. Surprisingly, mission-driven non-profit hospitals hedge more aggressively, reflecting their lack of geographic diversification and internal capital markets compared to large for-profit systems. Counties with higher pre-pandemic HDHP prevalence and non-profit dominance experienced greater COVID-19 mortality.

Keywords: Risk management; Business cycles; Hospital finance; Non-profit hospitals; High-deductible health plans

JEL Classification: G32; E32; I13; L31

1. Introduction

In the United States, sectors that deliver essential social benefits, including health care providers and universities, are dominated by 501(c)(3) entities, commonly known as non-profit organizations. These mission-driven institutions are expected to provide community benefits in exchange for tax exemption. The health care sector is the largest, accounting for more than 60% of all non-profit employment. Within this sector, hospitals play a central role with 79% of non-government hospitals organized as non-profit. Hospitals are widely regarded as part of the social safety net (Garthwaite et al., 2018), mandated under the Emergency Medical Treatment and Active Labor Act to treat patients regardless of their ability to pay. However, the tax-exempt status of non-profit hospitals has become increasingly controversial. Critics argue that many hospitals exploit tax exemption as a form of tax avoidance, despite being equally, if not more, profitable than their for-profit counterparts. In our sample, only 2 of the 50 most profitable hospital branches in 2021 are for-profit. Reflecting these concerns, recent regulations introduce excise taxes on executive compensation and programs such as Payment in Lieu of Taxes (PILOT) to recoup property tax revenues.

The dominance of non-profit hospitals in this institutional design, however, is not accidental. First, demand for healthcare services is historically inelastic, largely shielding hospitals from business cycle fluctuations. For example, healthcare employment has shown resilience during recessions (Chen et al., 2018, Dolfman et al., 2018). Figure 1 shows that the health sector's beta in the early 2000s was well below one, similar to that of consumer nondurables, consistent with the asset management industry's view of both as defensive sectors. Second, even when exposed to market volatility, mission-driven non-profit hospitals with government support are expected to prioritize the supply of public goods over profitability, sustaining healthcare benefits to society.

[Figure 1 Here]

This paper provides empirical evidence that suggests these expectations no longer hold. We find that hospital revenues have become increasingly correlated with local business cycles, exposing providers to greater income volatility. We also find that hospitals hedge this risk by reducing staffing, investment, and uncompensated care for patients, thereby under-

mining their community benefits. Surprisingly, we show that non-profit hospitals respond more aggressively than their for-profit counterparts, a pattern we attribute to differences in organizational structure.

Our formal analysis is motivated by recent structural changes in the healthcare market. The expectation that hospital revenues are acyclical assumes that people become sick independent of the business cycle and insurance largely covers the cost of services. The advent of high-deductible health plan (HDHP) enrollment undermines the assumption of insurance coverage. According to the 2018 U.S. Bureau of Labor Statistics National Compensation Survey, the median annual individual coverage deductible for HDHPs was about $2,000. In other plans, 16 percent have no deductible and, conditional on having one, the median is $500, implying substantially less initial risk sharing under HDHPs. Using MarketScan data, which contain granular enrollment and health care claims for more than 20 million individuals every year, we document that the share of HDHP enrollees more than doubled, rising from just above 10% in 2011 to over 30% in recent years. This shift fundamentally alters hospitals' risk exposure by transferring financial responsibility from insurers to patients, whose healthcare utilization depends on household incomes and local economic conditions. Consistent with this mechanism, Figure 1 also documents that the healthcare sector's beta has risen significantly in recent years and exceeded one before the pandemic, indicating that publicly traded health firms have become riskier. More broadly, we find that the correlation between hospital revenue, including that of non-profit hospitals, and regional income has steadily strengthened over time, providing the first evidence that hospitals are now less insulated from business cycles.

We formalize this descriptive evidence in a hospital-level panel regression with patient revenue and net income over total assets as outcome variables. The focal regressor is the interaction between lagged local HDHP utilization and logarithm of local income per capita, capturing how hospital cash flows respond to local business cycles under different existing insurance conditions. The coefficients on the interaction terms are positive and statistically significant, showing that hospital revenues are more sensitive to income shocks in high-HDHP markets.

This analysis raises endogeneity concerns since most people receive health insurance

through employers. Local labor market conditions could jointly affect insurance menu design, wage income, and hospital revenues. Our ideal experiment would compare two otherwise similar hospitals that experience the same exogenous income shock but differ in local HDHP penetration, with one operating in a high-HDHP market and the other in a low-HDHP market. We implement this empirical design using two approaches. First, we exploit stock-driven wealth shocks following Chodorow-Reich et al. (2021). By interacting aggregate stock market movements with local variation in pre-existing household stock wealth, we construct income fluctuations independent of local healthcare demand or supply conditions. This measure is essentially a shift–share design, which only requires that hospitals in high- versus low-stock-wealth areas are not systematically differentially exposed to other aggregate shocks correlated with stock returns. To support this identifying assumption, we show that our results are robust to various timing of the share variables used in the shift–share design, such as using pre-sample or lagged measures of HDHP exposure and local stock wealth. Consistent with our baseline results, we find that hospital revenue and income comove with stock-market-driven income fluctuations only in areas with higher HDHP exposure. Evaluated at the interquartile difference in pre-sample HDHP penetration, a one-standard-deviation increase in relative stock income raises net patient revenue by an additional $3.9 million and net income by $1.0 million in high-HDHP markets (75th percentile) relative to low-HDHP markets (25th). The latter is equivalent to about 5% of mean net income in the sample.

Second, building on Acemoglu et al. (2013), we exploit the sharp oil price collapse in 2015 as an unanticipated income shock to drilling-intensive regions. We measure regional exposure using pre-shock drilling intensity and confirm that areas reliant on oil extraction experienced significant income declines after the price drop. This identification strategy leverages the fact that drilling requires large irreversible investments based on long-term projections and that the unexpected collapse was driven by global rather than local factors. Supporting this argument, we plot dynamic coefficient estimates, confirming no pre-trends and that income falls only after the collapse. The interaction between oil shock exposure and pre-shock HDHP share is negative and statistically significant for hospital cash flows, implying that in areas with greater HDHP penetration, income losses from the oil bust translate into sharper declines in hospital revenues. In terms of magnitude, moving from the

25th to the 75th percentile of HDHP exposure, hospitals in drilling-intensive counties lost an additional $3 million in annual net income following the oil price collapse, equivalent to roughly 15% of the sample mean.

We hypothesize that the increased cyclicality of hospital revenues in high-HDHP regions is driven by the fact that higher out-of-pocket liability makes the utilization of care more sensitive to local income fluctuations. To test this hypothesis, we first show that hospital-level bed utilization becomes more procyclical in high-HDHP areas with sharper declines following the oil price collapse than those in low-HDHP areas. To further validate this mechanism, we use claim-level data that record each enrollee's insurance type and industry affiliation, allowing us to construct area–industry–year cohorts and compare oil versus non-oil workers within the same local area and year. We then calculate inpatient visit rates separately for HDHP and traditional enrollees in each cohort. The logic is straightforward: HDHP enrollees in oil-intensive industries are most exposed to the oil price drop and should reduce utilization, while enrollees in traditional plans serve as a natural placebo test since their more comprehensive coverage shields them from financial shocks. This is exactly what we find: HDHP enrollees in oil-exposed industries cut back sharply on hospital visits, while enrollees in traditional plans exhibit no significant change.

We then turn to how hospitals hedge this heightened exposure through operational adjustments that affect their provision of community benefits. As a first step, we examine short-term responses during economic downturns to establish that realized recession is a substantial constraint on hospital operations. Using claim-level data, we find that in high-HDHP markets hospitals respond to income shocks by raising prices for the patients who continue to seek care. This pattern holds across all groups of patients, consistent with a cross-subsidization channel in which providers offset reduced volumes by charging higher prices broadly. Overall, these results show that when HDHPs amplify volatility by depressing demand, hospitals use pricing adjustments as a short-run hedge to stabilize cash flows. This cost is borne by patients who still access care.

We argue that the increased cyclicality should be viewed as a risk factor, motivating hospitals to adopt longer-term hedging strategies. Classic finance literature shows that cash flow volatility constrains firm investment (Minton and Schrand, 1999), and hospitals

are particularly vulnerable given high operating leverage and limited flexibility, amplifying exposure to downturns and the risk of financial distress (Reinartz and Schmid, 2016, Clementi and Palazzo, 2019). Consistent with expectations, we document evidence that hospitals in high-HDHP regions invest less in capital, pay lower salaries, and employ fewer medical staff, consistent with hedging the business-cycle risk. To assess implications for hospitals' provision of community benefits, we focus on uncompensated care, a core component of hospitals' safety-net role. We find that higher HDHP penetration is associated with economically meaningful reductions in uncompensated care, consistent with hospitals scaling back financial assistance or tightening collection practices in response to heightened revenue risk.

To address endogeneity concerns, we exploit the 2017 Tax Cuts and Jobs Act (TCJA) as a plausibly exogenous shock that weakened incentives to enroll in HDHPs. The TCJA reduced the tax advantages of HDHPs through two main channels. First, because contributions to Health Savings Accounts (HSAs) are tax-deductible, the lower personal income tax rates introduced by the TCJA reduced the value of these deductions, thereby diminishing the incentive to adopt an HDHP. Second, only households that itemize can deduct unreimbursed medical expenses exceeding a threshold share of adjusted gross income, and higher deductibles increase the likelihood of surpassing this threshold. When the TCJA nearly doubled the standard deduction, fewer households found it beneficial to itemize, making HDHPs less attractive. Accordingly, we construct our instrument, TCJA exposure, as the interaction of the local pre-TCJA share of returns with medical deductions and a post-2017 indicator. It is highly relevant: HDHP enrollment declines significantly with TCJA exposure, with first-stage F-statistics above 37. In the second stage, predicted HDHP adoption is negatively and significantly associated with hospital capital expenditures, salaries, and uncompensated care, confirming the robustness of the finding that HDHP penetration constrains hospital operations.

As a complementary identification strategy, we employ a second, supply-side instrument that exploits variation in the relative pricing of HDHPs versus traditional plans in the small-group insurance market. Because premiums in this market are regulated, set in advance, and not experience-rated, differences in relative premiums primarily reflect insurer cost structures, competitive conditions, and regulatory environments rather than hospital demand.

Using a leave-one-out premium ratio that excludes plans offered in a hospital's own market, we find similarly strong first-stage relevance and second-stage effects that closely mirror those obtained using the TCJA instrument. Taken together, these two distinct sources of variation reinforce the conclusion that HDHP penetration affects hospital operations and reduce charity care.

While hedging against revenue risk, non-profit hospitals effectively reduce their operational capacity, raising concerns about care quality when demand surges. This concern becomes most apparent during public health crises. Using hospital-level emergency department data, we show that non-profit hospitals with greater pre-COVID HDHP exposure experience higher emergency room mortality during the pandemic. At the aggregate level, counties with greater pre-COVID HDHP penetration and higher concentrations of non-profit hospitals experienced significantly higher COVID-19 mortality. These findings suggest that pre-pandemic cutbacks in investment and staffing weakened hospitals' ability to meet community needs in emergencies, highlighting a trade-off between financial risk management and social responsibility.

Lastly, we return to the central question in our motivation: does the dominance of tax-exempt institutions help stabilize the hospital sector during heightened business cycle exposure? One might expect non-profit hospitals, supported by subsidies and community benefit requirements, to have fewer incentives to hedge than for-profits, which rely more on commercially insured patients. To start, we document that for-profit hospitals do experience three times larger revenue volatility given the same HDHP popularity than their non-profit counterparts. Yet, surprisingly, non-profits respond more aggressively by cutting staff, investment, and uncompensated care. We explain this unexpected result by examining organizational structure. In our data, fewer than 40% of non-profits belong to multi-state systems, compared with 70% of for-profits. Without geographic diversification, non-profits cannot offset losses in one region with gains elsewhere, making them more exposed to local downturns. We show that hospitals in cross-state systems or in high-profit systems are better able to cushion HDHP-driven volatility, reducing their cuts in investments and community care. Taken together, these findings suggest that organizational structure and internal capital markets, rather than tax-exempt status or mission mandates, determine how hospitals

adjust to business cycle risk.

Our paper contributes to the literature on the role of tax-exempt organizations in the healthcare sector. Earlier work in health economics and public health, often based on case studies, correlational evidence, or small localized samples, yields inconclusive results (Sloan, 2000). More recently, a growing finance literature on hospital ownership changes around M&As shows that for-profit conversions are associated with higher profit margins, reduced Medicaid admissions, and greater human capital turnover (Lewellen et al., 2025, Herpfer et al., 2024). Relatedly, Gupta et al. (2024) and Gao et al. (2025) document that private equity acquisitions of healthcare facilities reduce quality of care, while Liu (2022) finds that such acquisitions raise healthcare spending through higher prices. We address the question in a different setting by focusing on the long-term hedging responses to business cycle risk induced by the sustained rise of HDHPs. This approach allows us to study the behavior of a broad set of hospitals without relying on ownership change events, thereby alleviating selection concerns that target hospitals may already be in financial distress and that short-term recovery is their immediate priority.

Our paper is also related to how hospitals trade off between financial solvency and social benefit. Duggan (2000) shows that non-profit and for-profit hospitals respond to targeted government subsidies by cream-skimming profitable indigent patients and accumulating financial assets, rather than expanding access. Hospitals also adjust investments following financial windfalls in capital (Adelino et al., 2015) and shift treatment choices toward more profitable procedures during downturns (Adelino et al., 2022). Negative shocks to credit supply also affect patient welfare through investment decisions and quality of care (Aghamolla et al., 2024, Cornaggia et al., 2024, Gao et al., 2024b). Unlike this literature, which emphasizes responses to absolute changes in cash flow or financing, our paper highlights a "beta" effect. HDHPs do not reduce hospitals' revenues on average but increase their time-series variation. We show that hospital systems with greater geographic diversification or stronger finances are better able to absorb local economic shocks, mirroring findings for multi-plant firms in other industries (e.g., Giroud and Mueller, 2019), and pointing to an overlooked benefit of hospital mergers and consolidation (Gaynor et al., 2015).

Our paper also relates to prior work examining the economic impact of HDHPs on health-

care utilization. HDHPs have been shown to reduce the use of low-value services, as enrollees respond to higher out-of-pocket costs by cutting discretionary care (Brot-Goldberg et al., 2017, Rabideau et al., 2021). However, the aggregate cost implications remain ambiguous, since enrollees may also forgo necessary care, leading to long-term costly complications, particularly for patients with chronic conditions (McCoy et al., 2024, Gidwani et al., 2025). Rather than focusing on absolute changes in utilization, we examine the cyclicality induced by HDHP popularity and study its implications for providers.

2. Background and Data

2.1 Institutional Details

In the United States, the healthcare payment system relies heavily on the private sector, with employer-sponsored insurance serving as its cornerstone. The Affordable Care Act (ACA) requires employers with at least 50 full-time employees to provide health insurance meeting minimum standards or pay a penalty (Almeida et al., 2025). Most large firms offered employee coverage before the ACA mandate, reflecting both economies of scale and favorable tax treatment that make employer plans more attractive than those in the individual market. Indeed, more than 60% of the working population in 2023, approximately 164.7 million people, received health insurance through their employers.[1] Firms provide insurance through fully insured plans, self-insurance, or a mix of both. In a traditional fully insured plan employers purchase health policies from insurance companies. Self-insurance employers pay employees' medical claims directly, establish tax-exempt reserves for claim payouts, and contribute regularly to these reserves. Either way, rising healthcare costs have become an increasing burden on employers (Tong, 2024, Gao et al., 2024a). In 2023 private businesses spent $894 billion on healthcare, accounting for 18% of total U.S. health expenditures.[2] In response to rising costs, employers have increasingly shifted workers into HDHPs, thereby transferring more financial risk to households (Li and Tong, 2025). HDHPs lower upfront

[1] See "Employer-Sponsored Health Insurance 101," KFF (2024), https://www.kff.org/health-policy-101-employer-sponsored-health-insurance/?entry=table-of-contents-introduction (last accessed: July 2025).

[2] See "National Health Expenditures 2023 Highlights," CMS (2024), https://www.cms.gov/files/document/highlights.pdf (last accessed: July 2025).

premiums for fully insured employers. The average HDHP with saving options for single coverage in 2023 carried an annual premium of $7,753, compared with $8,906 for PPO and $8,203 for HMO plans.[3] HDHPs also reduce medical service utilization, which lowers the cost of reimbursement for self-funded plans (Brot-Goldberg et al., 2017).

Most health insurance plans feature an annual deductible, which covered individuals must pay before the plan begins cost sharing through coinsurance. HDHPs, as their name suggests, require substantially higher deductibles than traditional options. HDHPs are often described as a form of catastrophic coverage, designed primarily to protect against large and unexpected medical bills. This design shifts financial responsibility toward patients: rather than insurers covering most costs from the outset, individuals must first absorb a greater share of initial expenses.

Estimates of the income elasticity of healthcare expenditure vary widely, ranging from zero (Newhouse, 1993), moderate values (Acemoglu et al., 2013), to estimates substantially above one (Moran and Simon, 2006). This imprecision likely reflects heterogeneity across individuals and regions in both healthcare markets and economic conditions that confound the relationship. One prominent source of heterogeneity is household insurance coverage. For example, Gross et al. (2022) show that prescription fills rise following the distribution of Social Security checks only among Medicare beneficiaries with copayments. No such pattern is observed among beneficiaries with zero copayments, suggesting that the completeness of insurance coverage shapes the sensitivity of healthcare utilization to income. We hypothesize that healthcare providers' exposure to the business cycle will increase with the growing prevalence of HDHPs. When patients face higher deductibles, their access to care and ability to pay become more tightly tied to their own financial resources. During economic downturns, households exposed to high out of pocket costs may postpone or forgo treatment and delay or lapse on bill payments as budget constraints intensify. As HDHPs proliferate, these household level frictions are transmitted to providers, producing greater volatility in revenues, patient volumes, and ultimately hospital outcomes over the local business cycle.

[3]See 2023 Employer Health Benefits Survey," KFF (2023), https://www.kff.org/health-costs/2023-employer-health-benefits-survey (last accessed: July 2025). Employers cover about 80% of these premiums. See "Employer and employee shares of premiums for medical care benefits, private industry workers," BLS (2024), https://www.bls.gov/news.release/ebs2.t03.htm (last accessed: July 2025).

Figure 2 presents descriptive evidence consistent with this hypothesis using time series statistics from our sample. In each panel, the blue solid line reports the cross sectional correlation between the logarithm of county level income per capita and hospital utilization in the same area. Panels (a) and (b) show that the correlation between local income and net patient revenue increased substantially from 2011 to 2017, with a modest decline thereafter. The 2017 inflection point in HDHP growth coincides with the TCJA, an institutional timing detail that underpins our instrument.

Panels (c) and (d) display a similar pattern for inpatient service volume, although the subsequent decline is more moderate. These dynamics mirror the diffusion of HDHPs over the same period: enrollment expanded rapidly during the 2000s and early 2010s, then stabilized in more recent years. In each figure, the red dashed line indicates the average share of the population enrolled in HDHPs by year across areas. Although these correlations are descriptive rather than causal, they provide motivating evidence for our empirical analysis. As HDHPs expand, hospital cash flows become increasingly dependent on patients' out of pocket capacity. Because household income and wealth are strongly procyclical, hospital revenues and utilization become more procyclical as well. In Section 3 we establish causal effects using quasi exogenous variation in household income and HDHP penetration, and we examine how hospitals adjust strategically to this increased cyclicality.

[Figure 2 Here]

2.2 Data

We combine hospital, enrollment, claims, and regional level datasets to study two questions: Do hospital revenues become more exposed to local business cycles as HDHPs gain popularity? If so, do hospitals hedge this exposure through operational adjustments? We begin by describing the construction of our key regressors, namely local HDHP popularity and local income fluctuations, and then introduce the outcome variables measured at different levels of granularity.

HDHP Popularity We construct a measure of HDHP popularity using the Truven Health MarketScan Research Database (hereafter "MarketScan"), which collects information on health care utilization and enrollment in employer sponsored plans from approximately 350

payers. These payers include large commercial insurance companies such as Aetna and Blue Cross Blue Shield. Enrollees are employees and their dependents. For each enrollee, the annual enrollment table provides details on insurance type, which allows us to identify HDHP enrollment. For privacy reasons, MarketScan stopped reporting county level identifiers after 2013. Instead, each enrollee is linked to a geographic location at the Core Based Statistical Area (CBSA) level and one of ten broad industry classifications.

MarketScan is representative of the U.S. insured population (Aizcorbe et al., 2012) and is widely used in both the health economics literature (e.g. Ho, 2009, Clemens and Gottlieb, 2017, Deschenes et al., 2017) and the finance literature (e.g. Cornaggia et al., 2024, Ouimet et al., 2025). We focus on privately insured employees with the following restrictions: enrollees must be (1) between the ages of 21 and 64, (2) the employee or the spouse of the employee (rather than dependents), and (3) actively employed full time or part time. More than 12 million enrollees satisfy these criteria each year. To capture HDHP popularity, we calculate the fraction of qualified enrollees enrolled in HDHPs within each CBSA area. Because the MarketScan data are representative, our measure is likely representative for the general HDHP adoption pattern. Figure 2 suggests that an average area in 2017 has about 38% of enrollees in HDHPs. In the same year, the KFF Employer Health Benefits Survey reports that around 40% of covered workers enrolled in an HDHP, and the BLS National Compensation Survey indicates that about 42% of workers had HDHPs offered by their employer.

Household Income We measure local income fluctuations using three complementary approaches. As a baseline, we obtain county level income per capita from the Bureau of Economic Analysis (BEA). Second, we construct a measure of stock market income flows in each county year to capture local exposure to aggregate equity market fluctuations. Following Chodorow-Reich et al. (2021), we begin with county level dividend income from the IRS Statistics of Income (SOI) and capitalize it into an estimate of taxable stock wealth. We adjust for wealth held in retirement and other tax exempt accounts using relationships from the Survey of Consumer Finances (SCF). Then, we apply returns from the Center for Research in Security Prices (CRSP), along with county specific portfolio betas, to translate this stock wealth into county level changes in income attributable to stock market perfor-

mance. The resulting measure reflects the dollar value of personal income in each county tied to fluctuations in stock market returns. We also construct a scaled version, dividing by total county payroll, to capture the relative economic importance of stock market income at the local level. Intuitively, this "stock income" variable rises in years when equity markets perform well, boosting the income of local stock holding households and providing a source of variation that is plausibly external to local labor market conditions.

Third, following Acemoglu et al. (2013), we exploit the oil price collapse between late 2014 and 2016, one of the largest declines in modern history and the longest lasting since the crash of 1986. We measure local exposure to this shock with data on hydraulic fracturing activity. Fracking expanded rapidly from the early 2000s, with the number of new wells fractured each year rising sharply through 2014 and generating substantial local income flows (Feyrer et al., 2017, Gilje et al., 2016). After the collapse, drilling activity slowed and well completions fell, with long lasting effects on the oil and gas industry: 208 North American producers declared bankruptcy between January 2015 and December 2019, affecting more than $121 billion in debt.[4] We use well level data from FracFocus, a national registry of chemical disclosures for oil and gas wells. For each well, the dataset provides an API number, state and county identifiers, latitude and longitude, and the job start date, representing the initiation of hydraulic fracturing. We assign wells to calendar years based on the job start date and aggregate to construct a county year measure of new well activity, which serves as a proxy for local exposure to energy extraction and related income shocks. These county level datasets enable us to connect hospital performance to local economic shocks, including those originating in labor market fluctuations, asset price changes, or commodity price disturbances.

Hospital Financial Statements For the outcome variables, we first construct a sample of Medicare certified hospitals, which are required to file annual cost reports with the Centers for Medicare and Medicaid Services (CMS). These cost reports are analogous to annual reports for public corporations, disclosing financial variables such as total assets, patient revenues, operating expenses, net income, cash holdings, and liabilities. Unique to the hospital

[4]See "North American oil company bankruptcies jump in 2019 – report," Reuters (2020), https://www.reuters.com/article/markets/north-american-oil-company-bankruptcies-jump-in-2019-report-idUSL1N29R15H/ (last accessed: July 2025).

setting, they also provide detailed operational information, including patient discharges, bed utilization, uncompensated care, and staffing across treatment units. Our primary sample consists of general short term acute care hospitals, the most common type of hospitals, between 2011 and 2021. Long term care and rehabilitation facilities are not comparable due to different operational features and reimbursement policies. We further restrict the sample to proprietary hospitals and exclude government affiliated hospitals, which rely heavily on local or federal budgets. We classify tax exempt hospitals as non-profit and the remainder as for-profit. In our sample, 79% of the hospital-year observations are from non-profit organizations. The ACA introduced a major revision to the reporting format, and 2011 is the first year in which most hospitals adopted the new format. We truncate our sample at 2021 because substantial delays in filing make it the most recent year with nearly complete submissions. Finally, we merge external information from the American Hospital Association survey on system affiliation, which allows us to study heterogeneity in responses.

We begin by examining hospital revenues and profits to assess how cash flows are exposed to local business cycles as HDHPs gain popularity. Hospital cost reports distinguish between total revenues and net patient revenues. Total revenues are based on charges billed for inpatient and outpatient services, which are typically far above amounts collected. Insurers reimburse only part of the charges through contractual adjustments, and patients may fail to pay deductibles or receive discounted care, recorded as uncompensated cares. Net patient revenues, our main measure, reflect payments received and are analogous to sales in corporate finance, capturing potential shortfalls when patients lapse on copays and deductibles during downturns. Hospital net income is defined as net patient revenues minus operating expenses such as salaries and supplies, plus other income items. A large share of these items are tied to patient volume, such as rebates, refunds, sales of drugs and supplies, patient records, and government subsidies. Investment income and donations are less directly linked to patient activity.

Medical Inpatient Claims MarketScan provides encounter level data for every inpatient visit by covered enrollees, including payments, diagnoses, procedures, patient demographics, and insurance type. We use this database in two ways. We study the extensive margin by examining how inpatient visit volume changes for HDHP enrollees relative to other enrollees

following income shocks. To exploit the oil price collapse, we create a pair of observations for enrollees in oil related industries versus other industries within each region year, saturating the analysis with granular area year fixed effects. Within each cohort, we calculate inpatient utilization rates as the number of total, surgical, or medical visits per 1,000 enrollees.

We study the intensive margin by analyzing hospital pricing conditional on admission during downturns. Each observation is a single inpatient visit, and the outcome variable is payment, which combines insurance reimbursements and patient out of pocket spending. To address the concern that observed payments may reflect shifts in patient composition rather than pricing, each admission is assigned a Diagnosis Related Group (DRG) code based on condition and severity. Each DRG is associated with a national average length of stay (LOS) and a DRG weight, which reflects the relative resource intensity of the admission compared with the average case. In short, a weight of 1 corresponds to the average admission, and higher values imply greater complexity and costliness. We normalize actual payments by DRG weight or average LOS to generate condition adjusted prices for hospital visits.

Because we examine pre-existing HDHP popularity and include lagged variables as controls in regressions, our hospital-year sample covers the period from 2012 to 2021. Table 1 reports summary statistics for this sample. On average, 23.7% of enrollees in a hospital's area are covered by HDHPs, with a standard deviation of 12%. This variation reflects both the growing popularity in HDHPs over time and substantial geographic heterogeneity shown in Figure 3. Geographically, HDHP adoption is highest in northern states such as North Dakota, South Dakota, and Minnesota, and lower along the Pacific Coast, especially California, Oregon, and Washington. This regional ordering remains stable over time even as overall adoption continues to rise. Local per capita income averages about $48,000, and stock-based income contributes roughly $13,743 per capita. On hospital balance sheets, average total assets are $327.7 million and net income averages $20.5 million. Hospitals face high operating leverage, largely driven by labor costs, as salaries account for 66% of assets and capital expenditures for 6.6%. Community benefit is also a significant component of hospital costs, with more resources devoted to uncompensated care (8.3% of assets) than to capital expenditures. Finally, for-profit hospitals constitute 21.4% of observations, with non-profits accounting for the remaining 78.6%, consistent with the broader dominance of

non-profit institutions in the U.S. hospital sector.

[Table 1 and Figure 3 Here]

As robustness checks on our identification strategy and to examine implications for patient outcomes under acute stress, we complement the above panel with additional data sources as follows.

HIX Compare HIX Compare is a public-use, plan-level dataset covering health insurance plans offered through the U.S. Health Insurance Marketplaces established under the Affordable Care Act (ACA). The dataset is sponsored and maintained by the Robert Wood Johnson Foundation (RWJF) and provides standardized information on nearly all individual and small-group health plans available in the Marketplace. For each plan, HIX Compare reports premiums, deductible levels, cost-sharing structures, metal tiers (catastrophic, bronze, silver, gold, and platinum), issuer identifiers, and geographic availability. Premiums are reported for standardized ages (e.g., age 27), facilitating consistent comparisons across plans and markets.

Plan offerings in HIX Compare are observed at the rating-area–year level, reflecting variation in insurer participation, pricing strategies, and regulatory environments across local insurance markets. We link rating areas to counties using the official rating-area–to–county crosswalk. Variation in HIX Compare allows us to capture supply-side conditions, such as insurer cost structures, competitive dynamics, and regulatory constraints.

HCUP SEDD Mortality outcomes in emergency departments provide a setting in which hospitals' operational hedging behavior can be examined under binding capacity constraints. Our analysis uses data from the Healthcare Cost and Utilization Project (HCUP) State Emergency Department Databases (SEDD), which provide all-payer records of emergency department visits for participating states, including patient demographics, diagnoses, and discharge status. The focus is on the COVID-19 period, which represents a large, unanticipated shock to emergency care demand. During this period, SEDD data are available for 14 states in 2020 and 8 states in 2021.[5] We aggregate SEDD records to the hospital–year level and construct emergency department mortality as the number of deaths per 1,000 ED

[5]Our HCUP SEDD sample includes AR, AZ, FL, HI, IA, IN, KS, KY, MD, ME, NY, OR, UT, and WI in 2020, and AZ, FL, IA, KY, MD, NC, NY, and OR in 2021.

visits.

NCHS NVSS To address concerns that the HCUP SEDD data capture emergency department mortality in only a subset of participating states, we supplement our analysis with county-level mortality data from the National Center for Health Statistics' National Vital Statistics System (NVSS). The NVSS provides comprehensive records of deaths in the United States, including cause of death and county of residence, which allow us to construct annual county-level mortality measures.

3. Empirical Results

3.1 Hospital Cash Flows and Local Business Cycles

We estimate the following OLS specification to examine how hospital revenues and operations comove with the local business cycle as HDHPs expand:

$$y_{i,t} = \alpha + \beta\, HDHP_{i,t-1} \times Income_{i,t} + \gamma_1 HDHP_{i,t-1} + \gamma_2 Income_{i,t} + \gamma X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t}, \quad (1)$$

where $y_{i,t}$ denotes hospital profitability outcomes, including net patient revenue and net income, normalized by total assets for hospital i in year t. $X_{i,t-1}$ includes lagged hospital assets and beds as controls for hospital size, and μ_i and λ_t are hospital and year fixed effects. $HDHP_{i,t-1}$ is the lagged HDHP share in hospital i's local region, and $Income_{i,t}$ is one of the local income measures in year t. Standard errors are clustered at the area level.

Our parameter of interest is β, which captures the sensitivity of hospital profitability to local income shocks as a function of HDHP penetration. A positive β implies that hospital revenues and profits become more procyclical when local HDHP enrollment is high. Table 2 presents supporting evidence. Column (1) uses county per capita income as a proxy for local business cycles, reflecting broad fluctuations in household earnings and economic activity. Although this specification is correlational, it provides a useful starting point consistent with the stylized facts illustrated in Figure 2.

[Table 2 Here]

The coefficient on the interaction term in column (1) is subject to endogeneity concerns.

Because the focal regressor is the product of local income and HDHP penetration, the problem arises from their comovement: omitted local shocks that jointly shift wages and employer benefit menus load onto the interaction and bias the estimate. This comovement reflects that insurance coverage is largely employer-based, and that employers optimize total compensation by bundling salaries with health benefits. For instance, Koh (2018) shows that employers shifted to HDHPs during the Great Recession to reduce labor costs, and Li and Tong (2025) find that employers adopt HDHPs once non-compete agreements constrain labor mobility, diminishing the need for providing generous healthcare benefits to retain workers. To address this concern, our identification strategy compares two otherwise similar hospitals that face the same exogenous income shock but differ in local HDHP penetration before the shock. Because geographic HDHP penetration is highly persistent over time within areas, this design isolates differential exposure to the shock rather than endogenous post-shock changes in plan offerings. We hypothesize that hospitals in high-HDHP markets should exhibit larger revenue responses to the same income shock than hospitals in low-HDHP markets.

We first turn to stock market driven income shocks following Chodorow-Reich et al. (2021). This measure has a shift-share structure: the "shift" is in the aggregate stock market return in year t, a national shock plausibly exogenous to local hospital demand and labor market idiosyncrasies; and the "share" is each county's stock wealth relative to local labor income in year $t-1$, which evolves slowly with demographics and asset ownership patterns. Their interaction yields a measure of local income fluctuations driven by national asset prices but heterogeneous in regional exposures. We then interact the constructed stock income in year t with lagged HDHP popularity in the same region to mimic the design in column (1).

The validity of this design does not require pre-existing stock wealth or HDHP penetration to be randomly distributed. Instead, it requires that hospitals in high- versus low-HDHP markets are not systematically differentially exposed to other aggregate shocks correlated with stock returns. Put differently, aggregate returns provide the time series variation, local stock wealth determines cross sectional exposure, and HDHP penetration provides the institutional channel through which these shocks alter hospitals' cyclical sensitivity.

Coefficients on the interaction terms are positive and significant in columns (2) and (3),

confirming that stock market returns pass through to hospital revenues only in markets with higher HDHP penetration. In column (3), the coefficient on $HDHP \times$Relative Stock Income is 0.262. Evaluated at the interquartile difference in HDHP penetration (between the 75th and 25th percentiles), this coefficient implies that a one standard deviation increase in relative stock income (0.255) raises net patient revenue by an additional 1.2 percent of total assets in high-HDHP markets relative to low-HDHP markets, or about $3.9 million for the average hospital.[6] In all three columns, standalone income measures have insignificant coefficients with inconsistent signs, indicating that in areas with low HDHP penetration, local income fluctuations do not translate into substantial changes in hospital revenues. We conclude that insurance completeness is the key channel amplifying the cyclical exposure of hospitals.

In columns (4)–(6), we find qualitatively similar results with net income. In column (4), the interaction is positive but not quite significant ($t = 1.57$). In columns (5) and (6), the interactions are positive and significant, showing that net earnings are more sensitive to income shocks in high HDHP regions as well. Coefficients for net income are smaller than the corresponding coefficients for net patient revenue for two reasons. First, operating expenses compress profit margins, shrinking the magnitude of the effect relative to revenue losses. Second, net patient revenue reflects patient volume changes, whereas net income also incorporates hospitals' endogenous cost adjustments that partially offset revenue fluctuations. Although the coefficients are smaller, the magnitudes remain meaningful: for example, evaluated at the interquartile difference in HDHP penetration, the column (6) coefficient implies that a one standard deviation increase in relative stock income raises net income by about 0.32% of assets more in high-HDHP markets than in low-HDHP markets, roughly $1.05 million, or 5% of average net income.[7] In later sections, we document the specific strategies hospitals use to hedge these losses.

In Table 2, we interact the stock income in year t with the lagged HDHP utilization in the previous year. This one-year offset, however, may not fully resolve endogeneity if some

[6]The difference of HDHP utilization in these two markets are $0.316 - 0.140 = 0.176$. A one standard deviation increase in relative stock income (0.255) yields $0.262 \times 0.176 \times 0.255 \approx 0.012$. Multiplying by mean total assets (3.28×10^8) gives $\approx$ $3.9 million change in patient revenue.

[7]With a coefficient estimate of 0.071, an interquartile HDHP difference of 0.176, and a one standard deviation change in relative stock income of 0.255, the effect is $0.071 \times 0.176 \times 0.255 \approx 0.0032$, i.e., 0.32% of total assets. At the mean of $328 million in assets, this corresponds to about $1.05 million, roughly 5% of the sample mean net income ($20 million).

early-sample substantial stock shock has long-lasting impacts on later financial wealth and insurance choices. To address this concern due to serial correlation, we demonstrate that our results are robust to alternative designs that rely on pre-determined exposures in Appendix Table A1. To address this serial correlation concern, Appendix Table A1 shows that the results are robust to designs that use predetermined exposures. First, we interact year t stock income with HDHP penetration measured in 2010, which breaks feedback from recent stock shocks to the HDHP share used in the interaction. Second, we fix both exposures by interacting current aggregate stock returns with 2010 local stock wealth shares and 2010 HDHP penetration, yielding a shift share specification driven only by preexisting exposure differences.

After documenting the procyclical effects of HDHP penetration using local income-based variations, we turn to a second design that leverages the oil price collapse from 2014 to 2016 as a plausibly exogenous negative income shock. A further advantage is that MarketScan records each enrollee's industry, which allows us to compare HDHP and non-HDHP utilization across industries within the same area based on their differential exposure to the oil price shock.

Specifically, we measure each region's exposure to the oil shock using the logarithm of the average annual number of new oil and gas wells drilled between 2012 and 2014, the peak of the fracking boom, as an index of pre-shock drilling intensity. The subsequent collapse in oil prices, from about $100 per barrel in mid-2014 to below $50 in 2015 (Figure A1), provides a natural experiment that delivered a substantial and unanticipated negative wealth shock to drilling-intensive regions. This setting is attractive for several reasons. First, fracking activity generates large local income effects: Feyrer et al. (2017) estimate that each additional million dollars of production raises local wage income by about $80,000. Conversely, the collapse led to sharp cutbacks in drilling and a wave of bankruptcies among shale producers (Macalister, 2015, McLean, 2018, World Bank, 2018). As shown in Figure A2, counties with high pre-2014 fracking activity experienced steep declines in well completions, leading to contractions in local labor markets and household income. Second, drilling is a long-duration investment decision: it requires intensive upfront capital expenditures, with expected returns spread over a long payback period. As a result, pre-2014 drilling intensity reflects long-term

commitments rather than short-term expectations about future oil prices or local economic conditions, limiting concerns about selection or reverse causality. Third, the oil price decline was driven by global supply and demand dynamics, most notably OPEC's decision not to cut production, rather than by local fundamentals related to health care markets, making it plausibly exogenous for our purposes. Our approach is related to Acemoglu et al. (2013), who use time-series variation in oil prices between 1970 and 1990 to study the income elasticity of health care expenditure.

We moderate Equation (1) as follows:

$$y_{i,t} = \alpha + \beta_1 \, HDHP_{i,2014} \times Oil\,Exposed_{i,t} + \beta_2 \, OilExposed_{i,t} + \gamma X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t}, \quad (2)$$

We replace the income variable with $Oil\,Exposed_{i,t}$, which proxies the income loss from the oil price collapse. It is defined as $Wells_i \times \mathbf{1}\{t \geq 2015\}$, where $Wells_i$ is the logarithm of one plus average annual new wells drilled in hospital i's county during 2012–2014 and $\mathbf{1}\{t \geq 2015\}$ is an indicator for the post-collapse period. Intuitively, after 2014, counties with high pre-boom drilling intensity are the most oil-exposed and experience the largest negative income shocks, while counties with little or no drilling see negligible effects. We interact $Oil\,Exposed_{i,t}$ with the pre-shock HDHP enrollment rate in hospital i's region, $HDHP_{i,2014}$, to rule out concerns that employers in oil-intensive industries endogenously changed insurance offerings after the shock.[8] The identifying assumption is that insurance market structures are locally persistent, largely determined by insurer supply and regulatory environment, so pre-2014 HDHP penetration reflects slow-moving fundamentals rather than short-run employer adjustments. Under this assumption, β_1 captures how hospital cash flows are differentially affected by the oil price-induced income losses as a function of pre-existing HDHP adoption. The coefficient sign is expected to flip compared to Table 2, as $Oil\,Exposed_{i,t}$ captures negative income changes.

We report the results in Table 3. In column (1), because income is measured at the county level, we estimate the regression at the same level and weight each county–year observation by the number of sample hospitals located there, so the results mirror the implicit weights in the

[8]Hospital fixed effects absorb the level effect of $HDHP_{i,2014}$, so it is not separately estimated.

hospital-level analysis. Indeed, counties with higher pre-boom drilling intensity experienced significant income declines after 2014, with a t-statistic above 4. Figure 4 plots the dynamic estimates and confirms that there are no pre-trends and that income begins to fall only after the oil price collapse. Columns (2) and (3) present the estimates from Equation (2) and reveal that the interaction between oil exposure and pre-shock HDHP share is negative and statistically significant for both net patient revenue and net income. In terms of magnitude, the average exposure ($Wells_i$) is 2.13 for the drilling intensive counties, and the interquartile difference of 2014 HDHP utilization is 0.0845 ($0.2567 - 0.1722$). Following the oil price collapse, affected hospitals in high-HDHP markets (at 75th percentile) lost additional net income by almost $3 million annually, or 15% of the unconditional mean. This implies that in counties with greater HDHP penetration, income losses from the oil bust translated into sharper declines in hospital cash flows and profitability.

[Table 3 and Figure 4 Here]

3.2 Hospital Volume

The evidence so far suggests that HDHPs amplify the impact of income shocks on hospital revenues and profitability. We next examine the underlying mechanism, hypothesizing that households with HDHPs reduce care utilization when constrained by out-of-pocket liabilities during economic downturns. We extend our analysis from financial outcomes to hospital service volume, measured by the bed utilization rate. We define this variable as total inpatient days across all payers normalized by the number of hospital beds multiplied by 365, that is, the total available bed days. This outcome variable has an intuitive interpretation by measuring the average fraction of hospital beds being occupied on a typical day.

We evaluate this hypothesis using both income-based variation and oil price-driven wealth losses, with results reported in Table 4. Columns (1) to (3) show that the interaction between lagged HDHP share and each of the three income-based measures is positive and significant. These estimates mirror our revenue results: in counties with greater HDHP penetration, bed utilization rises more strongly in expansions and contracts more sharply in downturns, consistent with patients facing higher deductibles being more responsive to income fluctuations when deciding on inpatient care. Unlike revenue-based outcomes, these

results directly reflect changes in service volumes, uncontaminated by potential endogenous price adjustments. Column (4) employs the oil price collapse and shows a negative and significant interaction, indicating that hospitals in high-HDHP counties exposed to the downturn experienced larger declines in bed utilization. The coefficient implies that, based on a similar calculation of Table 3, affected hospitals in high-HDHP markets (at 75th percentile) lost an additional 0.76% utilization rate, or equivalently 471 inpatient service days in a year, than those in the low-HDHP markets (at 25th percentile) following the oil price drop.[9] Taken together, these findings demonstrate that HDHPs amplify the procyclicality of hospital service volume and point to reduced utilization as the primary mechanism through which household income shocks are transmitted to hospital finances.

[Table 4 Here]

To sharpen the argument, we turn to claim-level data to test whether the contraction in hospital utilization is concentrated among enrollees with HDHPs. We exploit industry affiliation reported by MarketScan, with oil extraction industries identified separately. We aggregate claims to the CBSA–industry–year level, constructing cohorts of enrollees in oil-related versus non-oil industries within each CBSA. This matching yields pairs of observations in the same CBSA–year, allowing us to include granular fixed effects and compare utilization across otherwise similar cohorts that differ only in their exposure to oil price shocks. We then calculate inpatient visit rates separately for HDHP and traditional low-deductible plan enrollees, defined as the number of visits per pre-shock 1,000 enrollees in each CBSA-industry group, which normalizes for differences in enrollment across plan types and industries. Intuitively, for all HDHP enrollees in a given area, those in oil-related industries are more exposed to the price collapse and therefore expected to adjust their utilization patterns more than those in other industries. By contrast, this difference should diminish or even disappear for individuals in traditional plans, since the greater completeness of coverage shields them from financial shocks, providing a natural placebo test.

In Table 5, our main regressor, $Oil\,Exposed_{i,t}$, is defined in the same way as in the hospital-level regressions, except that it is coded as zero for all non-oil observations. This

[9] The calculation is $0.0845 \times 2.13 \times 0.042 \approx 0.76\%$. The inpatient service days are estimated by multiplying 0.76% with 170 (average number of beds) and 365 (total avaiable days in a year).

specification is therefore analogous to a classic difference-in-differences design with continuous exposure, where oil-related industries serve as the treatment group and all other industries act as controls. The regressions include CBSA-by-industry fixed effects to capture persistent differences between oil and non-oil sectors within the same CBSA. In addition, we saturate the analysis with CBSA-by-year fixed effects to absorb region-wide shocks in a given year, such as insurer or provider concentration, thereby alleviating confounding from the supply side.

[Table 5 Here]

Columns (1) to (3) of Table 5 present the results for HDHP enrollees, beginning with total visits and then disaggregating into surgical and medical stays. The coefficients on oil exposure are negative and highly significant across all categories. The magnitudes for surgical and medical visits are similar, suggesting that the decline in utilization is broad based and does not vary systematically with the complexity of the condition. These results imply that patients facing high deductibles substantially reduce hospital use during adverse income shocks, providing direct evidence that HDHPs amplify the sensitivity of care seeking to household financial conditions. In terms of the magnitude, column (1) suggests that after the oil price crashed, in drilling-intensive areas, HDHP enrollees in the oil industry reduce annual inpatient visits by 2.9 times (per 1,000 enrollees), or equivalently 11.5% of the unconditional mean, compared to other non-oil HDHP enrollees in the same area. Columns (4) to (6) repeat the analysis for traditional low-deductible plan enrollees. Here, the coefficients are small and statistically insignificant across all visit types, underscoring that more comprehensive insurance effectively shields patients from income driven fluctuations in utilization. Taken together, the sharp contrast between HDHP and traditional plan enrollees highlights reduced service volume as the central mechanism through which household income shocks transmit into hospital finances.

3.3 Hospital Hedging Behavior

The previous section shows that HDHPs amplify hospital sensitivity to local business cycles. We now examine to how hospitals respond to this heightened exposure through operational adjustments that affect their provision of community benefits. Before examining

long-term hedging behavior, we first analyze short-term responses during economic downturns. Prior work shows that fluctuations in hospital cash flows and access to capital markets lead providers to adjust investment and treatment decisions (Adelino et al., 2015, 2022). By exploring short-term responses in our setting, we test whether the cash flow losses induced by HDHP adoption are a meaningful constraint on hospital operations.

The specific measures we investigate have direct implications for patient welfare. Specifically, we estimate a claim-level regression to test whether hospitals raise payments for patients who continue to seek care when overall demand falls during economic downturns. This analysis captures a direct cross-subsidization channel: by increasing prices for patients who utilize services, hospitals offset revenue shortfalls and reduce the risk of financial distress. This phenomenon is sometimes referred to as "pay-for-existence," reflecting the practice of charging higher prices to commercially insured patients or for profitable services, in order to maintain solvency and continue serving under-insured communities (David et al., 2014).

In Table 6, outcome variables focus on payments received by hospitals, including both insurance reimbursements and patient out-of-pocket contributions. In column (1), we use raw hospital payment amounts to gauge a direct economic magnitude. A concern, however, is that the composition of patients who continue visiting hospitals may be endogenously affected by economic shocks. To address this concern, we normalize payments by underlying disease conditions. Inpatient settings provide two severity measures defined in Section 2.2. DRG weight (column 2) and average length of stay (column 3) allow us to generate condition-adjusted prices for hospital visits. Each observation corresponds to a realized inpatient visit among enrollees in our sample. The focal regressor is the interaction between $HDHP_{i,2014}$ and $Oil\,Exposed_{i,t}$, defined in the same way as in Table 2. Unlike Table 5, we do not hard code this variable to zero for non-oil industries or traditional low-deductible plan enrollees. The rationale is that cross-subsidization is broad: to offset revenue losses from HDHP patients, hospitals raise prices across the board, affecting all patients regardless of their own deductible type. Table 6 is effectively a cross-sectional regression, since most enrollees have only a single inpatient visit in our sample, if any, and we cannot include enrollee fixed effects. Instead, we control for patient characteristics, CBSA fixed effects, year fixed effects, DRG fixed effects, and industry fixed effects.

[Table 6 Here]

Across all Table 6 columns, the coefficients on the interaction terms are positive and significant. To illustrate the magnitude, affected hospitals in drilling-intensive communities on average offset short-term revenue losses from oil price crashes by increasing payments by $608 in raw amounts, $483 for an average-severity patient, and $133 per average night of stay for all patients on average. Overall, these results support the interpretation that hospitals use pricing adjustments as a short-run hedge against financial strain. In downturns, when HDHPs amplify revenue volatility by reducing patient demand, hospitals respond by raising prices on the remaining patients in order to stabilize financial performance.

We argue that the increased cyclicality induced by HDHP adoption constitutes a risk factor for hospital operations, motivating hospitals to actively hedge over the longer term. Appendix Table A2 column (1) shows that local HDHP adoption is not associated with significant changes in average net revenues across business cycles. Intuitively, HDHPs increase time-series volatility: hospitals may experience higher patient flows in booms, offset by losses in recessions. However, this does not imply that hospital capital investment or community benefit expenditures will simply co-move with revenues and average out over time. Because hospitals operate with thin margins and limited access to external finance (Aghamolla et al., 2024, Cornaggia et al., 2024), they face heightened bankruptcy risk (Gao et al., 2024a). As a result, hospitals have strong incentives to respond to volatility by reducing expenditures at the absolute level as a form of active hedging. These reductions improve long-term profit margin, consistent with Table A2 column (2), which shows that hospitals become more profit-driven given higher HDHP adoption, even though average revenues remain unchanged.

Classic finance literature suggests that cash flow volatility constrains firm investment (Minton and Schrand, 1999). Hospitals are particularly vulnerable because they operate in a capital-intensive, labor-intensive environment, relying heavily on fixed infrastructure and skilled staff. This cost structure generates high operating leverage and limited flexibility. Consequently, operating leverage amplifies the sensitivity of profits to economic shocks and increases the risk of financial distress during downturns (Reinartz and Schmid, 2016, Clementi and Palazzo, 2019). We therefore hypothesize that hospitals exposed to business cycles will attempt to mitigate this risk by cutting back on capital expenditures and staffing,

a prediction tested in Table 7.

[Table 7 Here]

In Panel A, columns (1) and (2) report OLS regressions of capital expenditures and salary expenditures for medical staff, both normalized by total assets, on lagged HDHP share. Their coefficients are negative and statistically significant, indicating that hospitals in areas with higher HDHP penetration invest less in physical capital and pay lower aggregate salaries. In terms of economic magnitude, compare two otherwise similar hospitals, one in a region at the 25th percentile of HDHP penetration (14.0%) and the other at the 75th percentile (31.6%). The latter, facing more volatile revenues, cuts spending in these two dimensions by about \$3.9 million, equal to roughly 19.2% of the average hospital's net income.[10] Column (1) in Appendix Table A3 further shows that the number of medical staff declines significantly with rising HDHP adoption, suggesting that lower salary costs are at least partly explained by reductions in headcount.

Next, we examine how hospitals adjust their provision of community benefits in response to heightened business cycle exposure. Hospitals act as the "insurer of last resort" by providing free or discounted care to under-insured populations. Uncompensated care, however, directly erodes profitability and hospitals can adjust their charity levels. Hospitals typically maintain a financial assistance policy that specifies eligibility for free or discounted care, typically tied to thresholds of the federal poverty line. For uncollected out-of-pocket payments, hospitals can vary the aggressiveness of their collection practices, thereby influencing the effective level of uncompensated care. In column (3) of Table 7 (Panel A), we use uncompensated care, scaled by total assets, as the outcome variable, and find significantly negative coefficients. The estimates imply meaningful economic effects: moving from the 25th to the 75th percentile of HDHP penetration reduces charity care by about \$1.4 million.[11] Put

[10]The calculation is as follows. With coefficients of -0.005 and -0.038, the additional decreases when moving from the 25th to the 75th percentile of HDHP share ($0.316 - 0.140 = 0.176$) are $-0.005 \times 0.176 = -0.0009$ (–0.09% of assets) for capital expenditures and $-0.062 \times 0.176 = -0.011$ (–1.1% of assets) for salaries. At mean total assets of \$328 million, the combined cut of 1.2% amounts to roughly \$3.9 million, or about 19.2% of the average hospital's net income.

[11]The calculation is as follows. With coefficients of -0.024 in column (1), the additional decreases when moving from the 25th to the 75th percentile of HDHP share ($0.316 - 0.140 = 0.176$) are $-0.024 \times 0.176 = -0.0042$ (–0.42% of assets). At mean total assets of \$328 million, this amounts to roughly \$1.4 million cut in uncompensated care.

differently, the average hospital in a high-HDHP region forgoes an amount of community benefits comparable to nearly 7% of its average annual net income.

An additional way of boosting hospital profitability at the expense of social benefit is "cream skimming." Medicare reimbursements typically underpay hospitals, in the sense that the net profit margin from serving these patients is negative. Anecdotal evidence suggests that hospitals sometimes transfer unprofitable patients to nearby government-affiliated hospitals.[12] Columns (2) and (3) in Table A3 document that HDHP adoption is significantly associated with a lower share of Medicare patients admitted. The effect on Medicaid share is small and statistically insignificant, likely because Medicaid patients account for a relatively small fraction of overall hospital discharges (about 9%). Moreover, many hospitals must maintain a minimum threshold of Medicaid patients to qualify for Disproportionate Share Hospital (DSH) payments. Once these subsidies are taken into account, the effective profit margin from serving Medicaid patients is substantially higher compared to Medicare patients.

The first three columns in Table 7 Panel A may suffer from omitted variable bias, for example if local labor market conditions for medical staff affect both HDHP adoption and hospital investment. To address this concern, we first use the 2017 TCJA as a plausibly exogenous shock to instrument for HDHP adoption, which reduced HDHP tax advantages via two channels: tax-deductible HSA contributions and the itemized medical expense deduction. Specifically, by lowering marginal income tax rates, TCJA diminished the tax savings from HSA contributions, and by nearly doubling the standard deduction, it sharply reduced the number of itemizers eligible to deduct medical expenses. Consistent with this mechanism, Figure 2 shows that the steady rise in HDHP enrollment from 2012 to 2017 reversed in 2018, immediately after implementation.

Our instrument, *TCJA Exposed*, is the product of each county's share of tax returns claiming medical deductions in 2017 and an indicator for years after 2017. The instrument equals zero through 2017 and takes larger values thereafter in counties with greater pre-TCJA exposure. The relevance condition is twofold. First, a higher pre-TCJA share of

[12]See "A Tale of Two Hospitals in New York City," Lown Institute (2024), https://lowninstitute.org/a-tale-of-two-hospitals-in-new-york-city/ (last accessed: July 2025).

medical deduction claimants tends to reflect a greater prevalence of itemizers, who are more likely to be in higher tax brackets and display tax salience to the HSA benefit. Second, the medical expense deduction applies only when unreimbursed out-of-pocket spending exceeds the statutory threshold. Higher deductibles increase the likelihood that households cross this threshold. By increasing the standard deduction and reducing the value of these tax preferences, the TCJA weakened demand for HDHPs. Panel (a) of Figure 5 shows that the shares of itemizers and of filers claiming medical deductions were stable before 2017 and dropped sharply afterward, reinforcing the timing and relevance of the instrument.

To formalize this logic, we estimate the following first-stage regression:

$$HDHP_{i,t-1} = \pi_0 + \pi_1 TCJA\,Exposed_{i,t-1} + \gamma X_{i,t-1} + \alpha_i + \delta_{t-1} + \varepsilon_{i,t-1}, \tag{3}$$

Column (4) reports the first-stage estimates from Equation (3). The results show that HDHP share declines significantly with the instrument. The coefficient is negative and significant at the 1% level, with a t-statistic over 6, confirming that the TCJA reduced HDHP penetration. For all outcome variables, the first-stage F-statistics exceed 38, validating the instrument's relevance.

[Figure 5 Here]

A key identifying assumption is that the TCJA influences hospital outcomes only through its effect on HDHP adoption, not through direct changes in hospitals' own tax obligations. This restriction is plausible in our setting for two reasons. First, the majority of U.S. hospitals are non-profit institutions, which do not pay corporate income taxes and were therefore largely unaffected by the TCJA's changes to business taxation. Second, even among for-profit hospitals, the reform does not mechanically violate the exclusion restriction: we only require that any TCJA-induced corporate tax benefits do not vary systematically with the local pre-TCJA medical deduction share in a way that directly alters investment behavior. Moreover, the TCJA capped the deductibility of business interest, and many for-profit hospitals are highly leveraged, making the net direct tax effect ambiguous. Appendix Table A4 shows that within the for-profit sample there are no significant changes in net profits before and after the TCJA, nor differential changes across the pre-reform tax distribution.

Our instrument instead works through the household side, where the TCJA reduced the tax advantage of HSAs and medical deductions, thereby weakening incentives to enroll in HDHPs. If this is the only relevant channel, then we should observe no effect on HDHP adoption prior to the reform and a decline thereafter. In Figure 5 panel (b), we estimate the annual effects of TCJA exposure on HDHP enrollment in a CBSA-level event study with 2017 as the baseline year. We work at the CBSA level because MarketScan measures HDHP penetration at this geographic unit. The coefficients are statistically indistinguishable from zero in all pre-2017 years and become negative starting in 2018, supporting the parallel trends assumption underlying the IV strategy.

In Panel A of Table 7, columns (5) to (7) report the second-stage regressions of operational outcomes on the predicted HDHP share. The coefficients are negative and statistically significant across capital expenditures, total salaries, and uncompensated care, with magnitudes substantially larger than in the OLS results. The fact that the IV estimates are much larger than the OLS estimates likely reflects the distinction between average treatment effects (ATE) and local average treatment effects (LATE). Our instrument isolates a specific group of compliers: households in high-medical-deduction counties that initially enrolled in HDHPs because of the tax benefits of HSAs and medical deductions, and subsequently dropped them once the TCJA reduced the associated benefits. Importantly, these households cannot be characterized simply as "high-income" filers, because only unreimbursed medical expenses exceeding 7.5% of adjusted gross income can be deducted. With most health plans having out-of-pocket limits, high-income households are unlikely to satisfy this criterion. Instead, the compliers are most likely middle-income households that are therefore financially sophisticated and highly attentive to after-tax healthcare costs. From the hospital's perspective, such patients pose a distinctive risk when covered under HDHPs: they are disproportionately likely to defer elective care or default on deductibles in response to income fluctuations, thereby amplifying revenue cyclicality. Once TCJA induced these patients to shift into traditional coverage, hospitals experienced a marked reduction in cash-flow volatility and business-cycle exposure, producing much larger local responses in investment and staffing than those captured in the OLS estimates.

We utilize the 2017 TCJA as a demand-side shock to HDHP adoption. As a robustness

check, we employ a second instrumental variable that exploits supply-side variation in the relative pricing of HDHPs versus traditional plans, reported in Panel B. This instrument is constructed using small-group health insurance premium data from HIX Compare. The small-group market covers employer-sponsored insurance offered to firms with fewer than 50 full-time equivalent employees and is subject to ACA rating and benefit regulations. Plans in this segment must satisfy essential health benefit requirements, actuarial value constraints, and medical loss ratio rules. Importantly, premiums are set at the rating-area level, filed with and approved by regulators in advance, and may vary only by age, geography, family size, and tobacco use. Insurers are prohibited from experience-rating small employers, limiting the scope for employer bargaining or firm-specific risk to affect plan pricing. As a result, variation in relative premiums between HDHP and traditional plans primarily reflects insurer cost conditions, competitive dynamics, and regulatory environments at the rating-area level.

We construct a leave-one-out premium instrument based on the traditional-to-HDHP premium ratio.[13] Specifically, for each county–year, we compute the mean premium (for a standardized age) among traditional plans and among HDHP plans, form their ratio, and then construct a leave-one-out version that excludes plans offered in the hospital's own county. Intuitively, a higher ratio indicates that traditional plans are relatively more expensive than HDHPs for small employers, making HDHP enrollment more attractive and increasing local HDHP penetration.

Our analysis uses MarketScan data, which primarily capture large employer–sponsored insurance. Because large employers are not eligible to purchase small-group Marketplace plans, the relevance condition does not operate through direct price responses. Instead, we argue that insurer cost structures and regulatory constraints that shape plan design and pricing in the small-group market also influence plan offerings in the large-group market within the same rating area. This institutional feature also supports the exclusion restriction, as small-group pricing cannot be directly affected by large employers' demand or bargaining power. To further strengthen this argument, we adopt a leave-one-out design so that the instrument is driven by pricing variation determined outside the hospital's local market.

[13]We identify HDHP plans as those that meet either (i) a deductible-based criterion aligned with IRS minimum thresholds for HSA-qualified HDHPs, or (ii) a name- or metal-based criterion (e.g., plans labeled "HDHP," "HSA," or those in the bronze or catastrophic tiers).

In Panel B of Table 7, the first-stage coefficient is highly significant, with a t-statistic of approximately 6. The corresponding second-stage estimates are of similar magnitude to those reported in Panel A.

3.4 For-profit vs. Non-profit Hospitals

Lastly, we address the question of whether the tax-exempt status of hospitals shapes their responses to the business cycle. This issue carries important social welfare implications, as the U.S. hospital sector is dominated by non-profit institutions that receive favorable tax treatment in exchange for providing stable community benefits. The answer, however, is not straightforward. On the one hand, for-profit hospitals serve a larger share of commercially insured patients and are therefore more exposed to HDHP adoption, while non-profit hospitals treat more Medicare patients and receive various forms of government support. Regulated by the IRS, non-profit hospitals are required to provide minimum levels of charity care and are expected to prioritize social benefits over profitability. These facts suggest less operational hedging among non-profits.

On the other hand, most for-profit hospitals enjoy more flexible access to external financing through liquid equity markets, operate with higher profit margins, and benefit from internal capital markets due to their larger system size. These facts suggest less operational hedging among for-profits. The net effect of tax exemption on operational hedging ultimately depends on the relative quantitative importance of each channel.

Panel A of Table 8 focuses on financial outcomes, estimating Equation (2) separately for non-profit and for-profit hospitals. These subsamples are unbalanced, consistent with the dominant role of non-profit institutions. For both hospital types, revenues become more cyclical with rising HDHP adoption, as reflected in the negative and significant coefficients on the interaction terms. Consistent with for-profit hospitals' greater reliance on privately insured patients, the coefficient magnitude is more than three times larger than that of their non-profit counterparts, suggesting that HDHPs amplify revenue and income volatility more sharply for for-profit institutions.

[Table 8 Here]

Panel B reports results on operational and community benefit responses. Despite their

greater exposure, for-profit hospitals exhibit little evidence of adjustment, with coefficients small and statistically insignificant. In contrast, non-profit hospitals exhibit significant reductions across all three measures. This pattern suggests that, although non-profits are relatively less affected in terms of revenue cyclicality, they adjust more aggressively on the operational margin by cutting staff costs, investment, and uncompensated care provision. These responses help explain the differential effects of oil price crashes on net income as HDHP adoption rises. In Panel A, columns (3) and (4), the negative impact for for-profit hospitals is more than four times larger, while the coefficient for non-profits is only marginally significant. This difference reflects not only payer mix but also non-profits' tendency to hedge and adjust more aggressively.

Hedging through divestments raises potential concerns about hospitals' capacity to deliver high-quality services, particularly due to congestion when demand surges. While capacity constraints may be manageable during normal times, they become critical during public health crises. Table 9 provides correlational evidence of the costs associated with limited capacity during the COVID-19 pandemic, when shortages in hospital resources could directly translate into higher mortality.

[Table 9 Here]

We begin with granular evidence from hospital emergency departments, which represent the front line of acute care during public health emergencies. Columns (1) and (2) examine emergency department mortality outcomes at the hospital-year level using the HCUP SEDD. The dependent variable in column (1) is the total ER death rate per 1,000 ER visits, while column (2) focuses specifically on COVID-related ER deaths. For each hospital, we measure pre-COVID HDHP exposure in 2019 and interact this variable with the hospital's tax-exempt status.[14] The hypothesis is that non-profit hospitals, which hedge the business cycle risk more aggressively, are more exposed to the capacity consequences of HDHP-induced cost-cutting when emergency demand spikes. Consistent with this hypothesis, the interaction term is positive and statistically significant in both columns.

To generalize the hospital-level analysis, columns (3) and (4) turn to county-level mortal-

[14]Because this interaction term has no time-series variation at the hospital level, we cannot include hospital fixed effects. Instead, we include county fixed effects, which absorb the level effect of $HDHP_{2019}$.

ity data from the NCHS NVSS, which allow us to construct the annual number of COVID-related deaths among county residents from 2020 to 2023. We modify the interaction term to use pre-COVID HDHP prevalence and the fraction of non-profit hospitals in each county in 2019. The intuition is that in counties dominated by non-profit hospitals, Table 8 indicates that higher HDHP penetration lead these institutions to cut investments in order to reduce operational leverage, leaving them undercapitalized and less resilient to the unexpected COVID shock. Column (3) examines COVID-19 deaths per 100,000 residents, and column (4) uses the raw number of COVID-related deaths (winsorized at 2.5%). Consistent with the ER evidence, the interaction term is positive and statistically significant in both columns. The magnitudes are economically meaningful. Comparing two otherwise similar counties composed entirely of non-profit hospitals, a county at the 75th percentile of HDHP prevalence (41%) experiences approximately 5.2 more COVID-related deaths per year than a county at the 25th percentile (25%). Relative to the unconditional mean of 139 deaths, this represents an increase of roughly 4%.

What explains the different responses of for-profit and non-profit hospitals documented above? To better understand these differences, we examine the role of health system affiliation. Health systems have become increasingly prevalent: in our sample, roughly two-thirds of hospitals are system hospitals, meaning they are part of a broader network that provides profit sharing, pooled resources, and internal capital markets that can shape both operations and financial risk. However, the system structures of for-profit and non-profit providers differ markedly. Most for-profits belong to a handful of publicly traded systems with national networks and vertically integrated value chains (Lewellen et al., 2025). For example, HCA Healthcare operates approximately 190 hospitals and 2,400 ambulatory sites across 20 states in 2024. In contrast, most non-profit hospitals, if not standalone, tend to be part of regional systems that typically span a single state or a small group of neighboring states. These systems are smaller in scale, often comprising 10 to 20 hospitals, and lack the same degree of vertical integration as their for-profit counterparts.

[Table 10 Here]

Panel A of Table 10 examines whether geographic diversification mitigates hospitals' sensitivity to HDHP exposure. We define a cross-state system indicator for hospitals affiliated

with systems operating in multiple states, which should be better positioned to buffer local shocks through geographic risk pooling.[15] In our sample, fewer than 40% of non-profit hospitals belong to cross-state systems, compared to about 70% of for-profit hospitals. In the regressions, lagged HDHP share is negatively associated with salaries, capital expenditures, and uncompensated care. However, the interaction between cross-state system affiliation and lagged HDHP share is positive and significant for capital expenditures and uncompensated care in both the for-profit and non-profit subsamples. These findings suggest that cross-state affiliation provides an internal hedge, attenuating the localized impact of HDHP-induced volatility.

Panel B considers an alternative mechanism: system-level profit sharing through internal capital markets. Non-profit hospital systems generally operate with thinner margins, making them more sensitive to shocks and more likely to engage in aggressive operational cutbacks (see Table 8). In our sample, non-profit hospitals are affiliated with systems, or operate as stand-alone institutions, that average $270 million in annual net income, compared to $1.42 billion for for-profit hospitals. To test the relevance of this channel, we construct an indicator for hospitals affiliated with above-median profit systems (or, for stand-alone hospitals, based on their own net income). The interaction between high-profit status and lagged HDHP share is positive and significant for both non-profit and for-profit hospitals across most outcomes, with the exception of salaries in the for-profit subsample. This pattern suggests that higher profitability shields hospitals from the need to reduce investment and uncompensated care in response to HDHP exposure. In other words, system-level financial slack serves as a cushion, enabling hospitals to absorb revenue volatility rather than cutting back on operations or patient care.

In both panels, the interaction terms for a given outcome variable share the same sign for both non-profit and for-profit hospitals. Taken together, these results underscore that what ultimately determines how hospitals absorb the business cycle risks associated with HDHPs is not their tax-exemption status, but rather their organizational structure and access to internal risk-sharing mechanisms. Cross-state systems benefit from geographic diversification, and high-profit systems benefit from greater financial slack, both of which

[15]For stand-alone hospitals not affiliated with a system, the cross-state indicator is coded as zero.

insulate hospitals from the operational cutbacks that HDHP penetration would otherwise induce. We conclude that the community benefit obligations imposed on non-profit hospitals do not appear to be a first-order constraint on their behavior. Instead, non-profit hospitals respond to the same economic incentives as for-profit hospitals, and in some cases even more aggressively, revealing that profitability considerations dominate mission-driven mandates in shaping hospital responses to business cycle exposure.

4. Conclusions

This paper highlights the social welfare costs of exposing non-profit hospitals to business cycle risks through the growing prevalence of HDHPs. We show that hospitals in high HDHP areas experience significantly greater procyclicality in revenues, profitability, and service utilization. We find that hospitals attempt to hedge this volatility by raising payments per claim and by reducing staffing, investment, uncompensated care, and Medicare admissions. Our results have implications for hospital revenue management, particularly the diversification of income sources. Government subsidies are a historically important component of non-profit hospital income. Although we provide no overall welfare analysis and cannot prescribe optimal levels of insurance completeness, our results indicate that cuts to government subsidies exacerbate procyclicality and reduce provision of health care by non-profit hospitals.

We also document that non-profit hospitals, despite being mission driven and less dependent on privately insured patients, hedge more aggressively than for-profit hospitals. Examining the differential responses to the rise in HDHPs allows us to compare ownership structures in a broader sample, rather than relying on evidence from mergers and acquisitions where the priority is often short-term recovery of financial losses. We find that organizational structure, particularly geographic diversification and access to internal capital markets, mitigates the need for operational hedging (reduction in investment and service provision) against business cycle risk. Our findings call for closer scrutiny of non-profit community benefits and whether current IRS disclosure requirements effectively constrain non-profit operations. Finally, we point to a potentially overlooked benefit of hospital mergers, despite well recognized antitrust concerns, in providing additional financial flexibility.

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Figure 1: Rolling 5-Year CAPM Betas: Health vs. Consumer Nondurables

This figure plots rolling five-year CAPM betas for health and consumer nondurable sectors from 2000 to 2019, following the definition of Fama French 10 Industry classification. The health sector includes SIC codes 2830–2839, 3693–3693, 3840–3859, and 8000–8099. The consumer nondurable sector includes SIC codes 0100–0999, 2000–2399, 2700–2749, 2770–2799, 3100–3199, and 3940–3989. The solid blue line shows the beta for consumer nondurables, while the dashed red line shows the beta for health care. Shaded areas indicate NBER-dated recessions.

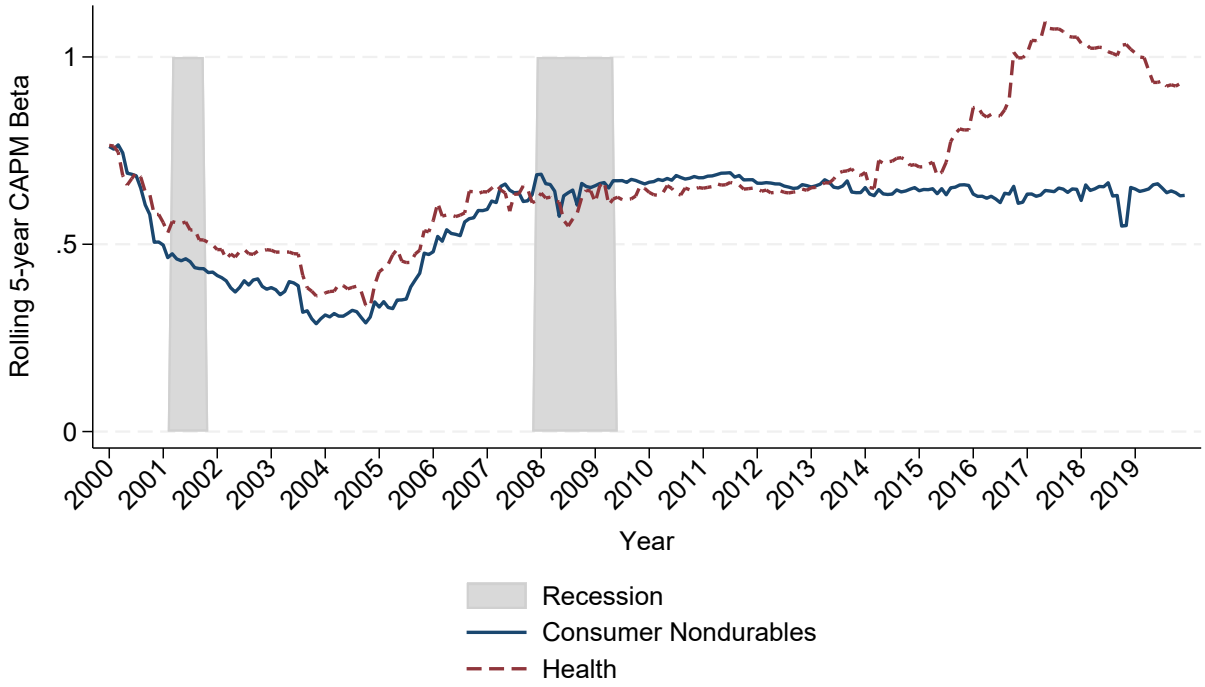


Figure 2: Hospital Outcomes, Local Income, and HDHPs: Correlations Over Time

This figure shows how the correlation between local income and hospital outcomes evolves alongside the rise in HDHP coverage from 2011 to 2021. In each panel, the red dashed line (right-hand axis) is the average share of the population enrolled in high-deductible health plans (HDHPs) by year; the blue solid line (left-hand axis) is the correlation coefficient between a hospital performance metric and a local income measure in that year. Panel (a) plots the correlation between local per capita income and local hospital patient revenue. Panel (b) plots the correlation between local stock income and local hospital patient revenue. Panel (c) plots the correlation between local per capita income and local hospital inpatient days. Panel (d) plots the correlation between local stock income and local hospital inpatient days.

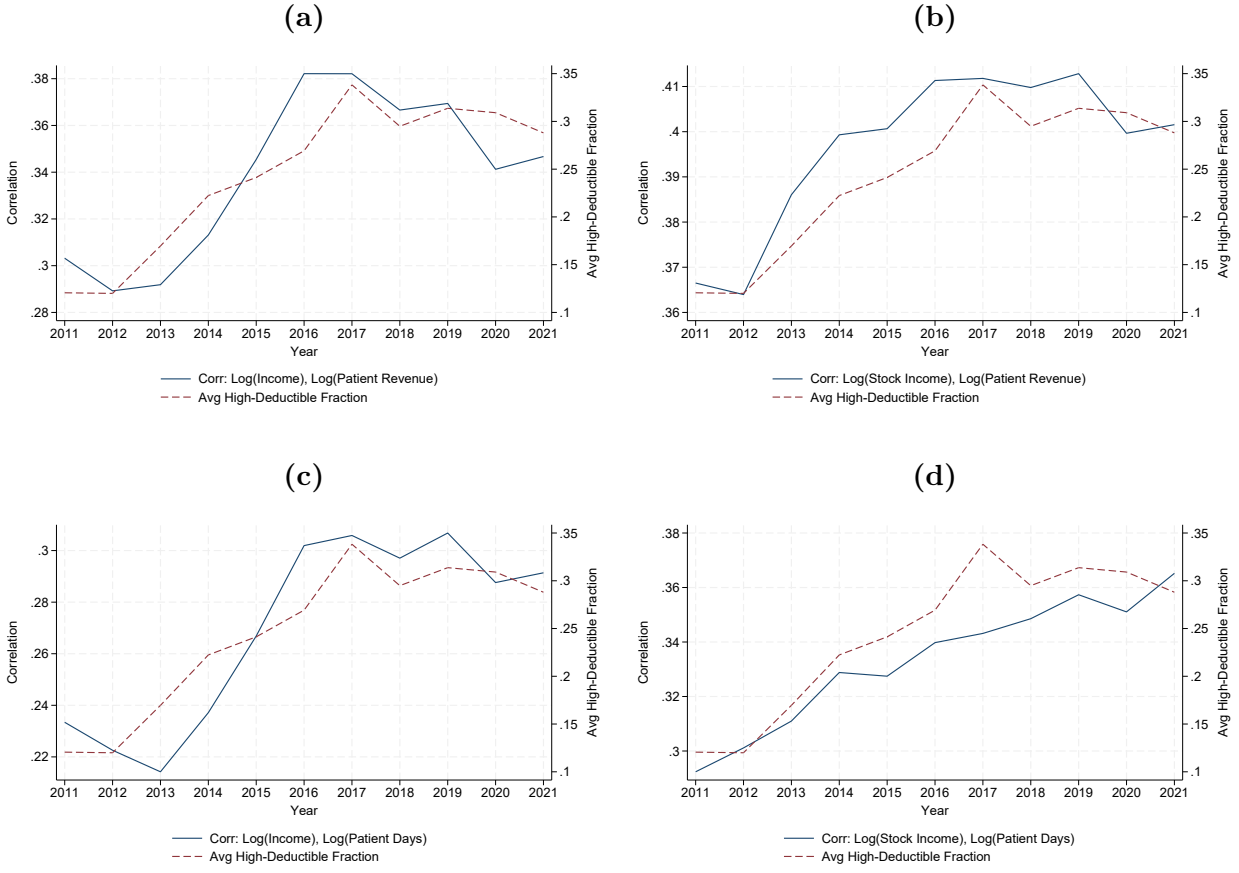
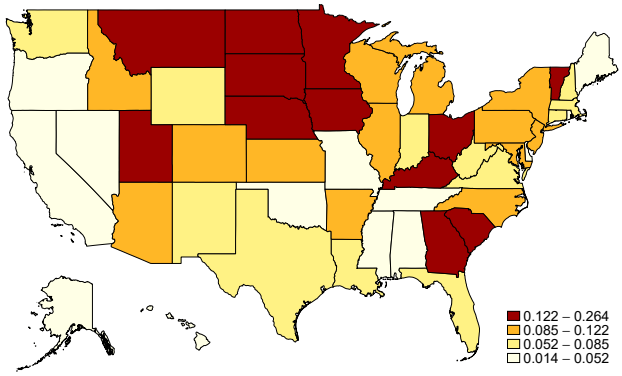
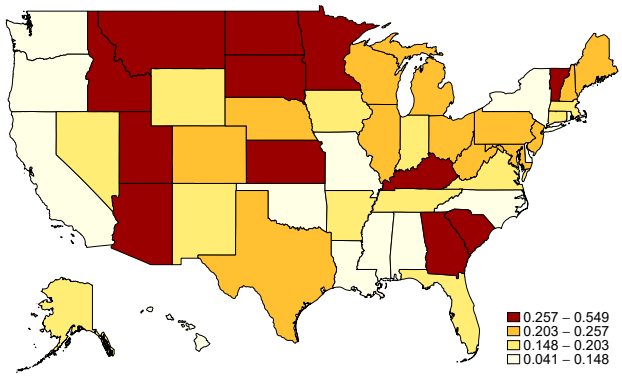


Figure 3: Geographic Variation in HDHP Penetration Across States

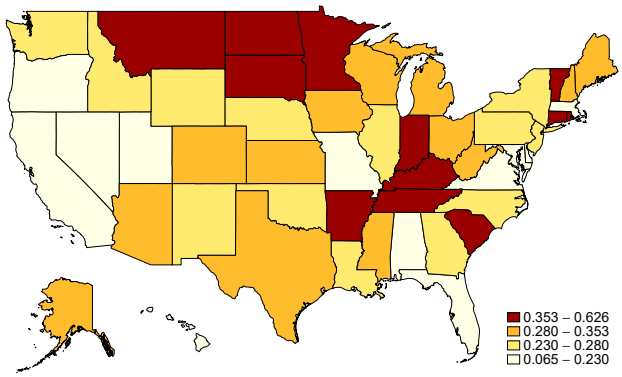
This figure maps the share of enrollees in high-deductible health plans (HDHPs) across states in 2010 (Panel a), 2014 (Panel b), and 2020 (Panel c). Darker shading indicates a higher fraction of enrollees in a given year.



(a) HDHP Share in 2010



(b) HDHP Share in 2014



(c) HDHP Share in 2020

Figure 4: Event Study: Impact of Oil Price Shock on Local Income

This figure plots a dynamic event-study of the 2014–2015 oil price collapse on county-level income over the sample period of 2012–2021. Each blue dot represents the estimated treatment effect of the oil shock on per capita income in a given year (with 95% confidence intervals). The shock exposure is measured by a county's pre-collapse oil development intensity (log(1 + avg. annual new wells over 2012–2014)). Year 2014 is the reference period (event time 0, marked by the vertical line). For post-event years 5–7, the effects are aggregated into a single point.

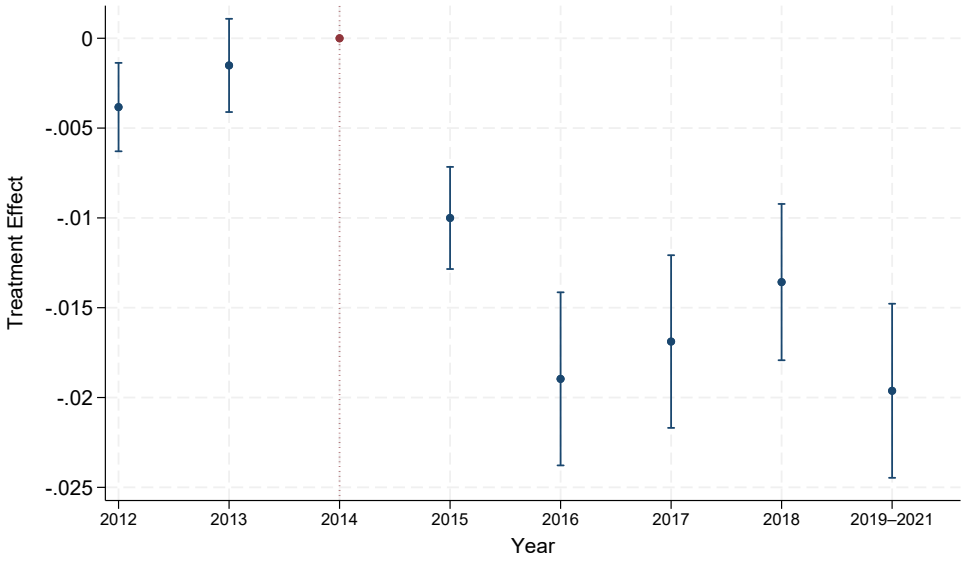
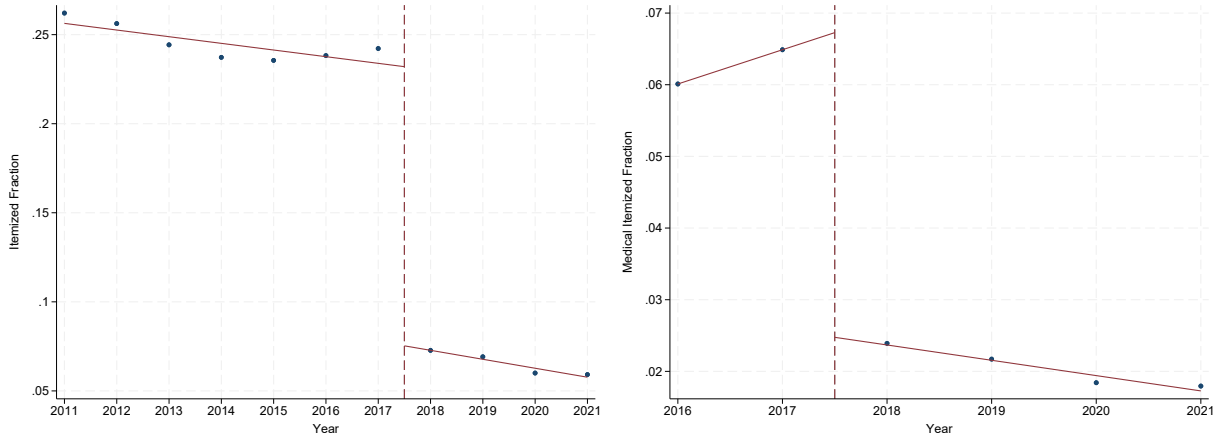


Figure 5: Event Study: Impact of the 2017 TCJA Shock on HDHP enrollment

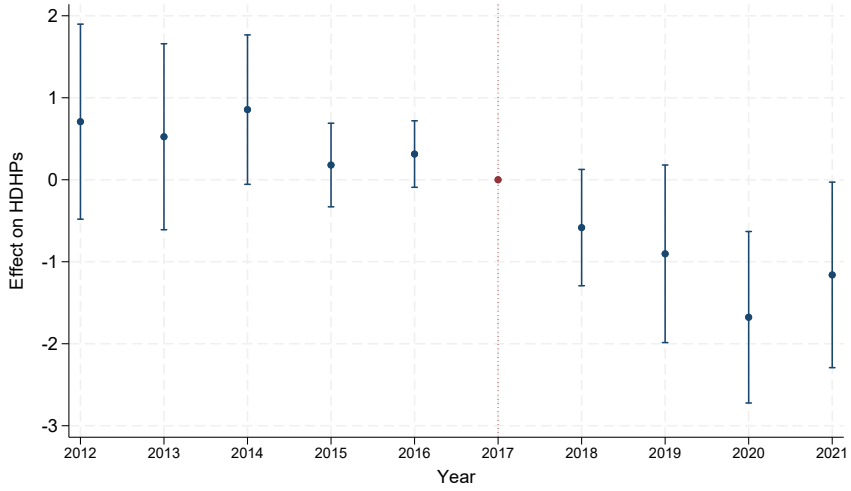
This figure shows the effects of the 2017 TCJA on HDHP utilization. Panel (a) shows the annual average share of taxpayers who itemize deductions (left, 2011-2021) and who claim medical itemized deductions (right, 2016-2021) from the IRS SOI data. 2016 is the earliest year with the medical itemized deduction item available. Blue dots denote yearly averages; the vertical dashed line marks TCJA implementation. Panel (b) shows the dynamic effects of the 2017 TCJA on CBSA-level HDHP enrollment rates over 2012–2021 as follows:

$$HDHP_{k,t} = \sum_{y=2012,\, y\neq 2017}^{2021} \beta_y \, MedShare_{k,2017} \times \mathbf{1}\{t = y\} + \nu_k + \lambda_t + \varepsilon_{k,t}.$$

Each blue dot plots β_y, the estimated effect of TCJA exposure proxied by the 2017 medical itemization share on the HDHP fraction in CBSA k in calendar year y. Because the raw medical deduction share is reported at the county level, $MedShare_{k,2017}$ is the average 2017 medical deduction share across all sample counties in CBSA k and weight the regression by the number of counties in each CBSA-year. 95% confidence intervals are shown, with standard errors clustered at the CBSA level. We use 2017 as the reference year, so its coefficient is omitted.



(a) Itemized and medical itemized fractions around TCJA



(b) Dynamic effects of TCJA on HDHP

Table 1: Summary Statistics of the Hospital Panel

This table summarizes the main variables in the hospital annual sample. *HDHP* is the lagged fraction of enrollees in high-deductible health plans in hospital i's CBSA. *Income* is per capita income in hospital i's county. *Stock Income* is the estimated income from stock wealth following Chodorow-Reich et al. (2021), and *Stock Income*^{Rel} is stock income scaled by local wage income. *Oil Exposed* is the interaction of the logarithm of average annual new wells between 2012 and 2014 in hospital i's area with an indicator equal to one for years strictly after 2014. *TA (mil)* and *Net Income (mil)* are total assets and net income of hospital i, measured in millions of dollars. *For-profit* equals one if hospital i is organized as for-profit and zero otherwise. *Net Patient Rev/TA*, *Net Inc/TA*, *Salaries/TA*, *CapEx/TA*, and *Uncompensated/TA* are net patient revenues, net income, salary expenditures, capital expenditures, and uncompensated care expenditures, each scaled by total assets. *Bed Utilization* is the average fraction of hospital beds occupied in a year. *Num. of Employees* is the number of hospital employees. *Num. of Beds* is the number of hospital beds. *Medicare Frac* and *Medicaid Frac* are the fractions of Medicare and Medicaid patients among all admitted patients.

Variable	**N**	**Mean**	**Std**	**p25**	**Median**	**p75**
HDHP	28,915	0.237	0.124	0.140	0.225	0.316
Income	29,133	47,907.074	14,794.370	38,299.000	44,792.000	53,609.000
Stock Income	29,109	13,743.317	16,302.053	4,776.009	9,270.615	16,689.512
Stock Income^{Rel}	29,109	0.304	0.255	0.126	0.229	0.398
Oil Exposed	29,133	0.228	0.854	0.000	0.000	0.000
TA (mil)	29,133	327.741	989.239	37.948	106.237	303.867
Net Income (mil)	29,131	20.445	68.770	0.463	5.894	23.158
For-Profit	29,133	0.214	0.410	0.000	0.000	0.000
Net Patient Rev/TA	29,127	1.161	0.688	0.665	0.985	1.491
Net Inc/TA	29,131	0.087	0.150	0.010	0.056	0.122
Bed Utilization	29,094	0.477	0.209	0.313	0.483	0.646
Salaries/TA	28,897	0.659	0.609	0.314	0.478	0.733
CapEx/TA	29,133	0.066	0.047	0.034	0.056	0.086
Num. of Employees	29,042	1,146.502	3,625.633	239.960	599.668	1,367.880
Num. of Beds	29,127	169.929	292.943	25.000	105.978	230.000
Uncompensated/TA	29,133	0.083	0.079	0.030	0.057	0.104
Medicare Frac	29,068	0.385	0.142	0.283	0.367	0.466
Medicaid Frac	27,552	0.094	0.086	0.028	0.061	0.140

Table 2: HDHPs and Hospital Cash Flow Exposure to the Business Cycle

This table reports the effects of HDHPs on hospital cash flow exposure to the business cycle using the hospital-year panel regression of Equation (1). In columns (1)–(3), the dependent variable is net patient revenue scaled by total assets; in columns (4)–(6), it is net income scaled by total assets. We include interactions between the lagged HDHP fraction and the logarithm of local income per capita, logarithm of stock income, and relative stock income, along with the standalone values of these variables. All regressions control for lagged log hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Net Patient Rev/TA			*Net Inc/TA*		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{HDHP}_{t-1} \times \text{Log(Income)}_t$	0.227*			0.058		
	(0.124)			(0.037)		
$\text{HDHP}_{t-1} \times \text{Log(Stock Income)}_t$		0.075***			0.011*	
		(0.025)			(0.006)	
$\text{HDHP}_{t-1} \times \text{Stock Income}_t^{Rel}$			0.262**			0.071***
			(0.105)			(0.026)
HDHP_{t-1}	-2.421*	-0.658***	-0.058	-0.590	-0.064	0.015
	(1.335)	(0.224)	(0.050)	(0.401)	(0.059)	(0.015)
Log(Income)_t	-0.114			0.020		
	(0.085)			(0.024)		
$\text{Log(Stock Income)}_t$		0.025			-0.004	
		(0.034)			(0.010)	
$\text{Stock Income}_t^{Rel}$			-0.041			-0.023**
			(0.044)			(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	28,908	28,890	28,890	28,912	28,894	28,894
Adj. R^2	0.80	0.80	0.80	0.67	0.67	0.67

Table 3: HDHPs and Hospital Cash Flow Exposure to the Oil Price Shock

This table reports the effects of HDHPs on hospital cash flow exposure to the 2014 oil price shock. $HDHP_{2014}$ is the fraction of enrollees in high-deductible health plans in 2014 (pre-shock). *Oil Exposed* is defined as the interaction of the logarithm of one plus average annual new wells between 2012 and 2014 in hospital i's county with an indicator equal to one for years strictly after 2014. Column (1) reports county-year regressions of the logarithm of income per capita on *Oil Exposed*, weighted by the number of hospitals in the county-year, and including county and year fixed effects. Columns (2)–(3) report hospital-year regressions where the dependent variables are *Net Patient Revenue/TA* and *Net Income/TA*, respectively, controlling for the lagged logarithm of hospital beds and total assets, and including hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Log(Income)*	(2) *Net Patient Rev/TA*	(3) *Net Inc/TA*
$\text{HDHP}_{2014} \times$ Oil Exposed$_t$		-0.291***	-0.050**
		(0.097)	(0.023)
Oil Exposed$_t$	-0.013***	0.062**	0.008
	(0.003)	(0.025)	(0.006)
Controls	Yes	Yes	Yes
County FE	Yes	No	No
Hospital FE	No	Yes	Yes
Year FE	Yes	Yes	Yes
N	16,389	28,101	28,105
Adj. R^2	0.98	0.80	0.67

Table 4: HDHPs and Hospital Bed Utilization

This table reports the effects of HDHPs on hospital bed utilization's exposure to the business cycle. The dependent variable in all columns is hospital i's bed utilization, which is the average fraction of hospital beds occupied in a year. In columns (1)–(3), we include interactions between the lagged HDHP fraction and the logarithm of one plus local income per capita, logarithm of stock income, and relative stock income, along with the standalone values of these variables. In column (4), $HDHP_{2014}$ is the fraction of enrollees in high-deductible health plans in 2014 (pre-shock). *Oil Exposed* is defined as the interaction of the logarithm of average annual new wells between 2012 and 2014 in hospital i's county with an indicator equal to one for years strictly after 2014. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Bed Utilization			
	(1)	(2)	(3)	(4)
$\text{HDHP}_{t-1} \times \text{Log(Income)}_t$	0.089**			
	(0.034)			
$\text{HDHP}_{t-1} \times \text{Log(Stock Income)}_t$		0.016**		
		(0.007)		
$\text{HDHP}_{t-1} \times \text{Stock Income}_t^{Rel}$			0.063*	
			(0.037)	
$\text{HDHP}_{2014} \times \text{Oil Exposed}_t$				-0.042*
				(0.022)
HDHP_{t-1}	-0.924**	-0.116*	0.007	
	(0.367)	(0.062)	(0.013)	
Log(Income)_t	0.040			
	(0.027)			
$\text{Log(Stock Income)}_t$		-0.003		
		(0.009)		
$\text{Stock Income}_t^{Rel}$			-0.048***	
			(0.012)	
Oil Exposed_t				0.008
				(0.005)
Controls	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	28,874	28,856	28,856	28,071
Adj. R^2	0.87	0.87	0.87	0.87

Table 5: Hospital Utilization under the Oil Price Shock: HDHPs vs. Traditional Plans

This table reports regressions of hospital utilization on the oil price shock, estimated separately for enrollees in high-deductible health plans (HDHPs) and traditional plans. Observations are at the CBSA-by-industry (oil-related vs. other industries) level for each year. Columns (1)-(3) present results for HDHP enrollees for each CBSA-industry group, where the dependent variables are utilization rates defined as total visits, surgical visits, and medical visits per 1,000 enrollees, respectively. Columns (4)-(6) report the corresponding results for enrollees in traditional plans. *Oil Exposed* is defined as the interaction of the logarithm of one plus average annual new wells between 2012 and 2014 in a CBSA with an indicator equal to one for years after 2014 for the oil industry, and zero otherwise. All regressions include CBSA-by-Year and CBSA-by-Industry fixed effects. *Y Mean* calculates the average utilization rates for enrollees in HDHP and traditional plan, respectively, at the CBSA-industry level. Standard errors, reported in parentheses, are clustered at the CBSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	High-deductible Plans			Traditional Plans		
	(1) *Total Visits*	(2) *Surgical Visits*	(3) *Medical Visits*	(4) *Total Visits*	(5) *Surgical Visits*	(6) *Medical Visits*
Oil Exposed$_t$	-4.249***	-1.425***	-1.383***	-0.416	0.238	-0.117
	(1.000)	(0.293)	(0.312)	(0.812)	(0.278)	(0.284)
CBSA-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
CBSA-by-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Y Mean	25.280	7.429	7.974	40.327	11.600	12.094
N	6,384	6,384	6,384	6,384	6,384	6,384
Adj. R^2	0.59	0.58	0.57	0.17	0.22	0.27

Table 6: Hospital Cross-Subsidization under the Oil Price Shock

This table reports claim-level regressions of the effects of HDHPs on how hospitals cross subsidize revenue losses during the oil price shock by raising payments. The dependent variables are raw hospital payments in dollars (column 1), Diagnosis-Related Group weight–adjusted payments (column 2), and length-of-stay–adjusted payments (column 3). $HDHP_{2014}$ is the fraction of enrollees in high-deductible health plans in 2014 (pre-shock). *Oil Exposed* is defined as the interaction of the logarithm of one plus average annual new wells between 2012 and 2014 in patient's CBSA with an indicator equal to one for years strictly after 2014. All regressions control for patient age, gender, length of stay, and an indicator for high-deductible plan, and include CBSA, year, DRG, and industry fixed effects. Standard errors, reported in parentheses, are double-clustered at the CBSA and DRG levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Hospital Payment*	(2) *DRG-adj. Payment*	(3) *LOS-adj. Payment*
$\text{HDHP}_{2014} \times$ Oil Exposed$_t$	906.747**	720.908**	198.950**
	(447.898)	(310.158)	(97.455)
Oil Exposed$_t$	-349.630***	-253.760***	-77.097***
	(93.445)	(63.923)	(20.515)
Controls	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
DRG FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	4,189,007	4,178,764	4,178,764
Adj. R^2	0.64	0.34	0.59

Table 7: HDHPs and Hospital Hedging through Operational Adjustment

This table reports OLS and 2SLS regressions of how hospitals hedge the business cycle exposure by operational adjustment. The outcome variables include capital expenditures over total assets (*CapEx/TA*), salaries over total assets (*Salaries/TA*), and uncompensated care expenditures over total assets (*Uncompensated/TA*). In Panel A, columns (1)–(3) report OLS estimates, column (4) reports the first-stage regression of the lagged HDHP fraction on lagged TCJA exposure, proxied by the share of tax returns claiming medical deductions in 2017. Columns (5)–(7) report the corresponding second-stage regressions of hospital operations on the predicted HDHP fraction. First-stage F-statistics are reported. Panel B has a similar structure of the last four columns of Panel A, except that the instrument is the price ratio between traditional and HDHP plans in the small group marketplace. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: OLS and TCJA Instruments

	OLS			1st Stage	2nd Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CapEx/TA	*Salaries/TA*	*Uncompensated/TA*	$HDHP_{t-1}$	*CapEx/TA*	*Salaries/TA*	*Uncompensated/TA*
$HDHP_{t-1}$	-0.006*	-0.061*	-0.024***		-0.079**	-0.657*	-0.125*
	(0.003)	(0.033)	(0.007)		(0.038)	(0.385)	(0.068)
TCJA $Exposed_{t-1}$				-0.692***			
				(0.112)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistics					38.10	39.09	38.10
N	28,914	28,680	28,914	28,914	28,914	28,680	28,914
Adj. R^2	0.78	0.86	0.73	0.78			

Panel B: Marketplace Instruments

	1st Stage	2nd Stage		
	(1)	(2)	(3)	(4)
	$HDHP_{t-1}$	*CapEx/TA*	*Salaries/TA*	*Uncompensated/TA*
Premium Ratio	0.122***			
	(0.021)			
$HDHP_{t-1}$		-0.078**	-0.875*	-0.152**
		(0.033)	(0.459)	(0.076)
Controls	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-Statistics		32.68	34.01	32.68
N	18,784	18,784	18,632	18,784
Adj. R^2	0.74			

Table 8: Differential Responses of For-Profit and Non-Profit Hospitals to HDHPs

This table compares the responses of for-profit and non-profit hospitals to HDHP exposure. Panel A examines the effects of HDHPs on hospital cash flow exposure to the oil price shock for for-profit and non-profit hospitals. Panel B examines how these two groups hedge through operational adjustments and community benefit provision. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Hospital Revenue

	Net Patient Rev/TA		*Net Inc/TA*	
	(1)	(2)	(3)	(4)
$\text{HDHP}_{2014}\times$ Oil Exposed$_t$	-0.701**	-0.207**	-0.143**	-0.034
	(0.293)	(0.096)	(0.066)	(0.023)
Oil Exposed$_t$	0.151**	0.049*	0.021	0.008
	(0.065)	(0.028)	(0.015)	(0.007)
Controls	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Subsample	For-profit	Non-profit	For-profit	Non-profit
N	5,867	22,244	5,866	22,249
Adj. R^2	0.74	0.79	0.73	0.53

Panel B: Hospital Operations

	Salaries/TA		*CapEx/TA*		*Uncompensated/TA*	
	(1)	(2)	(3)	(4)	(5)	(6)
HDHP_{t-1}	0.042	-0.079**	-0.003	-0.007**	-0.009	-0.027***
	(0.066)	(0.037)	(0.010)	(0.003)	(0.021)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	For-profit	Non-profit	For-profit	Non-profit	For-profit	Non-profit
N	6,178	22,515	6,213	22,717	6,213	22,717
Adj. R^2	0.80	0.87	0.71	0.76	0.69	0.74

Table 9: HDHP Exposure and COVID-19 Mortality

This table examines the relationship between pre-COVID HDHP prevalence, hospital ownership composition, and COVID-19 mortality. Columns (1) and (2) report the results of hospital-year level analysis. The dependent variables are the ER death rate per 1,000 ER visits (column 1), and the COVID-19 ER death rate per 1,000 ER visits (column 2). $HDHP_{2019}$ is the local share of HDHP utilization in 2019 for each hospital i. $NonProfit_i$ is one if hospital i is non-profit, and zero otherwise. Columns (3) and (4) report the results of county-year level analysis. The dependent variables are the COVID-19 death rate per 100,000 residents (column 3), and the raw number of COVID-related deaths (winsorized at 2.5%) (columns 4). $NPFrac$ is the fraction of hospitals that are non-profit in 2019. In columns (1) and (2), we control for the lagged logarithm of hospital beds and total assets, as well as county-level logarithms of population and income per capita. In columns (3) and (4), we control for county-level logarithm of population, and income per capita. Year fixed effects are included in all analyses, whereas county fixed effects are included in columns (1) and (2). Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Hospital ER		*County*	
	(1) *Death Rate*	(2) *COVID Death Rate*	(3) *COVID Death*	(4) *COVID Death Num*
$\text{HDHP}_{2019}\times$ NonProfit_i	3.759*	0.238*		
	(2.070)	(0.128)		
NonProfit_i	-1.133	-0.060		
	(0.704)	(0.046)		
$\text{HDHP}_{2019}\times$ NP Frac_{2019}			64.116**	90.706**
			(29.452)	(38.721)
HDHP_{2019}			-35.435	-52.620
			(24.633)	(35.727)
NP Frac_{2019}			-35.206***	-38.081***
			(10.312)	(13.472)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
N	901	901	6,429	6,429
Adj. R^2	0.34	0.15	0.51	0.68

Table 10: For-Profit vs. Non-Profit Hospitals: System Affiliations

This table examines how geographic diversification and internal capital markets through healthcare systems affect hospitals' incentives to hedge. In both panels, the dependent variables are salaries, capital expenditures, and uncompensated care, each scaled by total assets. Panel A examines hospital systems operating across multiple states, where *Cross-State* indicates systems spanning more than one state. Panel B examines hospital systems by profitability, where *High Profit* denotes systems with above-median aggregated net income. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Single-state vs. Cross-state Systems

	Salaries/TA		*CapEx/TA*		*Uncompensated/TA*	
	(1)	(2)	(3)	(4)	(5)	(6)
Cross-State$_t$× HDHP$_{t-1}$	0.053	0.101*	0.037**	0.011**	0.067**	0.036***
	(0.099)	(0.056)	(0.016)	(0.005)	(0.031)	(0.009)
HDHP$_{t-1}$	0.002	-0.119***	-0.032*	-0.011***	-0.059*	-0.041***
	(0.101)	(0.042)	(0.018)	(0.003)	(0.035)	(0.008)
Cross-State$_t$	-0.002	-0.002	0.011**	-0.000	-0.015	-0.006*
	(0.042)	(0.019)	(0.005)	(0.002)	(0.010)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	For-profit	Non-profit	For-profit	Non-profit	For-profit	Non-profit
N	6,178	22,515	6,213	22,717	6,213	22,717
Adj. R^2	0.80	0.87	0.71	0.76	0.69	0.74

Panel B: System Profitability

	Salaries/TA		*CapEx/TA*		*Uncompensated/TA*	
	(1)	(2)	(3)	(4)	(5)	(6)
High Profit$_t$× HDHP$_{t-1}$	0.054	0.224***	0.027*	0.015***	0.074***	0.027***
	(0.088)	(0.045)	(0.014)	(0.004)	(0.027)	(0.008)
HDHP$_{t-1}$	-0.049	-0.407***	-0.048*	-0.029***	-0.134**	-0.067***
	(0.166)	(0.076)	(0.029)	(0.007)	(0.055)	(0.014)
High Profit$_t$	-0.001	-0.057***	0.002	-0.004***	-0.018**	-0.008***
	(0.028)	(0.013)	(0.004)	(0.001)	(0.007)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	For-profit	Non-profit	For-profit	Non-profit	For-profit	Non-profit
N	6,178	22,514	6,213	22,716	6,213	22,716
Adj. R^2	0.80	0.87	0.71	0.76	0.70	0.74

Online Appendix

Hedging and Healing: How Business Cycle Exposure Affects the Safety Net

Figure A1: Oil Price Shock 2012–2016

This figure plots the annual average crude oil price per barrel between 2012 and 2016, using the annual average spot price of West Texas Intermediate (WTI) crude oil from the U.S. Energy Information Administration (EIA). The solid navy line with circular markers traces the price path, with labels indicating each year's value. The vertical dashed maroon line marks 2014, the onset of the sharp oil price decline.

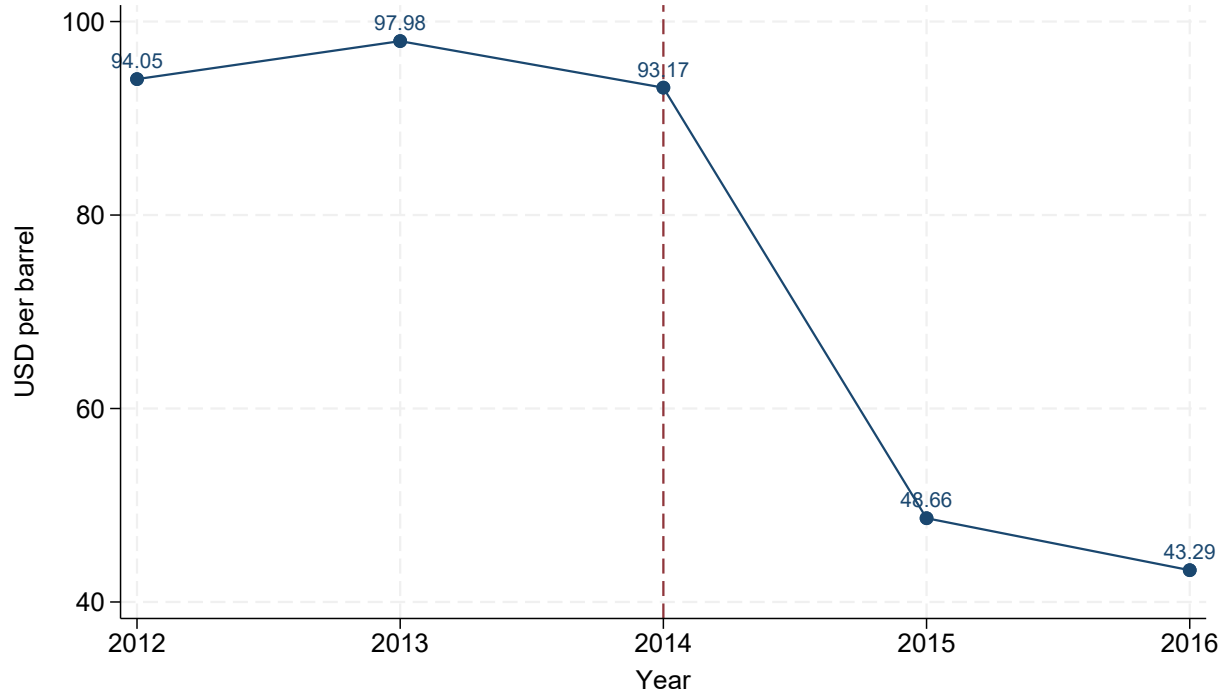
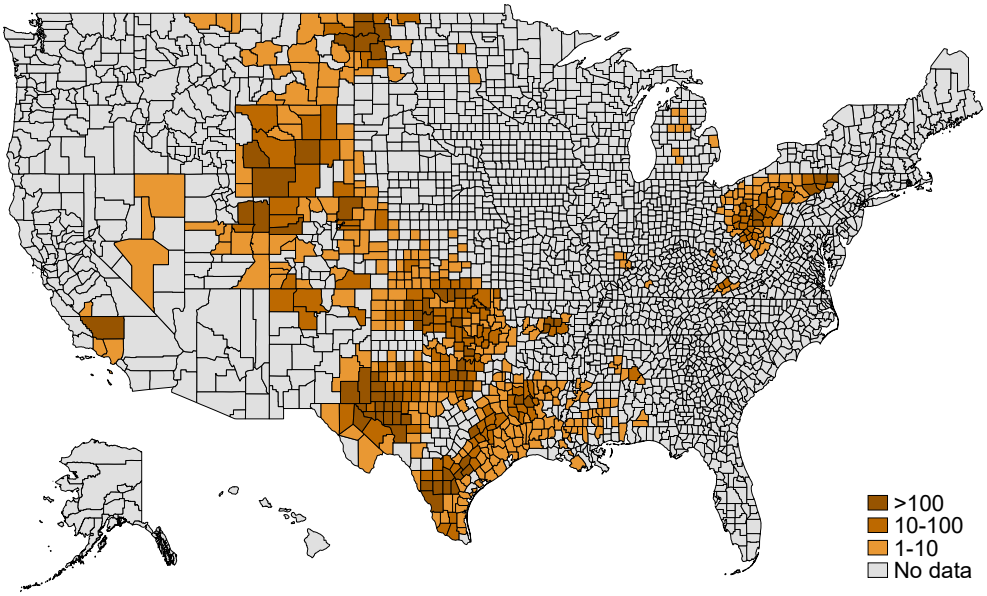
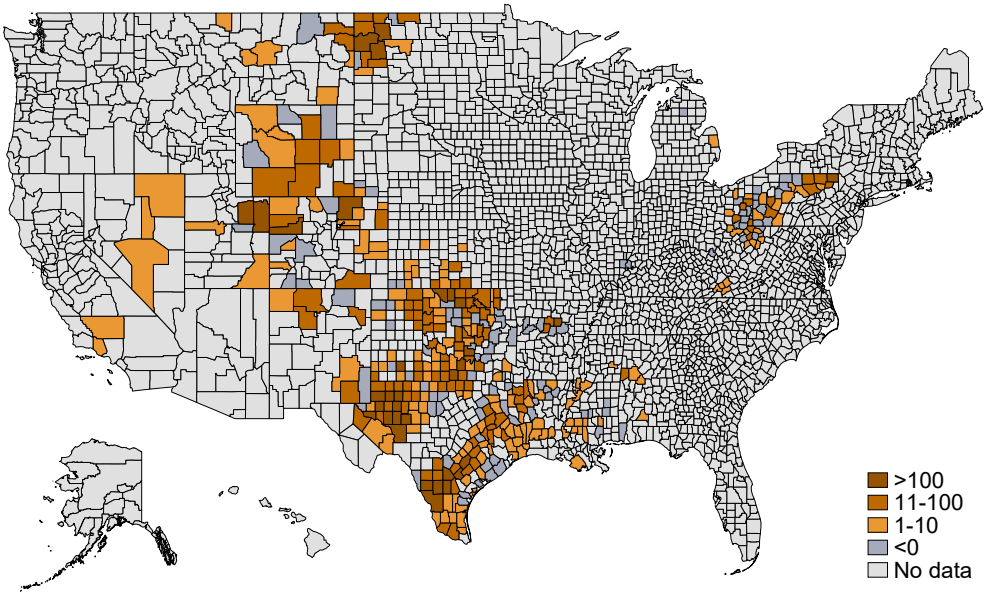


Figure A2: Geographic Distribution of Oil Drilling Activity and the 2014-2015 Collapse

This figure maps county-level oil well activity before and after the 2014-2015 oil price crash, illustrating the oil shock's local impact. Panel (a) shows the average number of new oil and gas wells drilled in each county over 2012–2014 (the peak fracking period). Panel (b) shows the change in new well drilling from 2014 to 2015 in each county (the decline following the price collapse). Darker shading indicates higher values in both panels: in (a) more intensive drilling activity, and in (b) a larger decline in well completions.



(a) Average wells over 2012–2014



(b) Decline in wells from 2014 to 2015

Table A1: Alternative Timings of HDHP Share and Stock Wealth

This table reports the robustness of using alternative timings of HDHP share and stock wealth in the stock-driven income shock design. HDHP_{10} is the local share of HDHP utilization for each hospital in 2010. $\text{Stock Income}_t^{10}$ is the approximated stock income by multiplying the stock return in year t with the local stock wealth in 2010. $\text{Stock Income}_t^{Rel10}$ is $\text{Stock Income}_t^{10}$ normalized by the 2010 local wage income. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Presample HDHP Share

	(1) *Net Patient Rev/TA*	(2) *Net Inc/TA*	(3) *Net Patient Rev/TA*	(4) *Net Inc/TA*
$\text{HDHP}_{10}\times$ Log(Stock Income)$_t$	0.126***		0.021**	
	(0.040)		(0.009)	
$\text{HDHP}_{10}\times$ Stock Income$_t^{Rel}$		0.484**		0.083**
		(0.189)		(0.037)
Log(Stock Income)$_t$	0.029		-0.004	
	(0.034)		(0.010)	
Stock Income$_t^{Rel}$		-0.028		-0.019**
		(0.040)		(0.009)
Controls	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	29,029	29,029	29,033	29,033
Adj. R^2	0.80	0.80	0.67	0.67

Panel B: Presample HDHP Share and Stock Wealth

	(1) *Net Patient Rev/TA*	(2) *Net Inc/TA*	(3) *Net Patient Rev/TA*	(4) *Net Inc/TA*
$\text{HDHP}_{10}\times$ Log(Stock Income^{10})$_t$	0.106***		0.016*	
	(0.037)		(0.009)	
$\text{HDHP}_{10}\times$ Stock Income$_t^{Rel10}$		0.409**		0.079*
		(0.204)		(0.042)
Log(Stock Income^{10})$_t$	0.022		-1.279*	
	(2.288)		(0.762)	
Stock Income$_t^{Rel10}$		-0.028		-0.011
		(0.036)		(0.007)
Controls	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	29,029	29,029	29,033	29,033
Adj. R^2	0.80	0.80	0.67	0.67

Table A2: HDHPs and Hospital Cash Flow

This table reports OLS regressions of hospital cash flows on lagged HDHP share. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Net Patient Rev/TA*	(2) *Net Inc/TA*
HDHP_{t-1}	0.019	0.036***
	(0.044)	(0.013)
Controls	Yes	Yes
Hospital FE	Yes	Yes
Year FE	Yes	Yes
N	28,908	28,912
Adj. R^2	0.80	0.67

Table A3: Additional Hedging Activities

This table reports OLS regressions of additional hedging activities. The outcome variables are the logarithm of employees in medical units, and fractions of Medicare and Medicaid patients among all admitted patients. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Log(EMP)	*Medicare Frac*	*Medicaid Frac*
	(1)	(2)	(3)
HDHP_{t-1}	-0.093***	-0.022***	-0.001
	(0.026)	(0.008)	(0.008)
Controls	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	28,822	28,848	27,320
Adj. R^2	0.98	0.91	0.75

Table A4: TCJA and For-profit Hospitals

This table reports the effects of the 2017 TCJA on hospital cash flows for for-profit hospitals. *TCJA* is the average county-level tax rate in 2017. *TCJA Exposed* is defined as the product of each county's average income tax rate in 2017 and an indicator for years after 2017. All regressions control for the lagged logarithm of hospital beds and total assets, and include hospital and year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Net Patient Rev/TA*	(2) *Net Patient Rev/TA*
TCJA	0.008	
	(0.005)	
TCJA Exposed$_t$		0.387
		(0.283)
Controls	Yes	Yes
Hospital FE	Yes	Yes
Year FE	No	Yes
N	6,233	6,233
Adj. R^2	0.72	0.72