Labor Market Regulation and Technology Adoption: Evidence from Nurse Staffing Mandate in California*

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Abstract

We study how quantity-based labor regulations affect technology adoption using California's nurse staffing mandate. Combining nationwide hospital data with a synthetic difference-in-differences design, we show that the mandate reduced adoption of Clinical Decision Support systems by up to 6.4 percentage points among hospitals with low baseline staffing conditions or tight financial constraints. Conversely, adoption of nurse staffing software increased by up to 9 percentage points among well-staffed, financially flexible hospitals. These patterns reflect the crowding out of quality-enhancing technologies and increased demand for compliance tools. Overall, staffing mandates shift the technology investment composition, with implications for mortality and clinical performance.

JEL codes: O33, L51, I18, J38

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The data used in this paper are from the Healthcare Cost Report Information System (HCRIS), publicly available from the Centers for Medicare & Medicaid Services (CMS): https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/Cost-Reports-by-Fiscal-Year. Hospital technology adoption measures are from the HIMSS Analytics database, which is proprietary and available to researchers upon formal request through HIMSS (https://www.himss.org/contact-us/). Data on nurse staffing and hospital characteristics are obtained from the American Hospital Association (AHA) Annual Survey Database, which requires purchase through AHA Data (https://www.ahadata.com/aha-annual-survey-database). The authors are willing to assist researchers with data access inquiries. Because the AHA and HIMSS data are subject to licensing and cannot be publicly shared, the authors respectfully request an exemption from the JHR replication policy. Upon acceptance, the authors will provide replication code and processed datasets that exclude proprietary variables, along with detailed documentation.

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1 Introduction

Technological differences are a key driver of productivity disparities across firms, regions, and countries, leading to growing interest in the determinants of technology adoption choices. Firms do not adopt technology in isolation but make these decisions along with other production inputs. Among these, labor plays a central role due to its direct interaction with technology—technology can either substitute for or complement labor (Katz and Murphy, 1992; Acemoglu, 2003). While extensive research has examined how technological change affects labor market outcomes, comparatively little is known about the reverse relationship: how labor market conditions affect firms' technology adoption decisions.[1] This paper studies how quantity-based labor regulations shape technology adoption, using California's nurse staffing mandate as a natural empirical setting.

Staffing mandates are a widely used form of labor market regulation, particularly in highly regulated industries, including healthcare, education, and public safety.[2] Unlike price-based regulations such as minimum wages, which affect marginal cost of labor, staffing mandates impose a binding requirement on the number of workers that must be employed. As a result, firms subject to staffing mandates may be forced to prioritize compliance by expanding labor inputs, potentially at the expense of technology investments. This tradeoff is especially salient in settings where firms must make larger staffing adjustments or where financial constraints limit their ability to absorb higher labor costs.

The effect of staffing mandates on technology adoption is theoretically ambiguous. First, the impact depends on whether labor and technology act as substitutes or complements in production. Mandates that require firms to expand labor may reduce incentives to adopt labor-saving technologies, while technologies that raise the productivity of labor may become more attractive. Second, mandated increases in labor spending may crowd out technology investment as firms that must prioritize regulatory compliance over other expenditures may become financially constrained. Finally, staffing mandates can create ongoing compliance requirements, generating demand for technologies that facilitate monitoring or scheduling, even if those technologies do not directly enhance productive efficiency.

To examine this, we study California's nurse staffing mandate implemented in the early 2000s. Assembly Bill 394 (AB394), passed in 1999, established minimum nurse-to-patient ra-

[1] Acemoglu and Finkelstein (2008) examine how changes in labor cost reimbursement regulations affect technology adoption in hospitals. Acemoglu (2010) find that labor scarcity can either impede or expedite technology adoption, depending on the complementarity or substitutability between labor and technology.

[2] Regulated sectors constitute a significant share of total GDP and employment. For instance, healthcare expenditures account for approximately 16.5% of U.S. GDP, while healthcare employment represents 12% of total U.S. employment. See World Bank Database (https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS) and the Kaiser Family Foundation (KFF) (https://www.kff.org/651d597/).

tios (NPRs) for general acute care hospitals, with detailed standards announced in 2002 and fully implemented by 2004. Although the regulation applied uniformly across hospitals in California, its implications varied by pre-existing conditions. All hospitals faced the requirement to maintain compliance with real-time staffing standards, but those with lower baseline staffing ratios had to hire additional nurses to meet the mandated ratios. At the same time, because investments in new technologies involve substantial fixed and ongoing costs, hospitals' financial conditions around the time of policy implementation played an important role in shaping their technological responses.

In this paper, we focus on two hospital technologies particularly relevant to nurse staffing mandates: Clinical Decision Support (CDS) systems and nurse staffing software (NSS). Health information technology (HIT) is widely studied in both the medical and economics literature as a key driver of healthcare quality, and CDS is a core component that supports this function (Buntin et al., 2011; Miller and Tucker, 2011). CDS helps clinicians—including nurses—reduce medical errors and generally complements, or is neutral to, nurse staffing. As a result, policy-induced increases in nurse employment may strengthen incentives to adopt CDS, while tighter budget constraints created by the mandate could dampen adoption.

In contrast, NSS is directly tied to staffing policy: it helps hospitals manage schedules, assign shifts, and match staffing to patient acuity. By improving labor allocation efficiency, NSS can help hospitals meet staffing mandates without simply increasing staff. Our conceptual framework shows that the mandate may encourage NSS adoption, particularly among hospitals that have sufficient baseline staffing ratios and face compliance risk driven by demand volatility rather than persistent understaffing. Taken together, these mechanisms imply that the staffing mandate can differentially affect technology adoption, shaping incentives for CDS through labor complementarity and financial constraints, while encouraging NSS as a compliance tool with real-time staffing requirements.

We combine nationwide hospital-level technology adoption data from the Health Information and Management Systems Society (HIMSS) with additional data sources on nurse staffing, patient volumes, and operating margin. The HIMSS data provide information on the adoption status of detailed healthcare technologies, allowing us to isolate the effects of the staffing mandate on particular technologies rather than broad measures of health IT use. We also use these data to examine heterogeneous responses along two dimensions. First, baseline staffing conditions are measured using average NPRs from 2000 to 2002, prior to the announcement of the staffing standards. Second, for financial conditions, we use operating margins and classify hospitals as financially constrained if they reported negative margins over the same period.

To estimate the policy's effect on technology adoption in California hospitals relative to those in other states, we use the synthetic difference-in-differences (SDID) method of Arkhangelsky et al. (2021), along with its event-study extension by Clarke et al. (2024). SDID relaxes the parallel trends assumption of standard difference-in-differences (DID) by reweighting control units to better align pre-treatment trends between treated and control groups and time periods to better predict the average post-treatment outcome with a weighted average of pre-treatment outcomes. This is particularly useful in our setting, where California hospitals may systematically differ from hospitals elsewhere, and underlying technology adoption trends can vary across regions. For robustness, we estimate a standard DID and DID combined with coarsened exact matching (CEM), which yield qualitatively similar results. To explore heterogeneity, we also estimate SDID separately by staffing and financial status.

We find that the staffing mandate reduces CDS adoption in California relative to other states, with the largest declines among hospitals with the lowest pre-policy staffing or tighter financial constraints. On average, CDS adoption falls by 3.8 percentage points in California, with event-study estimates showing a peak decline of 7 percentage points by 2007. Effects vary systematically by baseline staffing. Hospitals with low baseline staffing ratios see the largest decline, those with moderate staffing smaller declines, and those with high staffing little response. Heterogeneity by financial status indicates that these effects are concentrated among financially constrained hospitals, while unconstrained hospitals exhibit no significant change. These findings are aligned with the idea that increased labor costs tighten budgets and crowd out costly clinical technologies.

To illustrate the potential consequences, a back-of-the-envelope calculation suggests that the observed 3.8 percentage point decline in CDS adoption rates in California could have been associated with approximately 15 additional neonatal deaths per 100,000 live births and 75 additional deaths per 1 million elderly admissions. Importantly, these effects may be substantially larger for the most exposed or financially constrained hospitals, with implied impacts of roughly 27 additional neonatal deaths per 100,000 live births and 128 additional deaths per 1 million elderly admissions. While approximate, these figures indicate the possible public health costs of regulatory policies that crowd out investment in quality-enhancing technologies, highlighting the importance of understanding these trade-offs when designing labor market regulations in healthcare.

In contrast to CDS, the mandate increases NSS adoption, with effects driven by hospitals with higher baseline staffing ratios and those that are financially unconstrained. On average, hospitals in California increase NSS adoption immediately relative to hospitals in other states following the mandate, although this gap narrows toward the end of the sample period. Heterogeneity by the baseline staffing ratios reveals a monotonic pattern of policy impacts. Low-need hospitals increase NSS adoption by up to 8 percentage points by 2004 before gradually converging, moderate-need hospitals by up to 4 percentage points, and high-need hospitals show minimal change. These patterns are consistent with our framework where well-staffed hospitals derive greater value from reducing real-time compliance risk through NSS, while understaffed hospitals instead primarily respond by expanding nurse employment.

Financial conditions play an even more pronounced role in shaping NSS adoption behavior. Financially unconstrained hospitals increase the NSS adoption by around 9 percentage points, with event-study estimates peaking near 12 percentage points and remaining statistically significant throughout the post-mandate period. In contrast, financially constrained hospitals experience a statistically significant decline in NSS adoption of about 3.2 percentage points. Taken together, these results suggest that NSS serves as a key operational response to staffing mandates, which support compliance by reducing sudden nurse absences, while increasing job satisfaction and potentially improving the quality of care.

We conduct a series of robustness checks to assess the sensitivity of our findings. First, to account for potential transitional dynamics around policy implementation, we re-estimate our models excluding the years 2002–2004, when hospitals may have adjusted staffing and technology adoption in anticipation of full enforcement. Second, we address potential contamination of the control group by excluding hospitals in states neighboring California and by using a stricter definition of technology adoption that focuses on technologies that are fully implemented or operational. Finally, because the SDID estimator requires a balanced panel, we assess robustness to alternative panel windows that retain a broader set of hospitals. Across all specifications and sample definitions, our results—including heterogeneous effects by baseline staffing ratios and financial conditions—remain qualitatively unchanged.

This paper contributes to the literature in several ways. First, it is the first to examine the unintended consequences of staffing mandates on technology adoption. Previous studies examine effects on hospital care quality (Cook et al., 2012), nurses' labor market outcomes (Mark et al., 2009; Munnich, 2014; Harless, 2019), and other inputs (Raja, 2023). Most of this literature focuses on regulated inputs and related outcomes, such as quality or price. Raja (2023) finds that the policy had limited effects on non-nurse labor, supplies, and leases. Similar studies in other contexts, including nursing homes (Tong, 2011; Lin, 2014; Matsudaira, 2014; Chen and Grabowski, 2015) and child care (Blau, 2007; Hotz and Xiao, 2011), have examined staffing mandates, with Chen and Grabowski (2015) documenting unintended effects on indirect care staffing in nursing facilities. However, to our knowledge, no study investigates the impact of staffing mandates on technology adoption. Given the increasing role of technology in healthcare, our findings provide important insights for evaluating the broader effects of nurse staffing regulation.

Second, this paper contributes to the broader literature on labor market and technology adoption. While extensive research examines how technological change reshapes labor markets by altering demand for skills, wages, and employment structures (e.g. Autor et al., 2003; Acemoglu and Autor, 2011), fewer studies investigate the reverse relationship: how labor market conditions influence firms' technology adoption decisions. Existing work includes the impact of demographic changes (Acemoglu and Restrepo, 2021), labor costs (Fan et al., 2021; Ashenfelter and Jurajda, 2022), and labor scarcity (Acemoglu, 2010). We contribute to this literature by studying a quantity-based labor regulation that directly constrains staffing levels. Such regulations are common in regulated service industries and create different investment incentives, but remain largely understudied in studies of technology adoption.

Within this strand, our paper is closely related to Acemoglu and Finkelstein (2008), who show that price-based changes in Medicare reimbursement raise the relative cost of labor and induce hospitals to adopt more labor-saving technologies. Their setting highlights how labor price shocks encourage substitution toward capital when hospitals retain flexibility over staffing levels. We depart from their work by studying a quantity-based labor regulation that directly constrains labor inputs rather than their price. Staffing mandates force hospitals to hire up to a regulatory minimum and generate large compliance-driven expenditures, tightening financial constraints and altering the value of different technologies. As a result, technology adoption is shaped not only by technological substitutability or complementarity with labor, as in Acemoglu and Finkelstein (2008), but also by policy-driven cost pressures and the role of technology in managing regulatory risk. We show that mandated input increases can crowd out complementary and quality-enhancing technologies as a result of tightening financial constraints, while encouraging adoption of compliance-facilitating ones—a mechanism absent in price-based regulatory environments.

2 Institutional Background

In 1999, the California legislature passed Assembly Bill 394 (AB394), making California the first state to establish minimum NPRs for general acute care hospitals.[1] The specific staffing ratios were announced in 2002, with each hospital unit assigned a minimum required ratio based on the intensity of care provided. For example, intensive care units were required to maintain a ratio of one nurse per two patients, whereas general medical-surgical units were subject to a one nurse per six patients requirement.[2] These mandates became legally binding on January 1, 2004, with subsequent adjustments to the ratios implemented in 2005 and 2008.

[1] According to the Centers for Medicare and Medicaid Services (CMS), acute care hospitals provide short-term inpatient treatment for acute conditions, including surgery and emergency care. These hospitals contain units such as emergency, surgical, intensive care, and medical–surgical wards. General acute care hospitals are the most common hospital type in the United States, accounting for 55% of all hospitals in 2021. In California, the share is higher than the national average, with 72.7%.

[2] The initial staffing ratios mandated under AB394 included the following requirements across hospital units: 1-to-1 in operating rooms, 1-to-2 in critical care, labor and delivery, postanesthesia recovery, and emergency medical services units, 1-to-4 in postpartum, pediatric, and step-down units, 1-to-5 in telemetry and specialty care units, 1-to-6 in medical-surgical and psychiatric units.

Compliance with minimum NPRs is enforced by the California Department of Health Services (CDHS) through licensing surveys and complaint investigations. Hospitals that failed to meet the required ratios risked being forced to close units or suspend services, as staffing levels below the mandated minimum were deemed incompatible with continued operation of patient care units. Although hospitals raised concerns about financial constraints and nurse shortages, state regulators emphasized that implementation of the ratios could not be waived.

Importantly, the mandate required continuous compliance rather than compliance on average. The regulations defined minimum NPRs as the maximum number of patients that could be assigned to a nurse at any point in time. Compliance could not be assessed by averaging staffing levels across shifts or units, meaning that understaffing in one shift or unit could not be offset by higher staffing elsewhere. This feature made compliance operationally binding and increased the complexity of staffing decisions, particularly in the presence of fluctuating patient demand, nurse absenteeism, and shift-level variation in workloads (California Department of Health Services, 2003). As a result, hospitals faced strong incentives to adjust staffing practices in real time to comply with the mandate.

The mandate led to a well-documented increase in nurse employment in California, as hospitals expanded staffing to meet the required ratios (Harless, 2019). Consistent with this evidence, we proxy nurse staffing using total worker hours—of which nurses constitute roughly 30 percent (Bureau of Labor Statistics, 2020)—and find that California hospitals experienced a post-mandate increase relative to a synthetic control from other states (Figure A1).

Studies consistently find that hospitals with lower pre-policy NPRs hired more nurses than those already operating near or above the mandated thresholds (e.g., Cook et al., 2012; Munnich, 2014; Raja, 2023). We use data from the California Office of Statewide Health Planning and Development (OSHPD) and replicate the results of Munnich (2014), which focus on general medical-surgical units. Grouping hospitals into quartiles based on their 2000–2002 NPR, we find that those in the lowest quartiles experienced the largest post-2002 increases in nurse staffing, while those in the top quartile saw little to no change (Figure A2). This mirrors prior research and highlights the differential compliance burden across hospitals.

The mandate may also have affected equilibrium wages. While the evidence is mixed, most studies document modest increases in hourly nurse wages in California, though estimates vary by data source and specification (Mark et al., 2009; Munnich, 2014; Raja, 2023).[3]

[3] Mark et al. (2009) use the National Sample Survey for Registered Nurses (NSSRN), the Current Population Survey (CPS), and the National Compensation Survey (NCS), estimating wage increases of 7.8 percent, 5 percent, and 6.5 percent, respectively. Munnich (2014) finds a 4.3 percent wage increase using the American Community Survey (ACS) but no significant change using the CPS Merged Outgoing Rotation Group. Raja (2023) estimates a more modest 2.2 percent increase.

Despite the significant increase in nurse hours per patient day, studies find inconclusive evidence that the mandate led to meaningful improvements in patient health outcomes (Donaldson et al., 2005; Cook et al., 2012; Raja, 2023). This suggests that hospitals may have reallocated resources, potentially substituting other inputs. Raja (2023) finds limited substitution between nurses and non-nursing inputs, including aides, physicians, and capital investment. However, an important margin that has received little attention is hospitals' technological responses to the staffing mandate. Health information technologies are closely linked to nursing tasks and require sizable fixed and ongoing investments. As a result, mandated increases in nurse staffing may have either encouraged or crowded out technology adoption, with potential implications for clinical quality. This linkage highlights the importance of examining how staffing mandates affect hospitals' technology adoption decisions.

3 Conceptual Framework

We focus on two key healthcare information technologies: Clinical Decision Support (CDS) systems and Nurse Staffing Software (NSS).[4] CDS is one of the most widely studied innovations in health informatics and has been central to policy discussions on improving clinical decision-making. NSS, in contrast, directly addresses workforce management by optimizing staffing allocation and scheduling. These technologies are particularly relevant for analyzing the impact of labor regulations on technology adoption, as CDS is closely linked to patient care quality, while staffing software is designed to enhance hospital labor efficiency. In the following, we provide a conceptual framework on how hospitals change their decisions to adopt each technology in response to the staffing regulation.

3.1 Clinical Decision Support

CDS systems assist providers in clinical decision-making by identifying and preventing errors through real-time alerts, drug-dosing assistance, allergy checks, medical test reminders, and the enforcement of care guidelines. As illustrated in Figure A3, CDS tools involve diagnostic decision support, where the system analyzes narrative clinical notes, such as patient complaints and exam findings, and returns a list of likely diagnoses drawn from medical literature (left). In another example, the CDS engine flags potentially inappropriate medications for older adults, drawing on clinical guidelines (right). As such, CDS not only augments clinical judgment but also standardizes care delivery, especially in high-risk or complex patient scenarios. These systems interface with data from Clinical Data Repositories (CDRs), which aggregate patient information, including test

[4]The discussion of technology adoption and costs reflects the early-to-mid 2000s, the period relevant to this study. While both the capabilities and affordability of these systems have evolved since then, our focus remains on how hospitals responded to the policy environment at the time.

results, drug usage, pathology reports, and discharge summaries. Despite substantial costs that we illustrate in the following, studies suggest that CDS adoption can generate long-term cost savings and improve healthcare quality (Dranove et al., 2014; Atasoy et al., 2019).

The adoption of CDS and broader Electronic Medical Records (EMR) technologies entails substantial financial investment. According to Congressional Budget Office (2008), the implementation cost of EMR systems ranges from $25,000 to $45,000 per physician, with annual maintenance expenses between $3,000 and $9,000. For a 250-bed hospital, initial costs can reach $3 million, with annual operating costs of approximately $700,000. In 2002, the median annual salary expenditure among hospitals in our sample was approximately $40 million, implying that initial EMR adoption costs alone could amount to nearly 10 percent of a hospital's annual salary budget.

The introduction of nurse staffing mandate may have an influence on the adoption of CDS through two potential channels. First, CDS may augment nurses' productivity, enhancing hospitals' incentives to invest in technology when required to expand their nursing workforce. CDS provides health practitioners with comprehensive patient information and evidence-based guidelines, reducing potential medical errors and adverse events. Nurses are highly skilled users of CDS, and existing evidence suggests that EMR systems tend to be neutral or moderately complementary to nursing labor rather than substitutes (Bronsoler et al., 2022).

A second channel works through financial constraints. The staffing mandate raised hospitals' labor costs by requiring higher nurse staffing levels and by increasing demand and wages for nurses in the local labor market. Higher wage bills may have tightened hospitals' budget constraints, leading hospitals facing budgetary pressure to delay or forgo CDS adoption. This channel is particularly relevant given the substantial fixed and adjustment costs associated with CDS adoption, including extensive training and workflow integration. Prior work shows that EMR adoption can increase operating costs in the short run, with any financial benefits materializing only gradually over time (Furukawa et al., 2010; Dranove et al., 2014).

Two channels lead to different implications about the changes in the CDS adoption of California hospitals. If the CDS strongly complements nurse labor forces, Californian hospitals would increase its adoption after the mandate is implemented as they are forced to increase the nurse labors. In contrast, if the mandate makes hospitals' financial budget more tightened, they would defer the introduction of the CDS. Moreover, the delay should appear stronger for hospitals who had less nurses on average and were more financially constrained before the policy introduction.

3.2 Nurse Staffing Software

NSS, in contrast, is designed to optimize workforce planning by automating staffing, scheduling, and task allocation. Before the adoption of IT-based systems, nurse staffing relied on manual processes such as printed shift lists, phone calls, and emails, often leading to inefficiencies, overbooking, and communication delays. As shown in Figure A4 (a), floating nurses selected shifts from a physical list, and nurse managers coordinated assignments manually. In contrast, the implementation of digital scheduling tools, illustrated in (b), streamlined staffing by automatically generating compliant schedules based on staffing requirements, workload, and resident training levels (left). These systems assist hospitals in determining staffing needs, assigning shifts based on patient demand and nurse availability, and efficiently managing floating personnel. They also integrated features such as real-time day-off requests and automated conflict detection (right).

The cost of staffing software varies but is generally lower than that of EMR adoption. Integrated scheduling solutions for a 300-bed hospital range from \$60,000 to \$150,000, depending on system features and user capacity (Sabet, 2005). Stand-alone scheduling tools, which focus on specific functions such as shift bidding, often operate on a subscription model, with costs ranging from \$3,000 to \$9,000 per month. These features—improving nurse allocation and relatively low adoption costs—are particularly relevant in the presence of binding staffing requirements.

To comply with the staffing mandate, hospitals can respond along two margins. First, they can expand nurse employment, increasing the total stock of nurses available to cover patient care. By raising average level of NPRs, hospitals reduce the likelihood of falling below the mandated minimum. However, even hospitals with enough nurse staffing may violate the requirement if short-term surges in patient demand or unexpected absences lead to insufficient nurse coverage at specific times or units. A second strategy is to prevent this type of violation by adopting NSS, which improves the allocation of existing nurses across shifts or units. By reducing mismatches between nurse supply and patient demand at high-frequency intervals, hospitals can lower the probability of noncompliance without increasing headcount.

The relative value of these strategies depends on hospitals' baseline NPRs. Hospitals whose average pre-mandate staffing levels fall below the required minimum must prioritize hiring additional nurses to achieve compliance. Because expanding employment is costly, such hospitals are less likely to adopt new allocation technologies in the short run. In contrast, hospitals whose baseline staffing ratios are closer to—or exceed—the mandated threshold face lower marginal returns to additional hiring and benefit more from improvements in allocation efficiency. For these hospitals, nurse staffing software provides a cost-effective means of ensuring compliance in the presence of demand volatility. We therefore expect any post-mandate increase in nurse staffing software adoption to be driven primarily by hospitals with relatively higher baseline staffing ratios and lower incremental staffing needs.

To formalize these mechanisms, we develop a model that illustrates how the value of adopting software relative to hiring additional nurses differs across hospitals with varying baseline NPRs. In general, the staffing mandate introduces an expected compliance cost of falling below the required real-time staffing level, which arises probabilistically in case that hospitals are inspected and found noncompliant.

Formally, let c denote the penalty of violation and p the probability of inspection. Define the real-time NPR as $r(A, L|D, \sigma^2)$, a random variable determined by technology adoption A, total nurse staffing L, expected patient demand D, and baseline ratio variance σ^2. Hiring more nurses raises the mean of r, while adopting NSS reduces its variance by improving allocation efficiency. For example, we may approximate r as following a log-normal distribution with mean L/D and variance σ^2/A. The expected cost of noncompliance can then be expressed as:

$$C(A, L; D, \sigma, c, p, \underline{r}) = c \cdot p \cdot Pr[r(A, L|D, \sigma) < \underline{r} \ |D, \sigma] \tag{1}$$

where $\underline{r}$ represents the required minimum ratio.

Figure 1 illustrates the effect of each strategy on the distribution of NPRs, depending on the baseline ratio. In panel (a), for hospitals with lower ratios, hiring nurses shifts the mean ratio up and greatly reduces noncompliance risk. NSS alone helps less because variance reduction cannot offset a low mean. In panel (b), for hospitals with higher ratios, the marginal gain from hiring is smaller, and reducing variance via NSS becomes comparably effective at lowering risk. Given that NSS costs less than adding permanent staff, these dynamics imply that hospitals with higher ratios have stronger incentives to adopt NSS, while those with lower ratios mainly hire nurses.

4 Data

We combine multiple data sources to examine the impact of staffing mandates on hospitals' adoption of information technology. We construct a hospital-level panel by linking data on technology adoption, pre-policy nurse staffing, and hospital characteristics for U.S. hospitals spanning from 1998 to 2008.

Healthcare Technology Adoption.—Information on hospital technology adoption comes from the Healthcare Information and Management Systems Society (HIMSS) Analytics database covering U.S. hospitals (HIMSS, 1996-2008). The database primarily covers hospitals with more than 100 beds that are part of healthcare systems, representing approximately 90 percent of non-profit and for-profit hospitals and 50 percent of government-owned, nonfederal hospitals. As discussed earlier, we focus on two technologies that are most closely related to nurse staffing decisions: CDS and NSS. A technology is considered adopted in a given calendar year if a hospital reports it as contracted for installation, installed, or operational.

Pre-Policy Nurse Staffing Levels.—To measure hospitals' exposure to California's staffing mandate prior to its implementation, we construct hospital-level NPR using data from the the American Hospital Association (AHA) Annual Survey of Hospitals for the years 2000–2002 (AHA, 2000-2002). The AHA survey provides data on each hospital's full-time equivalent (FTE) nurses, patient days, and hospital operating days during the reporting period. We approximate the NPR for hospital i in period t using the following equation:

$$\mathrm{NPR}_{it} = \frac{\text{Nurse FTE}_{it} \times 40 \times 52}{\text{Adjusted Patient Days}_{it} \times 24} \tag{2}$$

where we assume that each nurse FTE works 40 hours per week for 52 weeks per year. We measure patient volume using adjusted patient days, which normalize outpatient days to inpatient equivalents based on the hospital's outpatient-to-inpatient ratio.

While OSHPD reports unit-specific nurse staffing data only for California, AHA offers aggregates from a nationwide sample. Despite differences in reporting scope and granularity, for hospitals observed in both sources, staffing and patient volume measures are strongly correlated (Figure A5), supporting the use of AHA-based NPRs as a proxy for mandate exposure in the national sample.

We define each hospital's pre-policy NPR as the average ratio over the 2000–2002 period. Based on this measure, we classify hospitals into three exposure groups reflecting the extent of staffing adjustment required to comply with the mandate. Hospitals in the lowest quartile of pre-policy NPRs are classified as high-need, as they faced the largest required increases in nurse staffing. Hospitals in the highest quartile are classified as low-need, having staffing levels already close to or above the mandated minimums. The remaining hospitals fall into a moderate-need category.This classification is consistent with Munnich (2014) who uses quartiles of hospital-level NPRs constructed from OSHPD data. Moreover, the cutoff for the lowest quartile—approximately 0.25—is comparable to the threshold used by Raja (2023) to identify treated hospitals under the staffing mandate.

Hospital Characteristics and Financial Constraints.—Finally, we integrate additional covariates using data from the Centers for Medicare and Medicaid Services (CMS) Healthcare Cost Report Information System (HCRIS) from 1998 to 2008 (CMS, 1996-2008). All Medicare-certified healthcare providers are required to report key hospital characteristics, including the number of beds, total patient days, percentage of Medicare and Medicaid patients, and for-profit status.

To examine the heterogeneous responses by hospitals' financial conditions, we construct hospital-level financial performance using the annual operating margin following Duggan et al.

(2022) and Richards et al. (2025), defined as:

$$OM_{it} = \frac{\text{Operating Revenue}_{it} - \text{Operating Cost}_{it}}{\text{Operating Revenue}_{it}} \tag{3}$$

Operating margin captures patient-care profitability by comparing net operating income to operating revenue and excludes non-operating income. We classify hospitals as financially constrained if their average operating margin over the pre-policy period (2000–2002) is negative. This measure reflects hospitals' baseline financial capacity to absorb higher labor costs and to invest in technologies. Our findings remain robust when using a stricter definition requiring negative margins in all pre-policy years.

Sample Construction and Balanced Panel for SDID.—We merge all data sources using the Medicare Provider Number to construct a hospital-level panel dataset. The sample is restricted to acute care hospitals, covering an 11-year period from 1998 to 2008. Our analysis uses three complementary estimators: standard DID, SDID, and CEM with DID. While DID and CEM-DID can be implemented using unbalanced panels, the SDID estimator, our preferred specification, requires a balanced outcome panel. Accordingly, we restrict the SDID analysis to hospitals with complete technology adoption data over the relevant sample window for each technology. The SDID balanced panel includes 3,290 hospitals for CDS adoption and 3,244 hospitals for NSS adoption, while 317 and 368 hospitals, respectively, are excluded due to incomplete reporting. The majority of hospitals in the estimation sample therefore report technology adoption status consistently over time.

Hospitals included in the balanced panel tend to be larger and report technology adoption consistently, raising potential concerns about nonrandom sample selection. In Table A1, we compare hospital characteristics in 2002 between balanced and excluded hospitals. Balanced hospitals have greater bed capacity, patient volume, and total employment, employ a more skilled nursing workforce as measured by the RN-to-LVN ratio, and are less likely to be for-profit. In contrast, balanced and excluded hospitals are similar in terms of pre-policy NPRs and payer mix. Moreover, Section 7 shows that SDID estimates are robust to alternative balanced panel windows, indicating that our findings are not driven by the balanced panel requirement.

In Table 1, we present summary statistics for hospitals in California and other states in 2002 for the balanced samples used in the CDS and NSS analyses. Across both samples, California hospitals have lower Medicare shares, higher Medicaid shares, higher wages, and larger scale, as measured by number of beds and patient volume. They also employ a more skilled nursing workforce, as evidenced by higher RN-to-LVN ratios. In contrast, baseline technology adoption and NPRs are similar between California and non-California hospitals, suggesting that pre-policy differences primarily reflect payer mix, labor costs, and scale rather than baseline staffing ratios or technology use.

5 Empirical Strategy

This section describes the empirical strategies used to estimate the causal effect of California's staffing mandate on hospital technology adoption. Our empirical analysis begins with a traditional difference-in-differences (DID) framework with two-way fixed effects, leveraging cross-state variation around the policy's implementation. It provides a transparent and interpretable baseline estimates: the policy represents a state-level intervention applied uniformly to all California hospitals, and no other state adopted a comparable staffing mandate during the study period. The identification assumption underlying this approach is that California hospitals would have followed parallel trends in technology adoption relative to hospitals in other states absent the policy change. Formally, we estimate:

$$Y_{it} = \alpha_i + \beta_t + \tau(\mathrm{CA}_i \times \mathrm{Post}_t) + \epsilon_{it} \tag{4}$$

where Y_{it} is an indicator of technology adoption for hospital i at period t, CA_i is an indicator of California hospital, and Post_t equals one if t is larger than or equal to 2003. We define the post-policy period as 2003 and later because the mandatory NPR was publicly announced in 2002.

However, systematic differences between California hospitals and those in other states may exist. As shown in Table 1, California hospitals differ significantly from non-California hospitals across several characteristics, including patient composition and wage levels. Moreover, California hospitals might have followed different pre-policy adoption trajectories than hospitals in other states.[5] Given these systematic differences, the parallel trends assumption may not hold, motivating the use of more flexible approaches that account for pre-policy trend differences.

To address this, we implement the synthetic difference-in-differences (SDID) approach introduced by Arkhangelsky et al. (2021). The key advantage of this method is that it reweights the control observations, thereby relaxing the parallel trends assumption. Specifically, SDID first estimates unit weights ($\hat{\omega}_i$) via ridge regression that align pre-treatment outcome trends of control units with those of treated units. It also constructs time weights ($\hat{\lambda}_t$) via unregularized least squares such that the post-treatment outcomes of control units differ from their weighted pre-treatment out-

[5]For example, California's Hospital Facilities Seismic Safety Act (SB1953), enacted in 1994, required hospitals to retrofit or rebuild facilities to meet seismic standards over several decades. The first major compliance deadline was January 1, 2002, when hospitals were required to address the most seismically vulnerable buildings. The regulation imposed large and persistent capital expenditures that may have influenced hospitals' broader investment behavior, potentially altering pre-trends in technology adoption.

comes only by a constant.[6] These weights are then incorporated into a weighted DID estimation with two-way fixed effects, which we specify as follows:

$$(\hat{\tau}, \hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}) = \underset{(\tau,\alpha,\beta)}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \alpha_i - \beta_t - \tau \mathrm{CA}_i \mathrm{Post}_t)^2 \hat{\omega}_i \hat{\lambda}_t \right\} \tag{5}$$

To compute standard errors, we use block bootstrapping with 1,000 bootstrap samples.

To examine the dynamics of the treatment effect over time, we employ an event study design based on the SDID estimation, following Clarke et al. (2024). We compute the difference in mean outcomes between treated hospitals and their synthetic control counterparts for each period, relative to the pre-treatment average of the outcome weighted by time weights. To construct 95 percent confidence intervals, we use bootstrap inference for each period's estimated difference.

As a complementary approach, we implement a matched DID estimator using Coarsened Exact Matching (CEM; Iacus et al., 2012). CEM is a procedure that exactly matches treated and control units within strata defined by coarsened covariates.[7] It addresses two limitations that either DID or SDID has. First, SDID requires a balanced outcome panel, which can induce nonrandom sample selection if hospitals with missing adoption data differ systematically from those with complete data. Second, unlike standard DID or SDID, CEM-DID explicitly restricts the estimation sample to the region of common support by removing treated and control hospitals that lack structurally comparable counterparts. This feature ensures that estimated effects are identified from comparisons among observationally similar hospitals. This design follows recent empirical work, including Aneja et al. (2025), Bessen et al. (2025), and Gumpert et al. (2022).

In our application, we construct matched sets of California and non-California hospitals based on predetermined and hard-to-modify characteristics measured in 2000: for-profit ownership, total beds, total patient days, and the Medicare and Medicaid share of patient days.[8] Continuous variables are coarsened into tertile bins. Importantly, the baseline year cleanly predates the 2002 announcement and 2004 enforcement, ensuring that the matching variables are unaffected by the

[6]See Arkhangelsky et al. (2021) for details of the procedure for obtaining the weights. The key idea of the unit weight is to align the pre-exposure trends in the outcome of the control units with those of the treated units. Suppose that $i = 1, \cdots, N_c$ are control units and $i = N_c, \cdots, N$ are treated units. Then, $\hat{\omega}$ is estimated through ridge regression so that $\sum_{i=1}^{N_c} \omega_i Y_{it} \approx N_t^{-1} \sum_{i=N_c+1}^{N} Y_{it}$ for all $t = 1, \cdots, T_{\mathrm{pre}}$, where $N_t = N - N_c$. Similarly, $\hat{\lambda}$ is determined through unpenalized least squares to have $\sum_{t=1}^{T_{\mathrm{pre}}} \lambda_t Y_{it} \approx T_{\mathrm{post}}^{-1} \sum_{t=T_{\mathrm{pre}}+1}^{T} Y_{it}$ for all $i = 1, \cdots, N_c$, where $T_{\mathrm{post}=T-T_{\mathrm{pre}}}$.

[7]Following Iacus et al. (2012), CEM forms strata based on the Cartesian product of the coarsened covariates and retains only strata containing at least one treated and one control hospital. Treated hospitals receive unit weight, while control hospitals are weighted to match the treated distribution across strata. Specifically, control units in stratum s receive weight $w_i = \frac{m_C}{m_T} \cdot \frac{m_T^s}{m_C^s}$, where m_T^s and m_C^s denote the number of treated and control units in stratum s, and m_T and m_C are the total numbers of matched treated and control units. Unmatched observations receive zero weight.

mandate. After matching, we estimate DID and event-study models using CEM weights.

We use SDID as our primary estimator because it more closely aligns pre-trends between treated and control units, while reporting results from traditional DID and CEM-DID for robustness. In the next section, we first present average effects comparing California and non-California hospitals using all three methods. We then examine heterogeneity in treatment responses along two dimensions to explore underlying mechanisms. First, we examine differential responses by pre-policy staffing levels, using the three exposure groups defined by baseline NPRs (high-need, moderate-need, and low-need). Second, we study heterogeneity by hospitals' financial capacity, measured by operating margins. These analyses are implemented by estimating models separately for each group.

6 Results

6.1 Main Results

We begin by studying the effect of California's nurse staffing regulation on hospitals' CDS adoption. The first three columns of Table 2 report estimates of the interaction between the California indicator and the post-policy period. Our preferred SDID specification indicates that CDS adoption in California declines by approximately 3.8 percentage points following the mandate, relative to the synthetic control group of hospitals in the other states. This effect is statistically significant and economically meaningful, corresponding to about 6 percent of the baseline adoption rate (0.62). Estimates from standard DID and CEM-DID are similar in magnitude and sign, reinforcing the robustness of this finding.

Panel (a) of Figure 2 illustrates the dynamic effects of the staffing mandate on CDS adoption. The left panel presents SDID event-study estimates relative to the pre-treatment weighted average, while the right panel displays the raw adoption rate trends for California hospitals and their synthetic control counterparts.[9] Adoption rates track closely prior to the policy, but begin to diverge shortly after the announcement of the staffing mandate. Relative CDS adoption in California begins to decline in 2003, reaching a decrease of approximately 7 percentage points by 2007, before showing signs of recovery. This peak decline exceeds 10 percent of the baseline adoption rate,

[8]Each variable captures a key dimension of hospital heterogeneity that may influence technology adoption. For-profit status is a stable structural attribute that shapes investment behavior and is invariant to the mandate. Second, to control for hospital size and actual utilization, we use the number of beds and total patient days in baseline year as matching covariates. Lastly, Medicare and Medicaid share, defined as Medicare and Medicaid patient days divided by total patient days, reflects patient-mix and reimbursement environments. Table A2 shows summary statistics for hospitals in California and other states in 2002 for the matched samples using CEM.

[9]Event-study estimates using standard DID and matched DID using CEM display similar post-treatment patterns, but show less stable pre-treatment estimates Figure A6, supporting SDID as our preferred specification.

hinting at the economic significance of the policy's dampening effect on technology advancement. Consistent with this pattern, the raw trends indicate that CDS adoption among California hospitals begins to diverge in 2002 and gradually converges back toward that of the synthetic control group by 2008.

As discussed in the conceptual framework, the decline in CDS adoption may reflect either changes in production choices or tighter financial constraints induced by the staffing mandate. Given that CDS is typically neutral or complementary to nursing inputs, it is unlikely that hospitals substitute CDS for nurse labor. A more plausible explanation is that higher labor costs tighten hospitals' budget constraints, reducing their ability to invest in costly clinical technologies. To explore this, we examine heterogeneity in treatment effects across hospitals facing varying staffing pressures and financial capacity in the next two subsections. If financial constraints are central, the decline in CDS adoption should be more pronounced among hospitals that experienced larger mandated staffing adjustments and among those with more limited financial flexibility.

We next turn to the result on NSS adoption, which is more directly related to hospitals' compliance with staffing requirements. Columns (4)–(6) of Table 2 report estimates from DID, SDID, and CEM-DID specifications. In contrast to CDS, we find no statistically significant average effect of the staffing mandate on NSS adoption. Our preferred SDID estimate suggests a positive but insignificant increase of 1.6 percentage points relative to a baseline adoption rate of 0.79, corresponding to roughly a 2 percent change.

The event-study estimates in Figure 2 reveal a different dynamic pattern for NSS adoption than for CDS. Following the announcement of the staffing mandate, NSS adoption in California rises by 4 percentage points in the first year after the announcement relative to the synthetic control. The magnitude of this increase attenuates over time. This pattern suggests that hospitals rely on NSS as a short-run adjustment to staffing constraints, since its relatively low fixed costs and immediate operational benefits make it a practical response to regulatory pressure.

The absence of a large average effect masks substantial heterogeneity in hospitals' responses to the staffing mandate. We therefore examine variation in NSS adoption by pre-policy staffing levels and financial capacity. Because the mandate imposed real-time compliance requirements on all hospitals, NSS may be especially valuable for hospitals with higher baseline staffing, where compliance risk stems from short-run fluctuations rather than persistently low average staffing. In this setting, NSS provides a cost-effective means of reducing staffing variability. At the same time, adoption still entails fixed and ongoing costs, so financially flexible hospitals may be more likely to adopt NSS, whereas constrained hospitals may have limited ability to invest in technology.

6.2 Heterogeneity by Pre-policy Staffing Levels

Hospitals differed in their exposure to the staffing mandate, depending on their pre-policy NPRs. Hospitals with baseline NPRs below the mandated threshold were required to increase nurse staffing after the policy's implementation, whereas those with higher staffing levels faced no additional hiring pressure. In this subsection, we examine whether technology adoption responses scale with the intensity of the regulatory shock. Using pre-policy staffing levels is standard in the literature on staffing mandates and has been shown to capture meaningful variation in hospitals' behavioral responses (e.g., Cook et al., 2012; Munnich, 2014; Raja, 2023). This variation suggests that effects on technology adoption may also vary across hospitals, depending on the baseline NPRs.

CDS.—Table 3 presents SDID estimates by pre-policy NPR groups, with high-need hospitals in the lowest quartile, moderate-need hospitals in the middle two quartiles, and low-need hospitals in the highest quartile. The estimates reveal a clear monotonic pattern in CDS adoption. Among high-need hospitals, the mandate reduces CDS adoption by 6.3 percentage points, which is a 10 percent decline relative to a baseline adoption rate of 60 percent. Moderate-need hospitals also experience a significant reduction in CDS adoption of 3.8 percentage points, while the effect for low-need hospitals is small and statistically insignificant. Consistent with their limited staffing adjustments following the mandate, low-need hospitals appear largely unaffected, suggesting that the potential rise in equilibrium nurse wages did not translate into changes in CDS investment.

In Figure 3, we illustrate the dynamics of the policy effects for each hospital group. Panel (a) shows that high-need hospitals experience a persistent decline in CDS adoption following the mandate. Relative adoption begins to fall right after the announcement and reaches a decrease of approximately 10 percentage points by 2007. On the right-hand side, the raw adoption trends reveal that California hospitals had higher adoption rates than their synthetic controls prior to the mandate. However, after the announcement, adoption rates among non-California hospitals surpassed those of California hospitals and did not converge by the end of the sample period.

Panel (b) displays a similar but attenuated pattern for moderate-need hospitals. CDS adoption declines after the policy announcement, reaching a maximum gap of approximately 7 percentage points in 2006, but the difference gradually narrows and converges by the end of the sample period. By contrast, panel (c) shows no systematic post-policy difference for low-need hospitals. Consistent with the average effects, these dynamics indicate that the decline in CDS adoption is concentrated among hospitals facing larger staffing shortfalls prior to the mandate.

The concentration of CDS reductions among high- and moderate-need hospitals is consistent with a financial-constraint channel. In Figure A7, we present evidence from OSHPD that these hospitals experience sharper increases in nurse salary expenditures, limiting resources available for costly clinical technologies. By contrast, hospitals with higher baseline staffing ratios face smaller labor cost increases and show no corresponding decline in CDS adoption. Together, these patterns point to tighter financial constraints rather than substitution between nurse labor and decision-support technologies.

NSS.—We next study NSS adoption by pre-policy staffing levels in columns (4)–(6) of Table 3. The point estimates differ across exposure groups: low-need hospitals show the largest increase of 4.2 percentage points, moderate-need hospitals exhibit a smaller increase of 1.5 percentage points, and high-need hospitals show little to no response. Although the estimates are insignificant, this monotonic pattern motivates examining dynamic responses in the event-study analysis.

In Figure 4, panel (a) shows that high-need hospitals exhibit no systematic change in NSS adoption following the mandate, with relative adoption remaining close to zero throughout the post-policy period. This pattern is consistent with these hospitals prioritizing direct nurse hiring over software-based staffing tools.

Panels (b) and (c) show similar adoption patterns for moderate- and low-need hospitals, with larger effects for low-need hospitals. In both groups, NSS adoption increases shortly after the policy announcement, with effects emerging in 2004. Adoption rises by about 5 percentage points among moderate-need hospitals and by about 7 percentage points among low-need hospitals relative to their synthetic controls. While the estimates attenuate later in the sample period, the common timing and larger responses among hospitals with higher baseline staffing ratios indicate that NSS serves as a short-run adjustment margin.

These heterogeneous adoption patterns align with the conceptual framework, which predicts that NSS functions as an operational adjustment tool. Hospitals with higher baseline staffing ratios face compliance risk mainly from real-time fluctuations in nurse availability, and NSS offers a relatively low-cost way to stabilize real-time NPRs through improved scheduling and allocation. By contrast, high-need hospitals are required to make substantial permanent staffing increases to meet the mandate, reducing the marginal benefit of software-based optimization. Consistent with this mechanism, NSS adoption rises among low- and moderate-need hospitals but not among hospitals facing the largest staffing pressures.

This interpretation is reinforced by evidence that hospitals with lower need also have more diversified inpatient units prior to the mandate (Figure A8).[10] Because diversified hospitals face more complex and variable staffing needs (Wang et al., 2009), NSS offers higher returns by stabilizing real-time NPRs.

[10] We measure inpatient service diversification using a Herfindahl–Hirschman Index (HHI) constructed from the

6.3 Heterogeneity by Financial Conditions

We now examine whether technological responses are further shaped by hospitals' financial conditions around the time of the mandate. Financial resources play a central role in firms' investment decisions, particularly when policy changes impose new costs. Prior research shows that firms often reduce or delay technology and capital investments when liquidity becomes limited. For instance, Rauh (2006) finds that required pension contributions crowd out capital expenditures of firms, while Campello et al. (2010) document that financially constrained firms scale back technology spending more sharply during the 2008 financial crisis.

Hospitals faced substantial financial pressure in the late 1990s and early 2000s due to cost-containment reforms by public and private payers—including the Medicare Prospective Payment System, the Balanced Budget Act of 1997, and the expansion of health maintenance organizations (HMOs), which substantially lowered Medicare margins and private payment-to-cost ratios (MedPAC, 2005). California's nurse staffing mandate further increased operating costs by raising nurse labor expenses. Given the high upfront and ongoing costs of information technologies, hospitals' adoption decisions likely varied by their pre-policy financial capacity.

Table 4 reports SDID estimates by financial status, measured by pre-policy operating margins. For CDS, financially constrained hospitals experience a statistically significant decline in adoption of 6.4 percentage points following the mandate. By contrast, unconstrained hospitals show no meaningful change in CDS adoption, with an estimate close to zero. For NSS, the pattern reverses: financially unconstrained hospitals increase adoption by 9.0 percentage points, while constrained hospitals reduce NSS adoption by 3.2 percentage points. This suggests that even relatively low-cost operational technologies were crowded out when budgets were tight.

Event study estimates reveal consistent dynamic responses. In Figure 5, CDS adoption among financially constrained hospitals begins to decline shortly after the policy announcement and continues to fall through 2007. In contrast, unconstrained hospitals exhibit no persistent changes from their synthetic controls over the post-policy period. Turning to NSS, in Figure 6, financially constrained hospitals experience a gradual decline in adoption, reaching approximately 5 percentage points by 2006, with the gap between California and non-California hospitals narrowing thereafter. Financially unconstrained hospitals, by contrast, show a sharp post-policy increase in NSS adoption, rising by roughly 12.5 percentage points immediately after the mandate.

Taken together, these patterns support a financial-constraint mechanism. Hospitals with lim-

distribution of pre-policy patient days across hospital unit types, including general medical-surgical, intensive care (intensive, coronary, burn, and surgical intensive), specialty care, nursery, and other units. For each hospital-year, we compute the share of patient days in each unit, square these shares, and sum them to obtain the HHI. Lower values indicate greater diversification and, correspondingly, more complex and variable staffing needs across units.

ited financial capacity respond to higher staffing costs by cutting back on both clinical and operational technologies, while unconstrained hospitals selectively adopt NSS to mitigate compliance costs. These responses align with the conceptual framework: financially unconstrained hospitals have the flexibility to adopt a software-based strategy to maintain compliance, while those with tightened budgets have less ability to absorb regulatory shocks.

6.4 Implications

The adoption of CDS, as an advanced feature of EMRs, has substantial potential to improve healthcare quality and patient outcomes (Buntin et al., 2011; Miller and Tucker, 2011; McCullough et al., 2016). Thus, the decline in CDS adoption following the staffing mandate likely represents a missed opportunity to enhance care quality. To illustrate the potential magnitude of this impact, we conduct a back-of-the-envelope calculation that combines our estimated adoption effects with evidence from prior studies. Based on Table 2, CDS adoption rates in California decline by approximately 3.8 percentage points.

Miller and Tucker (2011) find that a 10 percentage point increase in advanced EMR adoption with decision support functions is associated with a reduction in neonatal mortality of about 40 deaths per 100,000 live births. Applying this estimate, the observed decline in CDS adoption corresponds to an implied increase of approximately 15 neonatal deaths per 100,000 live births (3.8/10 × 40). Similarly, McCullough et al. (2016) find that EMR systems with decision support reduce mortality by roughly 200 deaths per 100,000 admissions among Medicare patients with complex conditions. Using this estimate, the decline in CDS adoption implies a potential loss of around 75 preventable deaths per 1 million elderly admissions (3.8/10 × 200).

Our heterogeneity analysis indicates that effects are substantially larger for hospitals with greater exposure to the mandate or those financially constrained prior to the policy. Based on our estimates, the reduction in CDS adoption among high-need hospitals (6.3 percentage points) or financially constrained hospitals (6.4 percentage points) corresponds to approximately 27 additional neonatal deaths per 100,000 live births and 128 deaths per 1 million elderly admissions. These estimates are conservative because they focus on neonatal and elderly patient populations studied in prior work; the potential public health impact could be even larger if we consider effects across the entire patient population.

The increased adoption of NSS also has important implications for hospital operations and public health. According to the literature, electronic scheduling enables hospitals to reassign staff more efficiently, reduce reliance on costly agency nurses, and enhance labor productivity by minimizing overtime and floating assignments. For instance, Tuominen et al. (2016) find that implementing staffing software reduces the number of nurse absences requiring external coverage and significantly eases the workload of ward managers. Similarly, Morse et al. (2024) report that NSS improves staff satisfaction and facilitates better coverage during capacity surges, resulting in fewer unstaffed shifts and more proactive patient bed management. While quantitative evaluations remain limited, qualitative evidence consistently suggests that the increased adoption of NSS—driven by nurse staffing regulations—can enhance operational responsiveness and contribute to improved healthcare service quality.

Together, these results highlight important policy implications. While the policy aimed to improve nurse staffing ratios, it may have unintentionally discouraged investments in CDS that improve quality of care and patient outcomes. At the same time, hospitals increasingly adopt NSS to manage compliance operations, particularly those with better staffing. These results imply the need for policymakers to consider how staffing mandates interact with hospitals' technology investments, as well as the potential consequences for patient care and the workforce.

7 Robustness

7.1 Robustness to Alternative Specifications

We conduct additional robustness checks across the DID, SDID, and CEM with DID specifications, with results reported in Table 5. First, we exclude transitional years surrounding the implementation of the staffing mandate (Panel B). While our baseline specification treats 2002 as the treatment timing to capture anticipatory responses following the announcement of the staffing mandate, the full implementation occurred in 2004. Consequently, outcomes observed during 2002-2004 may reflect a combination of pre-treatment behavior, anticipation effects, and partial compliance rather than a well-defined treatment effect. To separate longer-run policy effects from potential transitional dynamics, we re-estimate our models after excluding the years 2002–2004, focusing on hospitals' responses once the policy was fully implemented.[11]

Second, we exclude hospitals in states neighboring California (Oregon, Nevada, and Arizona) from the control group to address potential spatial spillovers (Panel C). Given their geographic proximity, hospitals in these states might have adjusted staffing levels or technology investments in anticipation of nurse migration or broader labor market changes, which could contaminate the control group.

Finally, we use a stricter definition of technology adoption using detailed adoption status information from the HIMSS database (Panel D). In particular, we restrict adoption to technologies at the implementation or operational stage, excluding early-stage contracting. This stricter definition focuses on technologies that are actively in use and mitigates concerns that our results reflect

[11] We also verify robustness to excluding only the announcement years (2002–2003).

differences in reporting practices or transitional adoption rather than realized implementation.

Across all alternative specifications, our results remain qualitatively consistent, reinforcing the robustness of our main findings to alternative definitions of policy treatment, control groups, and technology adoption.

7.2 Balanced Panel

The SDID estimator requires a balanced outcome panel, which may raise concerns that results are driven by the subset of hospitals that report technology adoption status every year. We further verify that our estimates are not driven by the balanced panel requirement by varying the panel window. Our baseline SDID estimates use the 1998–2008 panel. We estimate SDID using alternative balanced panels that shorten the sample window and therefore retain a broader set of hospitals with complete reporting over the included years: 1999–2008, 1999–2007, and 1999–2006.

The resulting estimates, reported in Table 6, are highly similar to the baseline in both sign and magnitude for CDS and NSS. We further verify that this robustness extends to our heterogeneity analyses: estimates by pre-policy staffing levels and by financial constraints remain qualitatively unchanged when alternative balanced panels are used (Appendix Table A3 and Table A4). These results indicate that our findings are not an artifact of the balanced panel requirement and are robust to reasonable changes in the reporting window used to construct the SDID sample.

8 Conclusion

This paper examines how labor quantity regulations affect technology adoption, using California's nurse staffing mandate for general acute-care hospitals. The policy requires hospitals to meet minimum NPRs, generating heterogeneous adjustments depending on baseline staffing ratios and financial conditions. We compare technology adoption in California with that in other states and then assess heterogeneity across pre-policy staffing levels and financial constraints.

We find that the announcement of the staffing mandate leads to a substantial decline in the adoption of CDS systems, particularly among hospitals with lower baseline staffing ratios. These hospitals face steep increases in labor costs, which appear to crowd out investment in new technologies. Consistent with the role of financial constraints, we find that the decline in CDS adoption is concentrated among hospitals with weaker pre-policy operating margins. Hospitals facing the largest compliance burdens and the tightest budgets crowd out costly, quality-enhancing technologies.

By contrast, we find limited average effects of the mandate on NSS adoption, but there exists substantial heterogeneity. California hospitals, especially those with higher baseline NPRs, increase adoption of NSS following the policy. NSS enables more efficient workforce allocation and helps maintain real-time compliance with staffing standards. This pattern aligns with our conceptual framework, in which NSS reduces the variance in real-time NPRs and the expected cost of noncompliance, making adoption more valuable for well-staffed hospitals. Hospitals with more diversified service offerings, often correlated with higher NPRs, also stand to benefit more from this optimization. We find that financially stronger hospitals are more likely to adopt NSS, reinforcing the importance of resource constraints in shaping adoption decisions.

These findings highlight an important unintended consequence of labor market regulation: the potential crowding out of productivity-enhancing technologies. A back-of-the-envelope calculation, based on estimates from prior work, suggests that the decline in CDS adoption may have led to substantial losses in mortality improvements, amounting to at most 27 additional neonatal deaths per 100,000 live births and 128 additional deaths per 1 million elderly admissions. Meanwhile, the rise in NSS adoption may have helped hospitals manage labor more effectively, potentially improving nurse satisfaction and reducing unstaffed capacity. If CDS adoption plays a broad and significant role in improving public health, as suggested by the literature, the decline in CDS adoption may help explain why prior studies find limited overall effects of staffing mandates on patient outcomes (Cook et al., 2012; Raja, 2023).

While our findings are specific to the healthcare sector, they may have broader relevance to many other regulated sectors. Industries such as education, transportation, and public safety also use staffing mandates to ensure service quality. These settings often face labor supply frictions and are not strictly profit-maximizing, making them susceptible to similar trade-offs between mandated labor inputs and investment in complementary technologies. Future work may explore whether labor quantity regulations in these sectors yield similar distortions in firms' technology adoption decisions and how these trade-offs ultimately shape service quality and productivity.

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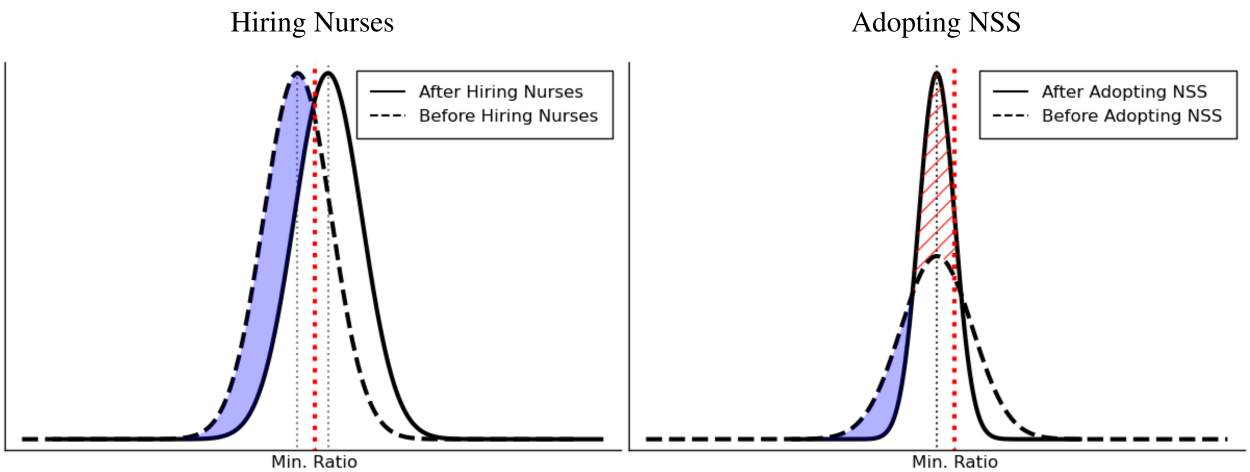
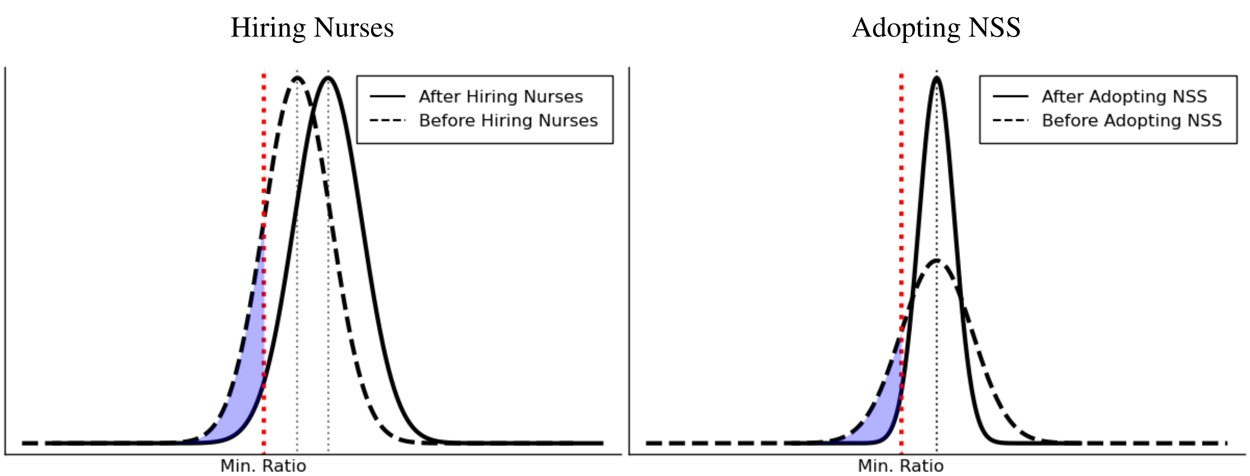
Figures and Tables

Figure 1: Compliance Risk in Real-Time Staffing

(a) Lower Baseline NPRs



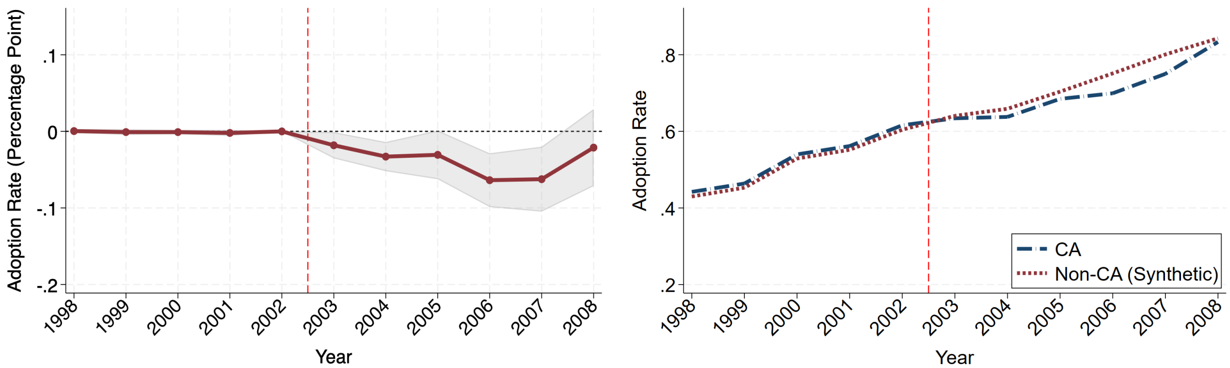
(b) Higher Baseline NPRs



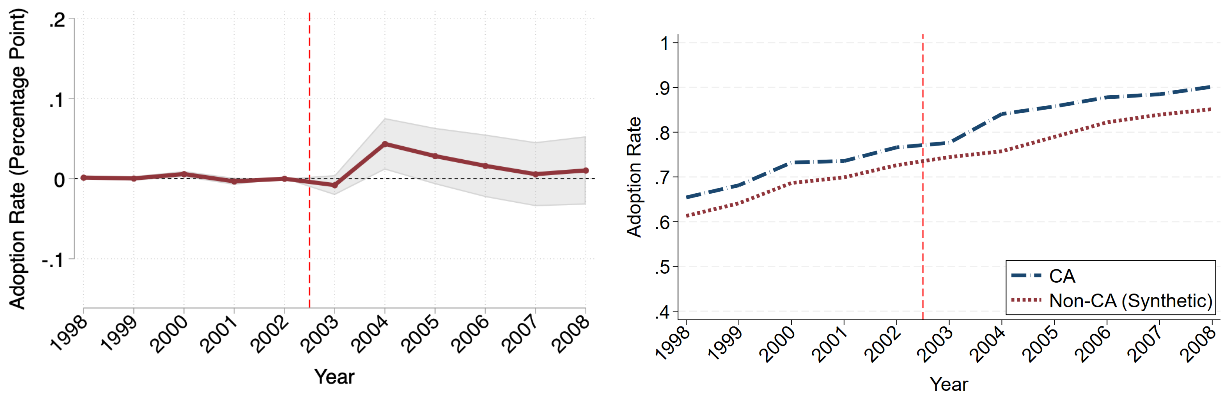
Notes: This figure illustrates how hiring nurses or adopting nurse staffing software (NSS) shifts the log-normal distributions of real-time nurse-to-patient ratios (NPRs) for hospitals with different baseline staffing. The shaded area represents the decrease of the probability that real-time NPR is below the mandatory minimum ratios. The hatched area represents the increase of such probability.

Figure 2: SDID Event Study

(a) Clinical Decision Support



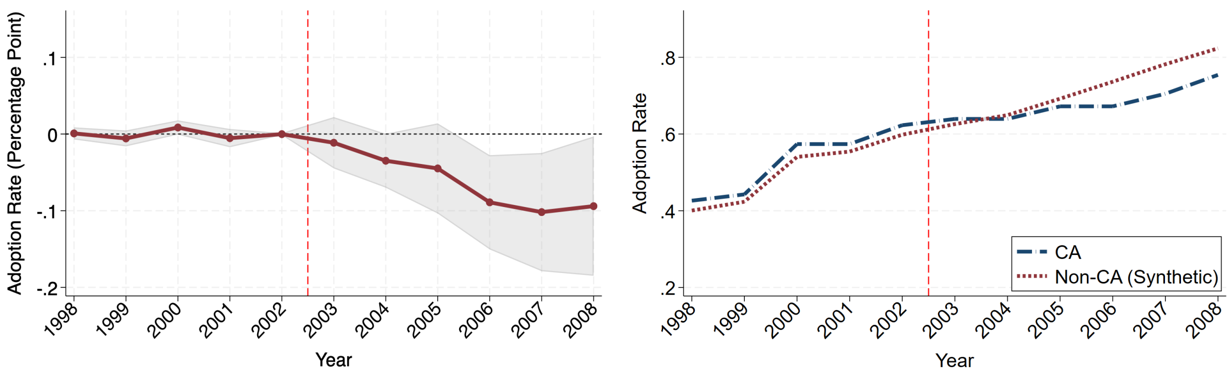
(b) Nurse Staffing Software



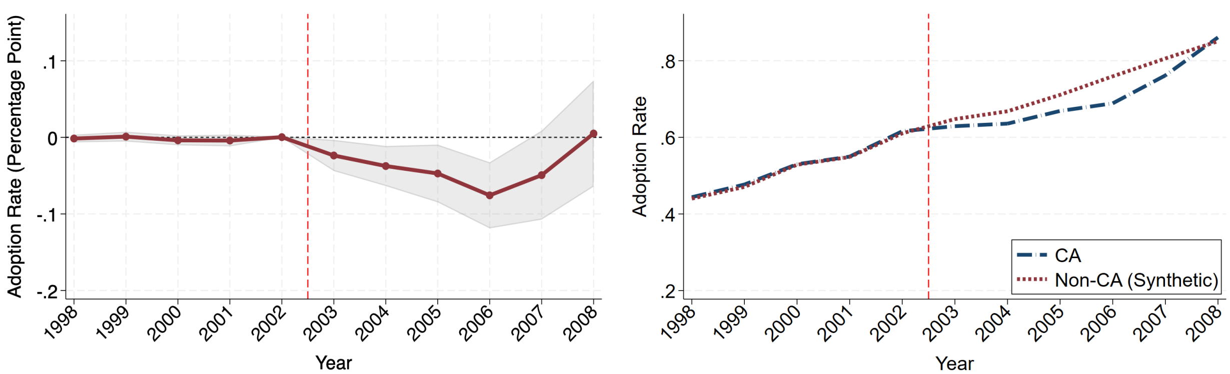
Notes: The left panel presents the results of event study using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (5). Each coefficient shows the difference between treated and synthetic control hospitals in each period relative to their pre-period average difference weighted by time weights. 95% confidence intervals are obtained by bootstrapping with 1000 bootstraps. The right panel shows the raw trend of adoption rate for treated (California) and synthetic control (Non-California) group.

Figure 3: SDID Event Study by Pre-policy Staffing Levels, Clinical Decision Support

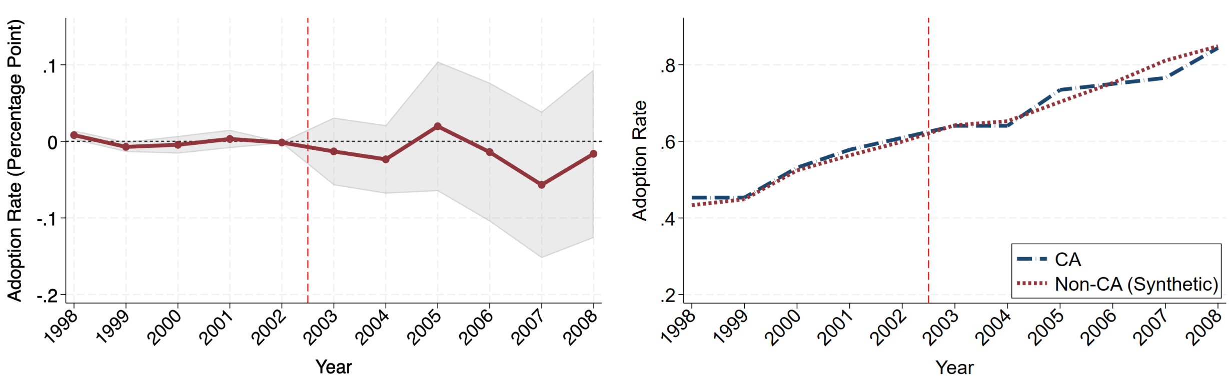
(a) High-need Hospitals



(b) Moderate-need Hospitals



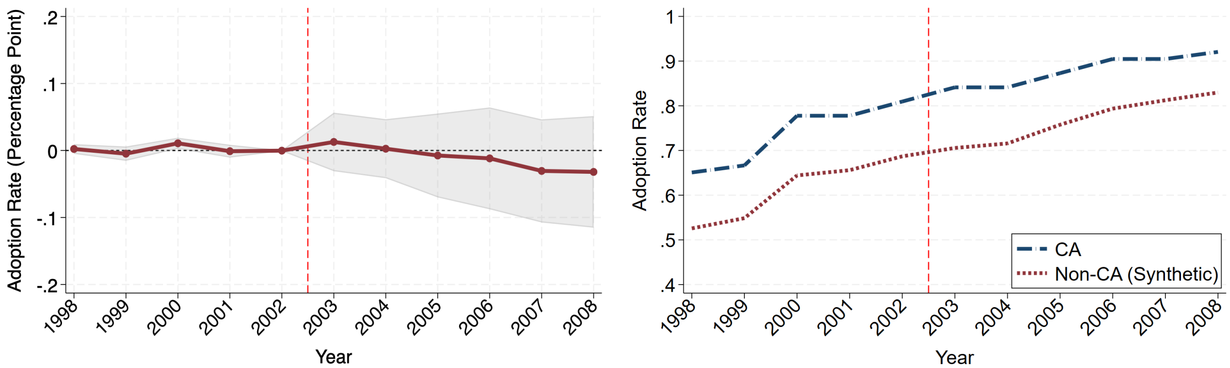
(c) Low-need Hospitals



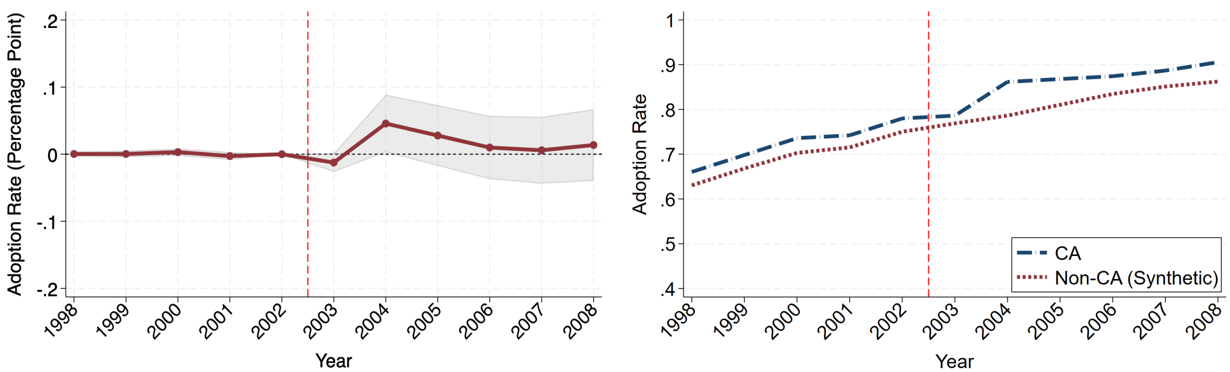
Notes: The left panel presents the results of event study on Clinical Decision Support (CDS) using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (5). Hospitals are grouped by pre-policy nurse-to-patient ratios (NPRs): high-need hospitals are in the lowest quartile of NPRs, moderate-need hospitals are in the middle two quartiles, and low-need hospitals are in the highest quartile. Each coefficient shows the difference between treated and synthetic control hospitals in each period relative to their pre-period average difference weighted by time weights. 95% confidence intervals are obtained by bootstrapping with 1000 bootstraps. The right panel shows the raw trend of adoption rate for treated (California) and synthetic control (Non-California) group.

Figure 4: SDID Event Study by Pre-policy Staffing Levels, Nurse Staffing

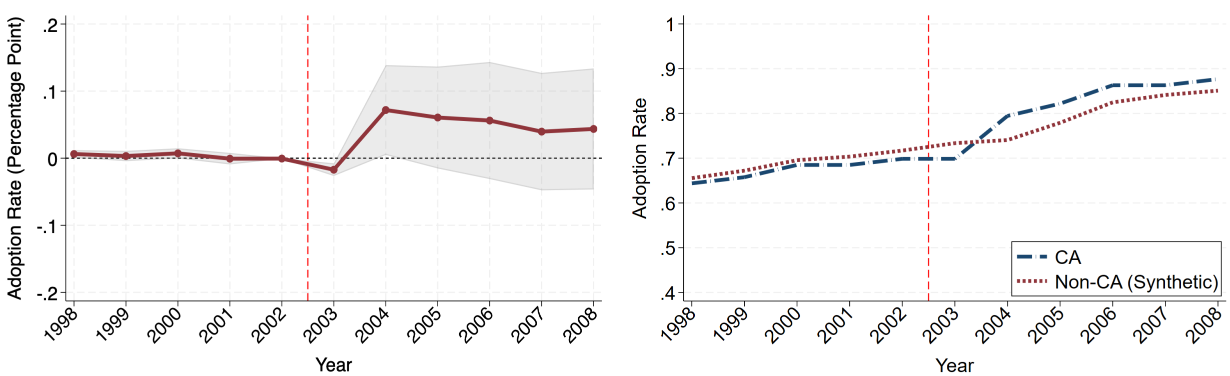
(a) High-need Hospitals



(b) Moderate-need Hospitals



(c) Low-need Hospitals

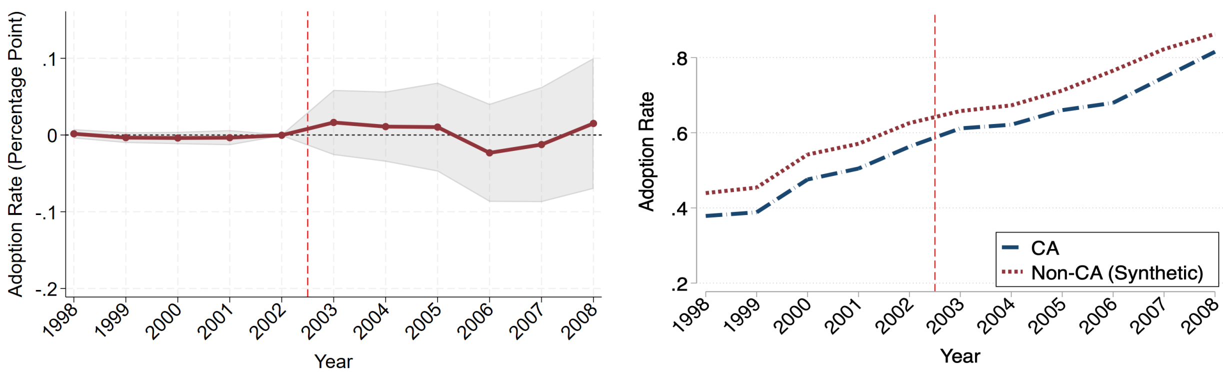


Notes: The left panel presents the results of event study on Nurse Staffing technologies using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (5). Hospitals are grouped by pre-policy nurse-to-patient ratios (NPRs): high-need hospitals are in the lowest quartile of NPRs, moderate-need hospitals are in the middle two quartiles, and low-need hospitals are in the highest quartile. Each coefficient shows the difference between treated and synthetic control hospitals in each period relative to their pre-period average difference weighted by time weights. 95% confidence intervals are obtained by bootstrapping with 1000 bootstraps. The right panel shows the raw trend of adoption rate for treated (California) and synthetic control (Non-California) group.

Figure 5: SDID Event Study by Financial Conditions, Clinical Decision Support

(a) Constrained Hospitals

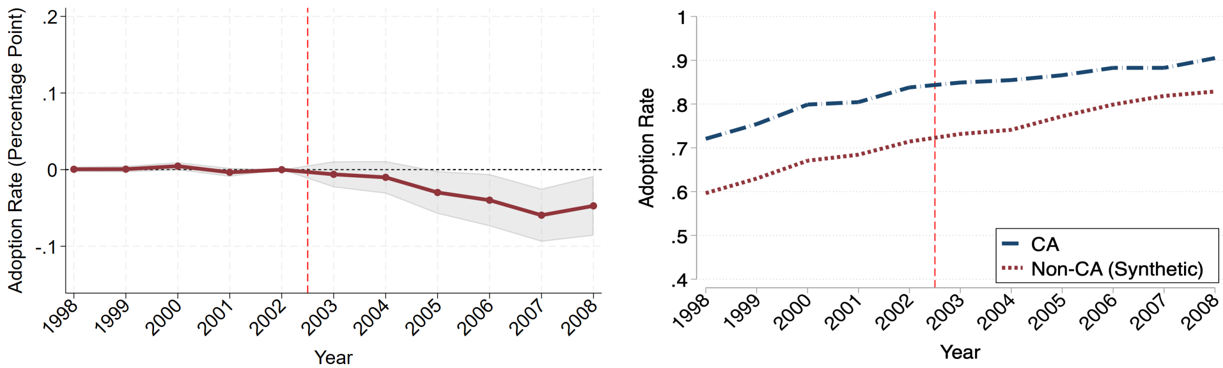
(b) Unconstrained Hospitals



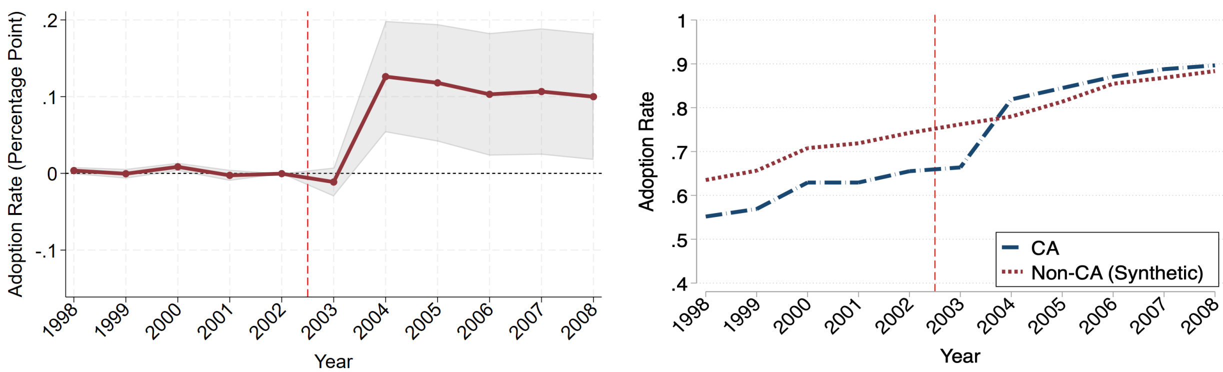
Notes: The left panel presents the results of event study on Clinical Decision Support (CDS) using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (5). Hospitals are classified as financially constrained if their average operating margin over the pre-policy period (2000–2002) is negative. Each coefficient shows the difference between treated and synthetic control hospitals in each period relative to their pre-period average difference weighted by time weights. 95% confidence intervals are obtained by bootstrapping with 1000 bootstraps. The right panel shows the raw trend of adoption rate for treated (California) and synthetic control (Non-California) group.

Figure 6: SDID Event Study by Financial Conditions, Nurse Staffing

(a) Constrained Hospitals



(b) Unconstrained Hospitals



Notes: The left panel presents the results of event study on Nurse Staffing technologies using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (5). Hospitals are classified as financially constrained if their average operating margin over the pre-policy period (2000–2002) is negative. Each coefficient shows the difference between treated and synthetic control hospitals in each period relative to their pre-period average difference weighted by time weights. 95% confidence intervals are obtained by bootstrapping with 1000 bootstraps. The right panel shows the raw trend of adoption rate for treated (California) and synthetic control (Non-California) group.

Table 1: Summary Statistics

	CDS Sample			NSS Sample		
	CA	Non-CA	Δ	CA	Non-CA	Δ
Technology adoption	0.62	0.61	0.00	0.76	0.73	0.03
NPR	0.31	0.3	0.01	0.32	0.3	0.01
RN-LVN ratio	0.86	0.84	0.03***	0.86	0.83	0.03***
For-profit	0.19	0.19	0.00	0.25	0.19	0.07***
% Medicare	0.34	0.51	-0.17***	0.34	0.51	-0.17***
% Medicaid	0.19	0.13	0.06***	0.19	0.13	0.06***
Log Beds	5.21	5.07	0.14**	5.16	5.08	0.09
Log Patient Days	10.31	10.01	0.30***	10.26	10	0.26***
Log FTEs	6.51	6.4	0.11*	6.46	6.4	0.07
Log Hourly Wage	3.45	3.24	0.21***	3.45	3.24	0.22***
Log Revenue	17.51	16.6	0.92***	17.5	16.59	0.91***
N	273	2967		292	2899	

Note.–This table presents statistics in 2002 of the balanced sample for estimation. The first three columns show statistics for the sample for Clinical Decision Support (CDS) analysis and the next three columns show those for Nurse Staffing Software (NSS) analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Main Estimates

	Clinical Decision Support			Nurse Staffing Software		
	DID	SDID	CEM	DID	SDID	CEM
$CA_i \times Post_t$	-0.039**	-0.038***	-0.050***	-0.003	0.016	0.001
	(0.017)	(0.014)	(0.017)	(0.016)	(0.015)	(0.018)
Baseline Mean	0.63	0.62	0.62	0.76	0.79	0.76
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
N	38,720	36,190	36,481	38,691	35,728	36,466

Note.–This table presents coefficient estimates for Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) adoption. Each column reports the coefficient on the interaction between a California indicator and a post-policy indicator using three methods: traditional DID, synthetic difference-in-differences (SDID), and Coarsened Exact Matching (CEM) with DID. All specifications include hospital and year fixed effects. Baseline mean shows the adoption rate in 2002 for California hospitals. Standard errors in parentheses are obtained by clustering at the hospital level for DID and CEM-DID, and by block bootstrapping with 1000 bootstraps for SDID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Heterogeneity by Pre-Policy Staffing Levels

	Clinical Decision Support			Nurse Staffing Software		
	High need	Moderate need	Low need	High need	Moderate need	Low need
$CA_i \times Post_t$	-0.063**	-0.038**	-0.017	-0.011	0.015	0.042
	(0.025)	(0.018)	(0.034)	(0.029)	(0.020)	(0.033)
Baseline Mean	0.6	0.63	0.6	0.85	0.79	0.75
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
N	8,481	18,051	9,658	8,261	17,820	9,647

Note.–This table presents synthetic difference-in-differences (SDID) estimates for Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) adoption, following Arkhangelsky et al. (2021). Hospitals are grouped by pre-policy nurse-to-patient ratios (NPRs): high-need hospitals are in the lowest quartile of NPRs, moderate-need hospitals are in the middle two quartiles, and low-need hospitals are in the highest quartile. Each column reports the coefficient on the interaction between a California indicator and a post-policy indicator. All specifications include hospital and year fixed effects. Baseline mean shows the adoption rate in 2002 for California hospitals. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Heterogeneity by Financial Conditions

	Clinical Decision Support		Nurse Staffing Software	
	Constrained	Unconstrained	Constrained	Unconstrained
$CA_i \times Post_t$	-0.064***	0.003	-0.032**	0.090***
	(0.014)	(0.027)	(0.013)	(0.031)
Baseline Mean	0.64	0.56	0.82	0.66
Hospital FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	21,274	14,916	20,790	14,938

Note.–This table presents synthetic difference-in-differences (SDID) estimates for Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) adoption, following Arkhangelsky et al. (2021). Hospitals are classified as financially constrained if their average operating margin over the pre-policy period (2000–2002) is negative. Each column reports the coefficient on the interaction between a California indicator and a post-policy indicator. All specifications include hospital and year fixed effects. Baseline mean shows the adoption rate in 2002 for California hospitals. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Robustness to Alternative Specifications

	Clinical Decision Support			Nurse Staffing Software		
	DID	SDID	CEM	DID	SDID	CEM
Panel A: Baseline						
$CA_i \times Post_t$	-0.039**	-0.038***	-0.050***	-0.003	0.016	0.001
	(0.017)	(0.014)	(0.017)	(0.016)	(0.015)	(0.018)
Panel B: Excluding Implementation Transition Years						
$CA_i \times Post_t$	-0.044**	-0.038*	-0.056**	-0.008	-0.001	-0.003
	(0.022)	(0.021)	(0.023)	(0.021)	(0.020)	(0.021)
Panel C: Excluding Nearby States from Control Group						
$CA_i \times Post_t$	-0.038**	-0.039***	-0.050***	-0.004	0.015	-0.002
	(0.017)	(0.014)	(0.017)	(0.016)	(0.015)	(0.017)
Panel D: Stricter Technology Adoption Definition						
$CA_i \times Post_t$	-0.033**	-0.025*	-0.042**	-0.008	0.011	-0.001
	(0.017)	(0.014)	(0.017)	(0.016)	(0.015)	(0.016)

Note.–This table presents robustness checks for estimates for Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) adoption. Each column reports the coefficient on the interaction between a California indicator and a post-policy indicator using three methods: traditional DID, synthetic difference-in-differences (SDID), and Coarsened Exact Matching (CEM) with DID. Panel A reports the baseline specification. Panel B excludes the transitional implementation period (2002–2004). Panel C excludes hospitals in states neighboring California (Oregon, Nevada, and Arizona) from the control group. Panel D restricts adoption to technologies at the implementation or operational stage, excluding early-stage contracting. All specifications include hospital and year fixed effects. Standard errors in parentheses are obtained by clustering at the hospital level for DID and CEM-DID, and by block bootstrapping with 1000 bootstraps for SDID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

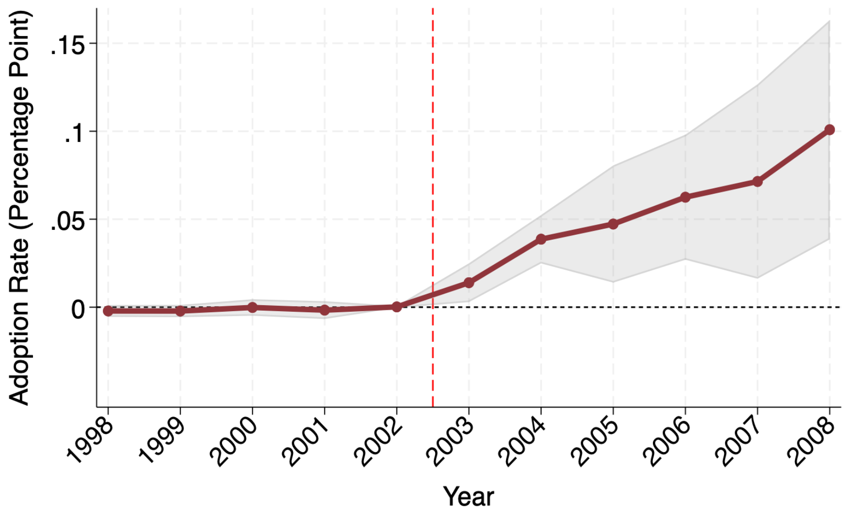
Table 6: Robustness to Alternative Balanced Panel

	1998–2008	1999–2008	1999–2007	1999–2006
Panel A: Clinical Decision Support				
$CA_i \times Post_t$	-0.038***	-0.035***	-0.039***	-0.034***
	(0.014)	(0.013)	(0.012)	(0.011)
Panel B: Nurse Staffing Software				
$CA_i \times Post_t$	0.016	0.018	0.019	0.021
	(0.015)	(0.015)	(0.014)	(0.013)

Note.–This table presents synthetic difference-in-differences (SDID) estimates for Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) adoption, following Arkhangelsky et al. (2021). Each column corresponds to a different sample window. The baseline specification uses the 1998–2008 panel; alternative specifications shorten the window to retain a larger set of hospitals with complete reporting. All specifications include hospital and year fixed effects. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

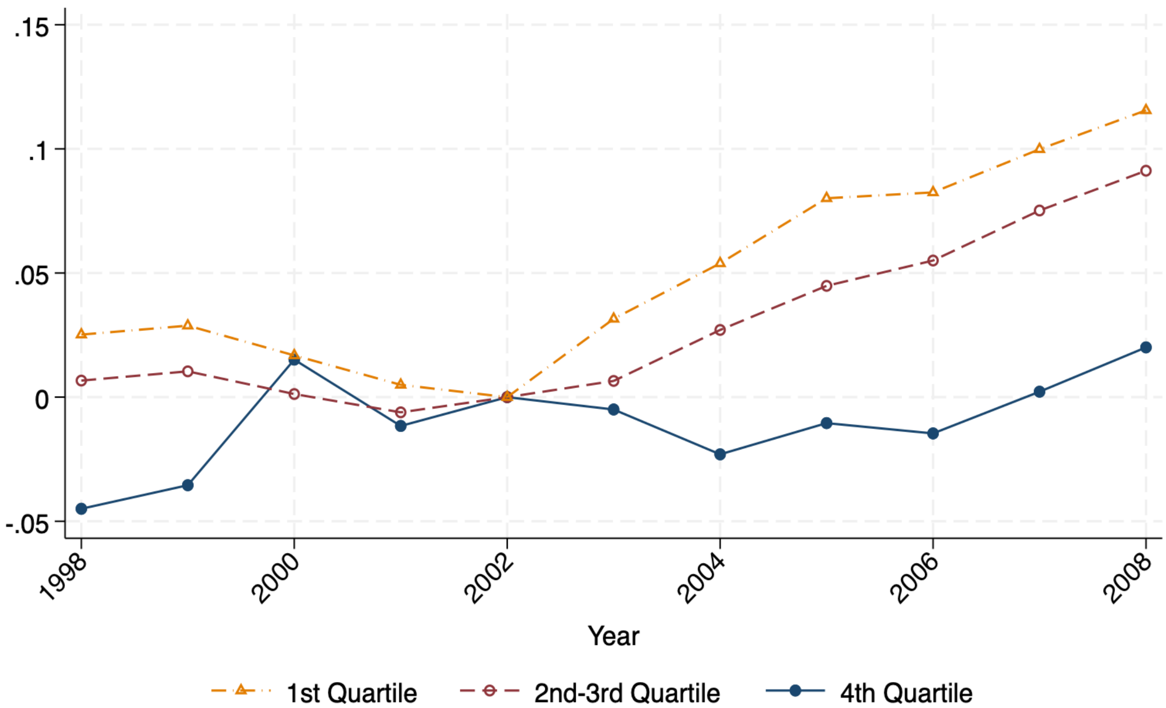
A Online Appendix

Figure A1: SDID Event Study: Total Hours Worked



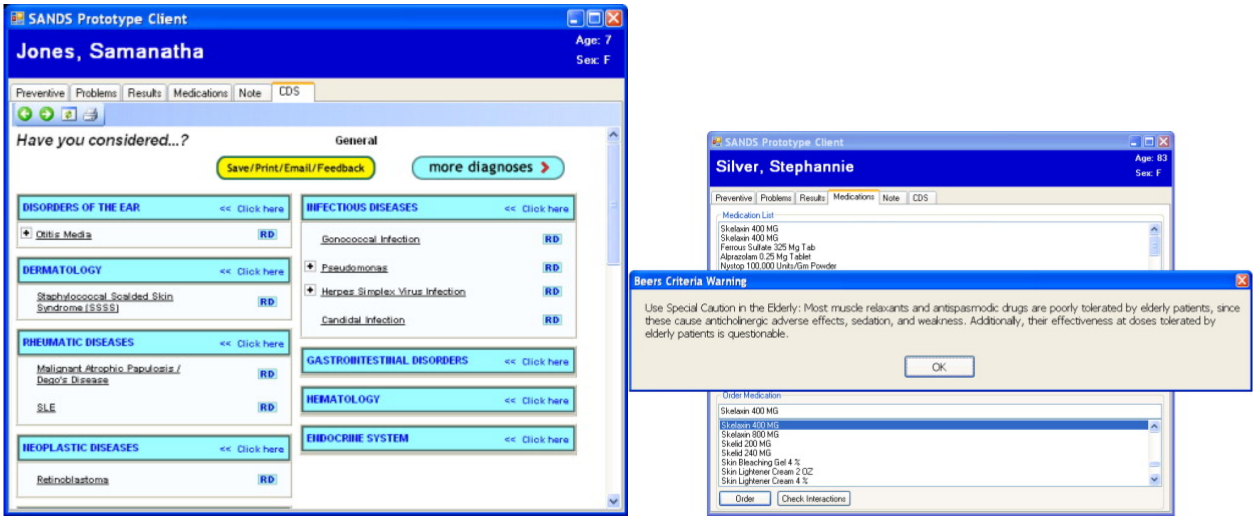
Notes: This figure presents the results of event study using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024) on total hours worked across all hospital employees. The estimation specification is presented in equation (5). Each coefficient shows the difference between treated and synthetic control hospitals in each period relative to their pre-period average difference weighted by time weights. 95% confidence intervals are obtained by bootstrapping with 1000 bootstraps.

Figure A2: Change in Nurse-to-Patient Ratios (Base Year = 2002)



Notes: Sources are California's Office of Statewide Healthcare Planning and Development (OHSPD) financial reports. Following Munnich (2014), nurse-to-patient ratios are measured using the ratio of reported annual productive hours to total number of patient days divided by 24 hours in general medical-surgical units. Hospitals are categorized by quartiles of pre-policy nurse-to-patient ratios (average between 2000 and 2002).

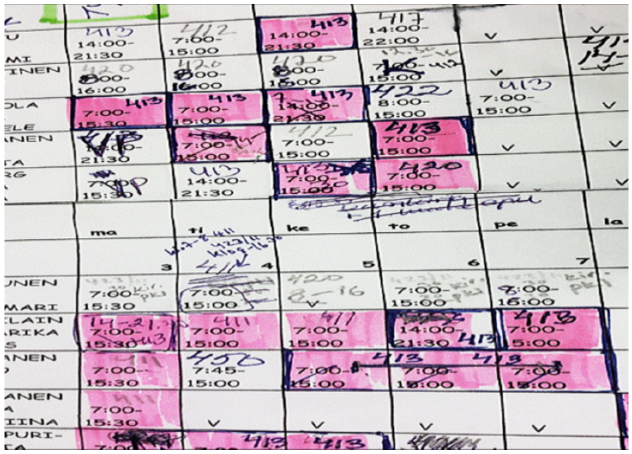
Figure A3: Examples of Clinical Decision Support in Practice



Notes: Figures are adapted from Wright and Sittig (2008). Left panel shows a diagnostic decision support interface suggesting differential diagnoses based on patient symptoms. Right panel shows a prescribing alert triggered by entry of a medication contraindicated for older adults based on Beers criteria.

Figure A4: Comparison of Nurse Staffing Systems Before and After IT Adoption

(a) Paper-based Scheduling System

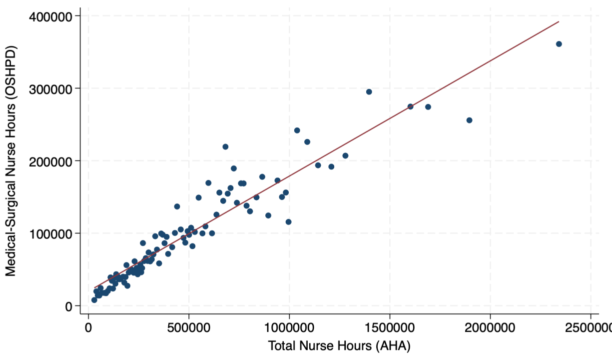


(b) IT-based Scheduling System

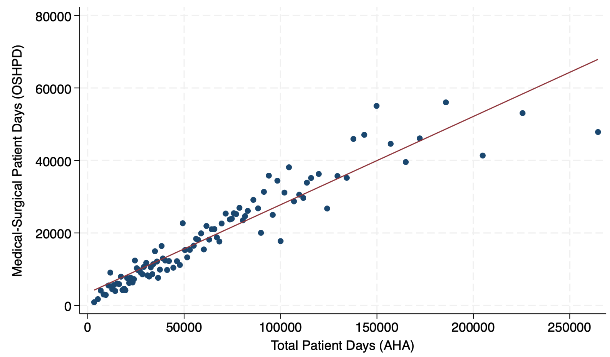
Notes: Panel (a) is adapted from Tuominen (2020), while (b) screenshots are from the MedRez.net Scheduling Tool, circa 2009 (https://www.medrez.net/index.php). Panel (a) illustrates the manual reservation of float pool nurse shifts via printed lists. Left figure of panel (b) shows a digital scheduling interface with real-time feedback on scheduling constraints; right figure shows an online day-off request system with manager approval functionality.

Figure A5: Comparison of OSHPD and AHA Measures: Nurse Hours and Patient Days

(a) Nurse Hours

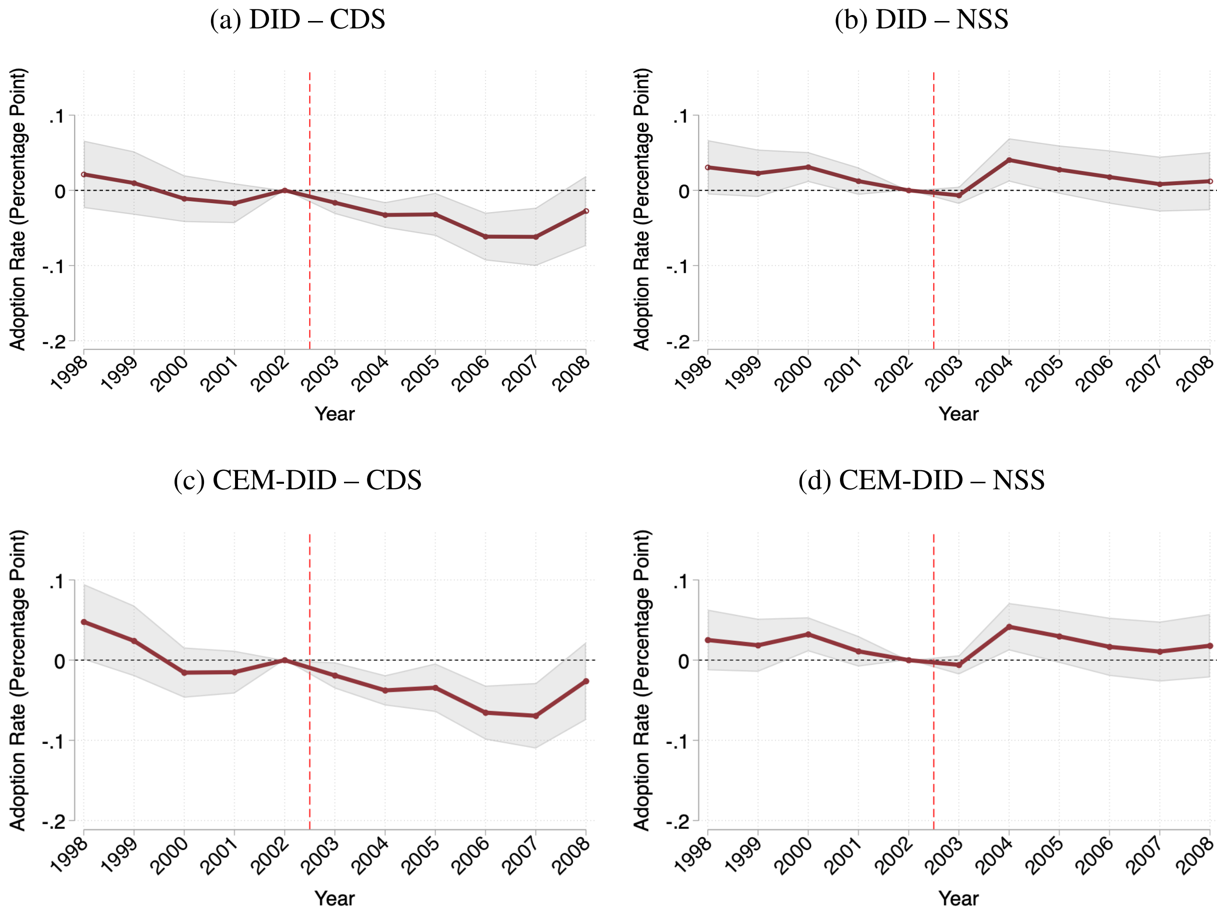


(b) Patient Days



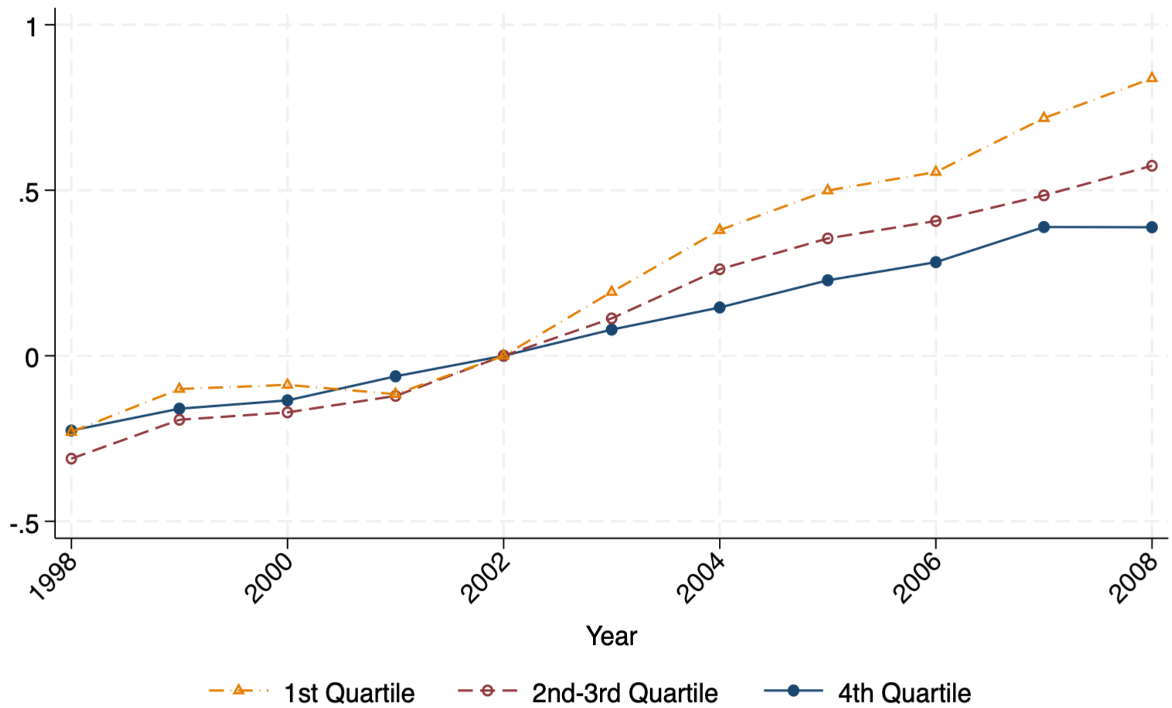
Notes: This figure compares hospital-level nurse staffing and patient volume across two datasets for California hospitals observed in both OSHPD general medical-surgical units and AHA during the 2000–2002 pre-policy period. The left panel shows a binned scatterplot of total nurse hours, and the right panel shows total patient days.

Figure A6: Alternative Event Study Estimates: DID and CEM-DID



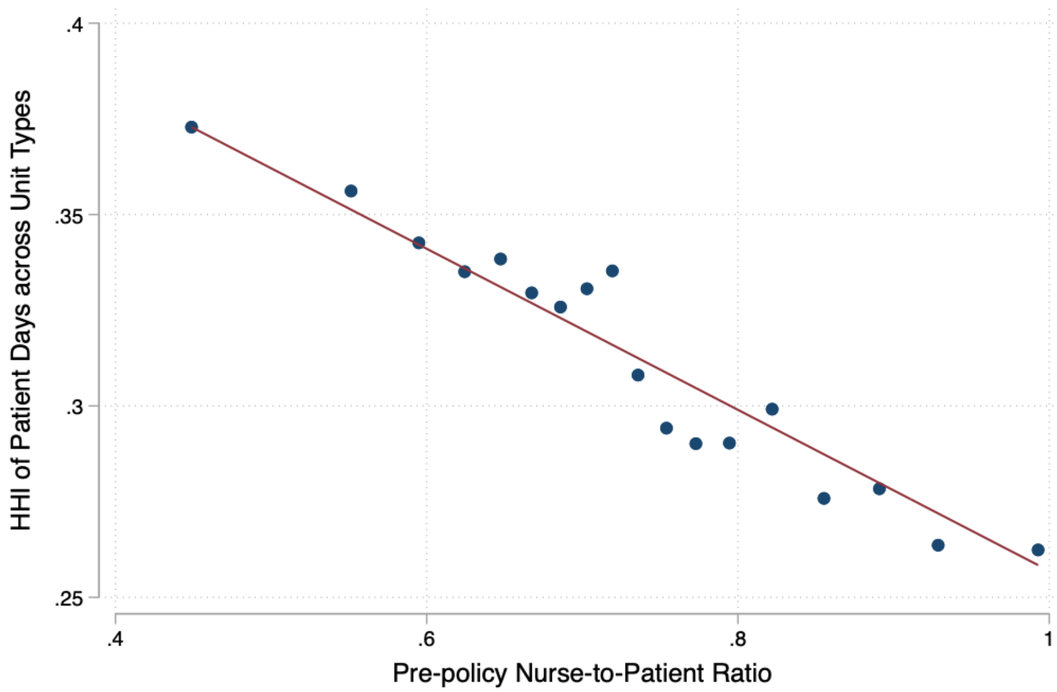
Notes: This figure reports event study estimates from alternative estimators comparing California hospitals to hospitals in other states. The top row shows standard difference-in-differences (DID) estimates; the bottom row shows estimates using Coarsened Exact Matching (CEM) with DID. The left column reports effects on Clinical Decision Support (CDS) adoption and the right column on Nurse Staffing Software (NSS). Coefficients are relative to the year before implementation, with 95% confidence intervals.

Figure A7: Change in Log Total Salaries for Nurses (Base Year = 2002)



Notes: Sources are California's Office of Statewide Healthcare Planning and Development (OHSPD) financial reports. Following Munnich (2014), nurse-to-patient ratios are measured using the ratio of reported annual productive hours to total number of patient days divided by 24 hours in general medical-surgical units. Hospitals are categorized by quartiles of pre-policy nurse-to-patient ratios (average between 2000 and 2002).

Figure A8: Relationship Between Pre-Policy Staffing Levels and Service Diversification



Notes: This figure plots the relationship between hospitals' pre-policy nurse-to-patient ratio (NPR) and the Herfindahl–Hirschman Index (HHI) of patient days across unit types. A lower HHI indicates a more diversified distribution of patient care across different units (e.g., intensive care, general medical-surgical, specialty care). The negative relationship suggests that hospitals facing smaller required staffing increases under the mandate tended to have more diversified inpatient services.

Table A1: Hospital Characteristics in Balanced and Excluded Samples

	Clinical Decision Support			Nurse Staffing Software		
	Balanced	Excluded	Δ	Balanced	Excluded	Δ
Adoption	0.62	0.45	0.17***	0.74	0.59	0.15***
NPR	0.31	0.3	0.01	0.31	0.3	0.01*
RN-LVN ratio	0.84	0.81	0.03***	0.84	0.81	0.03***
For-profit	0.19	0.32	-0.13***	0.19	0.25	-0.06**
% Medicare	0.49	0.5	-0.01	0.49	0.49	0.00
% Medicaid	0.14	0.14	0.00	0.14	0.15	-0.01
Log Beds	5.08	4.54	0.54***	5.09	4.58	0.51***
Log Patient Days	10.04	9.59	0.45***	10.03	9.71	0.32***
Log FTEs	6.42	6.1	0.32***	6.41	6.21	0.20***
Log Hourly Wage	3.26	3.26	0.00	3.26	3.24	0.02*
N	3290	317		3244	368	

Note.–This table reports hospital characteristics measured in 2002 for hospitals included in and excluded from the balanced panel used in the synthetic difference-in-differences (SDID) analysis. The first three columns correspond to the Clinical Decision Support (CDS) adoption sample, and the last three columns correspond to the Nurse Staffing Software adoption sample. Balanced hospitals report complete technology adoption status over 1998–2008, while excluded hospitals have missing adoption information in at least one year. Δ reports the difference in means between balanced and excluded hospitals. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Summary Statistics for Matched Sample

	CDS Sample			NSS Sample		
	CA	Non-CA	Δ	CA	Non-CA	Δ
Technology adoption	0.62	0.65	-0.03	0.76	0.79	-0.03
NPR	0.32	0.33	-0.01	0.32	0.33	-0.01
RN-LVN ratio	0.86	0.87	-0.01	0.86	0.87	-0.01
For-profit	0.25	0.25	0.00	0.25	0.25	0.00
% Medicare	0.34	0.45	-0.11***	0.34	0.45	-0.11***
% Medicaid	0.19	0.13	0.06***	0.19	0.13	0.06***
Log Beds	5.16	5.28	-0.12***	5.16	5.28	-0.12***
Log Patient Days	10.26	10.29	-0.03	10.26	10.29	-0.03
Log FTEs	6.46	6.61	-0.15***	6.46	6.61	-0.15***
Log Hourly Wage	3.45	3.29	0.16***	3.45	3.29	0.16***
Log Revenue	17.52	16.98	0.54***	17.52	16.98	0.54***
N	315	3021		315	3021	

Note.–This table presents statistics in 2002 of the matched sample for estimation. Coarsened Exact Matching (CEM) is done on pre-policy covariates in 2000 for each hospital group, using for-profit ownership, total beds, total patient days, and the Medicare and Medicaid share of patient days. The first three columns show statistics for the sample for Clinical Decision Support (CDS) analysis and the next three columns show those for Nurse Staffing Software (NSS) analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Alternative Balanced Panel by Pre-Policy Staffing Levels

	Clinical Decision Support			Nurse Staffing Software		
	High-need	Mod-need	Low-need	High-need	Mod-need	Low-need
Panel A: 1998–2008 (Baseline)						
$CA_i \times Post_t$	-0.063**	-0.038**	-0.017	-0.011	0.015	0.042
	(0.025)	(0.018)	(0.034)	(0.029)	(0.020)	(0.033)
Panel B: 1999–2008						
$CA_i \times Post_t$	-0.061**	-0.039**	-0.010	-0.010	0.015	0.044
	(0.025)	(0.017)	(0.034)	(0.030)	(0.021)	(0.033)
Panel C: 1999–2007						
$CA_i \times Post_t$	-0.055**	-0.047***	-0.011	-0.006	0.016	0.044
	(0.023)	(0.016)	(0.032)	(0.028)	(0.020)	(0.031)
Panel D: 1999–2006						
$CA_i \times Post_t$	-0.044**	-0.046***	-0.003	-0.000	0.018	0.044
	(0.021)	(0.014)	(0.030)	(0.026)	(0.018)	(0.028)

Note.–This table presents coefficient estimates from synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024) with various samples. Each panel corresponds to a different sample window. The baseline specification uses the 1998–2008 panel; alternative specifications shorten the window to retain a larger set of hospitals with complete reporting. High-need hospitals are in the lowest quartile of pre-policy nurse-to-patient ratios (NPRs), moderate-need hospitals in the second and third of quartiles, and low-need hospitals in the highest quartiles. All columns control hospital fixed effects and year fixed effects. Standard errors in parenthesis are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Alternative Balanced Panel by Financial Conditions

	Clinical Decision Support		Nurse Staffing Software	
	Constrained	Unconstrained	Constrained	Unconstrained
Panel A: 1998–2008 (Baseline)				
$CA_i \times Post_t$	-0.064***	0.003	-0.032**	0.090***
	(0.014)	(0.027)	(0.013)	(0.031)
Panel B: 1999–2008				
$CA_i \times Post_t$	-0.062***	0.007	-0.030**	0.092***
	(0.014)	(0.027)	(0.013)	(0.031)
Panel C: 1999–2007				
$CA_i \times Post_t$	-0.066***	0.004	-0.027**	0.090***
	(0.012)	(0.025)	(0.012)	(0.029)
Panel D: 1999–2006				
$CA_i \times Post_t$	-0.060***	0.006	-0.020*	0.085***
	(0.010)	(0.024)	(0.011)	(0.028)

Note.–This table presents coefficient estimates from synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024) with various samples. Each panel corresponds to a different sample window. The baseline specification uses the 1998–2008 panel; alternative specifications shorten the window to retain a larger set of hospitals with complete reporting. Hospitals are classified as financially constrained if their average operating margin over the pre-policy period (2000–2002) is negative. All columns control hospital fixed effects and year fixed effects. Standard errors in parenthesis are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$