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

Woosuk Choi† So Young Kim‡

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

*We are deeply grateful to Lisa B. Kahn, Ronni Pavan, John D. Singleton, David Figlio for their invaluable support and comments. We also thank Elena Prager, Travis A. Baseler, Kegon T.K. Tan, and all participants in the University of Rochester Applied Reading Group and the WEAI Conference. All errors are those of the authors.

†Korea Insurance Research Institute. woosukchoi92@gmail.com. 13th floor, KFPA Blog, 38, Gukjegeumyung-ro 6-gil (35-4 Yoido-Dong), Yeongdeungpo-gu, Seoul, Korea, 150-606.

‡Department of Economics, University of Rochester. soyoung.kim@rochester.edu. 280 Hutchinson Road, Rochester, NY, United States, 14627.

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.

The authors have no relevant financial interests that relate to the research described in this paper. No IRB approval was required because this study does not involve any identifiable information on individual human subjects.

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

[1] Acemoglu and Finkelstein (2008) examine how changes in labor cost reimbursement regulations affect technology adoption in hospitals. Acemoglu (2010) finds 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 18% of U.S. GDP in 2024, while healthcare employment represents 11.7% of total nonfarm U.S. employment. See NHE Fact Sheet (https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/nhe-fact-sheet) and the BLS's Employment Situation (https://www.bls.gov/news.release/empsit.t17.htm).

2000s. Assembly Bill 394 (AB394), passed in 1999, established minimum nurse-to-patient ratios (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 reweights 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. To validate the design, we estimate SDID weights using only 1998–1999 and find no evidence of significant divergence during the omitted pre-policy years 2000–2002. 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.

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.

To illustrate the implications for patient outcomes, we conduct back-of-the-envelope calculations that consider both the technology and staffing margins. Applying prior mortality estimates to our results, the 3.8 percentage point decline in CDS adoption implies approximately 7.6 additional deaths, while the mandate-induced increase in nurse staffing implies approximately 158 fewer deaths per 100,000 admissions. The increase in NSS adoption may provide additional operational benefits through improved scheduling and staffing allocation. Although these benchmarks come from different empirical settings, they suggest that reduced technology investment is an important unintended cost of the mandate but is unlikely to fully offset the benefits associated with increased staffing. This highlights the importance of understanding potential trade-offs when designing labor market regulations in healthcare.

We conduct a series of robustness checks to assess the sensitivity of our findings. First, we vary the policy window and comparison sample by excluding the 2002–2004 transition period and hospitals in states neighboring California. Second, we use a stricter technology adoption definition that excludes early-stage contracting. Third, we assess the heterogeneity results under alternative pre-policy staffing windows and cutoffs, alternative definitions of financial constraints, and alternative estimators. We also verify robustness to alternative balanced-panel windows required by SDID. Finally, we examine broader measures of health IT adoption and alternative hospital IT outcomes. Across these exercises, the decline in CDS adoption remains highly robust, while the NSS results continue to show larger positive effects among lower-need and financially unconstrained hospitals, although some estimates are less precise.

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 (Lewis, 2011; 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.

Compliance with minimum NPRs is enforced by the California Department of Health Services (CDHS) through licensing surveys and complaint investigations. Verification of the compliance was intermittent and stochastic from the hospital's perspective. Acute care hospitals in California are surveyed routinely through the Consolidated Accreditation and Licensing Survey (CALS) process once every three years. It is supplemented by unannounced visits by surveyors investigating complaints received at the Licensing and Certification Program's district offices. The staffing mandate did not alter the number or frequency of these surveys; it only added the step of verifying compliance with the ratios (California Department of Health Services, 2003).

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 B1).

[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.

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 B2). 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]

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] The two technologies represent distinct margins along which hospitals may respond to the mandate: CDS is a clinical technology aimed at improving the quality and efficiency of patient care, whereas NSS is a workforce management technology that can facilitate compliance with staffing requirements.

[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.

[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.

Among the applications comprising an EMR system, we focus on CDS for two reasons. First, CDS is the EMR component most closely related to patient outcomes. Since improving care quality is a primary objective of the staffing mandate, a mandate-induced change in CDS adoption is directly relevant to its broader effects on healthcare delivery, particularly given the mixed evidence on the mandate's effects on patient outcomes. Second, CDS provides a relatively clean setting for identifying the financial crowding out channel we emphasize. CDS does not directly facilitate compliance with the staffing mandate, and it is not closely tied to nursing tasks, so a post-mandate decline cannot easily be attributed to compliance incentives or to a substitution response in nurse labor. [5]

NSS, by contrast, directly addresses workforce management by optimizing staffing allocation and scheduling. Because the mandate requires compliance at all times, hospitals face compliance risk from real-time fluctuations in staffing relative to patients, and NSS offers a means of managing that risk without additional hiring. In the following, we provide a conceptual framework for 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 B3, 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 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 main-

[5] The closest alternative is the clinical data repository (CDR), which stores the clinical information on which CDS operates. CDR, however, is associated with routine nursing documentation, so its response to the mandate may reflect changes in nursing workflow as well as financial constraints, making the mechanism harder to isolate. As a robustness check, we construct a broader measure defined as the adoption of either CDR or CDS and obtain qualitatively similar results.

tenance 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. The magnitude was substantial: our back-of-the-envelope calculation implies approximately $2.5 million in additional annual nurse salary expenditures per hospital, equivalent to about 12 percent of the observed increase in average real operating costs over the sample period.[6] 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 financial benefits materializing only gradually (Furukawa et al., 2010; Dranove et al., 2014).

These two channels generate different predictions for CDS adoption. If CDS strongly complements nursing labor, California hospitals should increase CDS adoption as the mandate induces them to expand nurse staffing. In contrast, if the mandate tightens hospitals' financial constraints, they may delay or forgo CDS adoption. This decline should be larger among hospitals with lower baseline staffing and weaker pre-policy financial conditions.

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

[6]The average nurse-to-patient ratio in California increased from 0.226 before the mandate to 0.306 afterward. Using hospitals' pre-policy patient days and assuming 40 hours per week and 52 weeks per year, this change implies an average increase of 41.8 nurse FTEs. Valued at the 2002 average annual California registered-nurse salary of $60,350, the additional salary expenditure is approximately $2.52 million per hospital. Average real operating costs in the CDS analysis sample increased from $194.7 million in 1998–2001 to $216.0 million in 2002–2008.

processes such as printed shift lists, phone calls, and emails, often leading to inefficiencies, overbooking, and communication delays. As shown in Figure B4 (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. For comparison, the average annual salary of a registered nurse in California in 2002 was approximately $60,350. Thus, the estimated $3 million initial cost of EMR implementation for a 250-bed hospital corresponds to roughly 50 registered-nurse annual salaries, whereas the lower end of the NSS cost range, $60,000, is approximately equivalent to one registered nurse's annual salary.

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 the average level of NPRs, hospitals reduce the likelihood of falling below the mandated minimum. However, even hospitals with sufficient 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.

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.[7] Because the mandate requires compliance at all times, a hospital faces an expected penalty proportional to the probability that its real-time NPR falls below the mandated minimum $\bar{r}$. Taking the penalty and the probability of investigation as given, both compliance strategies serve to reduce the probability of noncompliance.[8]

We formalize the real-time NPR as $r = (L/D)e^{\sigma\epsilon}$, where L/D is the hospital's average ratio and the multiplicative shock $e^{\sigma\epsilon}$ captures shift-level fluctuations in staffing relative to demand. ϵ is drawn from any mean-zero scale-family distribution. In logs, this gives a location-scale structure, with $\ln r = \mu + \sigma\epsilon$ and $\mu \equiv \ln(L/D)$. In this setting, the two compliance strategies map into the change of two parameters: hiring nurses raises the location μ, while NSS improves the allocation of a given stock of nurses across shifts and units and thus reduces the scale σ.

Two results follow. First, hiring always reduces the probability of falling below the mandated ratio $\bar{r}$. Second, reducing dispersion lowers that probability if and only if $\mu > \ln \bar{r}$. In other words, only hospitals whose average staffing already meets the requirement benefit from the decline of scale σ. The intuition is that reducing dispersion means realized ratios are more concentrated around the mean, and when the mean lies below the mandated minimum, this makes noncompliance more likely. Moreover, among hospitals that benefit from NSS, the value of reducing dispersion relative to hiring is increasing in baseline staffing.

Figure 1 illustrates these results for the special case of log-normally distributed real-time ratios. In panel (a), for hospitals with lower baseline ratios, hiring shifts the distribution up and substantially reduces noncompliance risk, whereas reducing variance alone cannot offset a mean below the threshold. In panel (b), for hospitals with higher baseline ratios, the marginal gain from hiring is smaller while reducing variance via NSS becomes comparably effective. The figure is illustrative and the comparative statics hold for any scale-family distribution.

These results deliver the predictions we take to the data. Hospitals with low baseline ratios comply primarily by hiring, since NSS does not help them; hospitals already staffed above the minimum face compliance risk arising from real-time fluctuations rather than persistent understaffing, and for them NSS offers a lower-cost margin of adjustment. We therefore expect any post-mandate increase in NSS adoption to be concentrated among hospitals with higher baseline staffing ratios.

[7] For details, please see Online Appendix A.

[8] We abstract from potential endogeneity in inspection intensity. More frequent inspections of persistently understaffed hospitals would strengthen hiring incentives, while responses to staffing volatility or prior violations could affect other margins less predictably.

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, 1998-2008). 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 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. We include contracting because it represents a commitment to adopt and captures the investment decision of interest. We use the annual implementation status, supplemented by the reported contract year when available, and assign the earliest observed adoption year. Adoption is treated as an absorbing state, so subsequent vendor changes, system replacements, or upgrades are not counted as new adoption events.[9]

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 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:

$$\text{NPR}_{it} = \frac{\text{Nurse FTE}_{it} \times 40 \times 52}{\text{Adjusted Patient Days}_{it} \times 24} \tag{1}$$

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

[9]Our adoption measure is broader than measures in some prior studies using HIMSS data. Dranove et al. (2014) primarily identify adoption using contract dates, while Bronsoler et al. (2022) use EHR measures requiring multiple applications to be jointly adopted. Reported adoption levels are therefore not directly comparable across these definitions.

hospitals observed in both sources, staffing and patient volume measures are strongly correlated (Figure B5), 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.[10] 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:

$$OM_{it} = \frac{\text{Operating Revenue}_{it} - \text{Operating Cost}_{it}}{\text{Operating Revenue}_{it}} \tag{2}$$

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

[10]The statutory minimum for general medical–surgical units was one nurse per six patients in 2004 and one per five beginning in 2005. Raja (2023) uses a pre-policy acute-care NPR cutoff of 0.25, compared with our high-need cutoff of 0.242. However, Raja (2023) uses unit-specific staffing, whereas our AHA measure is an annual hospital-wide ratio. We therefore interpret our groups as relative exposure categories rather than a measure of legal compliance.

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 B1, 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.[11] 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 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 identifica-

[11] Appendix Tables B2 and B3 report corresponding summary statistics separately by hospitals' pre-policy staffing needs and financial conditions.

tion 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:

$$Y_{it} = \alpha_i + \beta_t + \tau(\mathrm{CA}_i \times \mathrm{Post}_t) + \epsilon_{it} \tag{3}$$

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.[12] 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 outcomes only by a constant.[13] These weights are then incorporated into a weighted DID estimation with two-way fixed effects, which we specify as follows:

$$(\hat{\tau}, \hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}) = \underset{(\tau,\alpha,\beta)}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \alpha_i - \beta_t - \tau \mathrm{CA}_i \mathrm{Post}_t)^2 \hat{\omega}_i \hat{\lambda}_t \right\} \tag{4}$$

Because SDID weights are estimated separately for each outcome, the synthetic control composition may differ between the CDS and NSS analyses. Accordingly, each estimate is relative to its outcome-specific counterfactual, and comparisons across technologies should not be interpreted as effects relative to an identical set of weighted control hospitals. To compute standard errors, we use block bootstrapping with 1,000 bootstrap samples.

[12] 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.

[13] See Arkhangelsky et al. (2021) for details of the procedure for obtaining the weights. The key idea of the unit

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.

Because the unit weights are selected to align outcomes during the training period, close pre-treatment fit within that period does not by itself validate the research design. For example, weighting on short-run pre-treatment outcomes may generate subsequent divergence through regression to the mean rather than the mandate. We therefore conduct an out-of-training-sample validation exercise. We estimate the SDID unit weights using only outcomes from 1998–1999, hold those weights fixed, and examine the resulting differences during the omitted pre-policy years 2000–2002. Continued similarity during this period would support the credibility of the weighted comparison group as a counterfactual for California.

Figure 2 presents the validation results. For CDS, the California–synthetic differences remain statistically insignificant through 2002 and become significantly negative only afterward. For NSS, the estimates are noisier, but the downward pre-policy trend reverses around the mandate's implementation. Although this exercise cannot establish the parallel-trends assumption or rule out all California-specific shocks, it weighs against the concern that the post-policy patterns arise simply from regression to the mean in the weighted control group.

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.[14] 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).

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 $i = N_c + 1, \cdots, N$ 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 $t = 1, \cdots, T_{\text{pre}}$, where $N_t = N - N_c$. Similarly, $\hat{\lambda}$ is determined through unpenalized least squares to have $\sum_{t=1}^{T_{\text{pre}}} \lambda_t Y_{it} \approx T_{\text{post}}^{-1} \sum_{t=T_{\text{pre}}+1}^{T} Y_{it}$ for all $i = 1, \cdots, N_c$, where $T_{\text{post}=T-T_{\text{pre}}}$.

[14] 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

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, urban status, baseline technology adoption, total beds, separate Medicare and Medicaid patient shares, and baseline staffing-exposure groups.[15] 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 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.

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.

[15] These variables capture several dimensions of hospital heterogeneity that may affect technology adoption and exposure to the staffing mandate. For-profit status and urban status are stable structural attributes that shape investment behavior and are invariant to the mandate. To control for hospital size, we use the number of beds. Separate Medicare and Medicaid patient shares capture differences in payer mix and reimbursement environments. Baseline technology adoption accounts for pre-existing differences in technology use, and the staffing-exposure groups capture differences in pre-policy nurse staffing conditions. Table B4 reports summary statistics for hospitals in California and other states in 2002 for the matched samples.

Panel (a) of Figure 3 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.[16] 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, 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 3 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

[16] Event-study estimates using standard DID and matched DID using CEM display similar post-treatment patterns, but show less stable pre-treatment estimates (Figure B6), supporting SDID as our preferred specification.

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 4, 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 B7, 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 5, 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. Because our staffing data are measured annually at the hospital level, however, we cannot directly test the model's prediction that the return to NSS also increases with high-frequency variation in real-time staffing ratios.

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.[17] 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, 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 6, 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 7, financially constrained hospitals experience a gradual decline in adoption, reaching approximately 5 percentage

[17] Financially constrained hospitals have somewhat higher baseline CDS adoption in the SDID sample, partly reflecting the balanced-panel requirement, which disproportionately retains higher-adoption hospitals in this group. This baseline difference is substantially smaller under alternative balance-sheet measures of financial constraints, while the estimated effects remain qualitatively similar.

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 limited 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, might improve healthcare quality and patient outcomes (Buntin et al., 2011; McCullough et al., 2016). The decline in CDS adoption following the staffing mandate therefore represents a potential offsetting cost against the intended benefits of the policy. To illustrate the magnitudes involved, we conduct back-of-the-envelope calculations for both the mortality cost associated with delayed CDS adoption and the benefit of increased nurse staffing.

On the technology side, we draw on McCullough et al. (2016), who estimate the effect of health IT adoption on mortality among Medicare patients hospitalized for acute conditions. They show that health IT adoption reduces 60-day mortality among Medicare patients with these conditions by about 200 deaths per 100,000 admissions, with the largest effect, 500 per 100,000, for pneumonia. Applying these estimates to our 3.8 percentage point decline in CDS adoption implies roughly 7.6 (0.038×200) additional deaths per 100,000 Medicare admissions across the high-mortality conditions they study, and about 19 (0.038×500) per 100,000 Medicare pneumonia patients.

These costs must be weighed against the benefits of increased nurse staffing. Prior evaluations of AB394 find little evidence of improvements in patient outcomes (Cook et al., 2012; Raja, 2023). Our results suggest that reduced technology investment may help explain why improvements in patient outcomes were limited despite higher staffing. To benchmark the staffing benefit separately, we turn to evidence from other settings that more directly links nurse staffing to mortality, focusing on more recent periods in which health IT is already widely diffused.

McHugh et al. (2021) provide quasi-experimental evidence on the mortality effects of higher nurse staffing in Australia.[18] They find that a one-patient reduction in the medical-surgical ratio

[18]Cross-sectional studies generally report larger associations. Dierkes et al. (2022) find that each additional patient per nurse is associated with a 10 percent increase in the odds of 60-day mortality among Medicare sepsis patients.

reduces 30-day mortality with an odds ratio of 0.93. In California, average nurse-to-patient ratios rose from 0.226 to 0.306, corresponding to a decline in patients per nurse from 4.43 to 3.27, or 1.16 patients. Applying the estimate to this change, with a baseline 30-day mortality rate of 2 percent (Aiken et al., 2002), implies about 158 fewer deaths per 100,000 Medicare admissions.

The mandate also raised NSS adoption among well-staffed and financially flexible hospitals, and this margin carries benefits that our mortality calculation does not capture. Reviews of staffing methodologies find no demonstrated improvement in patient outcomes from the use of such tools once staffing levels are held constant (Griffiths et al., 2020), so we do not assign NSS a direct mortality effect. Instead, its documented benefits operate through hospital operations and the nursing workforce: electronic scheduling reduces absences requiring external coverage and eases the workload of ward managers (Tuominen et al., 2016), and improves staff satisfaction and coverage during capacity surges, resulting in fewer unstaffed shifts (Morse et al., 2024). These gains may reduce reliance on agency nurses, improve retention, and facilitate real-time compliance, representing additional benefits outside the mortality metric. They may also matter for compliance itself, since NSS helps hospitals sustain real-time staffing standards without further hiring.

These calculations yield two implications. First, reduced technology investment represents an unintended cost of the mandate that is not captured by prior evaluations. Second, this technology cost appears unlikely to fully offset the mortality benefit associated with increased staffing. Under these benchmarks, the staffing benefit of 158 fewer deaths per 100,000 admissions substantially exceeds the implied technology cost of 7.6 additional deaths. The increase in NSS adoption may generate additional operational benefits that are not captured in this mortality comparison.

Several caveats apply. First, the health IT estimates are based on Medicare patients with selected acute conditions, so their applicability to the broader hospital population is uncertain. Restricting attention to a subset of conditions may understate the aggregate mortality effect, while focusing on older, high-mortality patients may overstate the effect per admission. Second, the health IT estimates pertain to broader EMR and CPOE adoption rather than CDS specifically, making their application to our CDS estimate approximate. Third, the staffing and technology benchmarks are not directly comparable: they come from different countries, populations, clinical settings, and mortality horizons. Finally, AB394 was implemented during a period of rapid health IT diffusion, so the technology-adoption channel may have been more important then than it would be in a setting where these technologies are already widely adopted.

Similarly, Lasater et al. (2021) find a 12 percent increase in the odds of in-hospital mortality and a 6 percent increase in the odds of 60-day mortality among Medicare sepsis patients in New York. These estimates may overstate the causal effect of staffing if better-staffed hospitals also differ in equipment, management, physician quality, or other dimensions of care quality.

7 Robustness

7.1 Alternative Specifications and Measures

We examine whether our results are sensitive to alternative choices in three dimensions: the policy window and comparison sample, the measurement of technology adoption, and the classification of hospitals by staffing needs and financial conditions.

First, we vary the policy window and comparison sample. While our baseline specification allows treatment effects to begin in 2003 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 (Table 5, Panel B).[19] 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.

Second, we assess whether the results depend on how technology adoption is constructed. We restrict adoption to technologies at the implementation or operational stage, excluding early-stage contracting (Panel D). This stricter definition focuses on technologies that are actively in use and mitigates concerns that our results reflect differences in reporting practices or transitional adoption rather than realized implementation.[20]

Finally, we examine the classifications used in the heterogeneity analysis. For staffing needs, we vary both the pre-policy period used to construct nurse-to-patient ratios and the cutoffs used to define high-, moderate-, and low-need hospitals. For financial conditions, we consider alternative cutoffs for operating margins and alternative balance-sheet measures, including liabilities-to-assets, fund-balance-to-assets, and working-capital-to-assets. While operating margin captures current operating profitability, these measures capture complementary dimensions of hospitals' financial capacity: leverage, net assets, and short-run liquidity. We classify hospitals as financially constrained when these measures indicate weaker pre-policy financial positions.[21] The results are

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

[20] We also verify that these alternative specifications yield qualitatively similar heterogeneity patterns when estimated separately by pre-policy staffing need and financial condition (Appendix Tables B5 and B6).

[21] For each measure, we average values over 2000–2002 and classify hospitals as financially constrained if they have

available from Table B7 through Table B12. Overall, the results remain qualitatively consistent across these exercises.

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 B13 and Table B14). 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.

7.3 Alternative Technology Outcomes

Our main analysis focuses on CDS because it most closely matches the welfare implications and mechanism of interest. CDS is directly linked to care quality and patient outcomes, while at the same time, it does not directly facilitate compliance with the staffing mandate. CDR is the closest related technology in our data because it provides the underlying clinical information infrastructure on which CDS functions are often built, although CDR is more directly embedded in routine clinical documentation and workflow. To assess whether our findings depend on this particular technology definition, we construct a broader clinical-IT measure that equals one if either CDS or CDR has been adopted.

As shown in Figure B8, the aggregate and staffing-need results closely mirror the baseline CDS estimates. The heterogeneity by financial condition is somewhat less pronounced: the decline remains more precisely estimated among financially constrained hospitals, but the estimate for unconstrained hospitals also becomes negative and statistically significant. Thus, broadening the outcome preserves the overall post-mandate decline in clinical-IT adoption while weakening the differential by financial condition. These results indicate that the main finding is not specific to CDS alone or to differences in the sequencing of CDR and CDS adoption.

above-median liabilities-to-assets, below-median fund-balance-to-assets, or below-median working-capital-to-assets. The same pattern holds when we use quartile rather than median cutoffs to define financial constraints.

We also examine other hospital IT applications observed consistently over our sample period to assess whether the mandate generated a broad decline in technology investment or instead affected particular types of technologies. As shown in Table B15, we find little evidence of systematic changes in systems related to core hospital functions, such as emergency room, intensive care, and radiology. By contrast, laboratory information systems, which are more closely related to the clinical information functions performed by CDS, decline significantly. Administrative applications associated with patient allocation, such as operating room and patient scheduling, increase after the policy introduction. These results suggest that the mandate did not uniformly reduce hospital IT adoption, but instead affected clinical and operational technologies differently.

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 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 is 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. 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: mandated increases in labor inputs can crowd out investment in quality-enhancing technologies. Our back-of-the-envelope calculations suggest that the 3.8 percentage point decline in CDS adoption implies approximately 7.6 additional deaths per 100,000 admissions, while the mandate-induced increase in nurse staffing implies approximately 158 fewer deaths per 100,000 admissions.

Although these benchmarks come from different empirical settings, they suggest that the technology crowd-out is a meaningful unintended cost of the mandate but smaller in magnitude than the mortality benefit associated with increased staffing. The increase in NSS adoption may provide additional operational benefits through improved scheduling and staffing allocation. These offsetting responses highlight the importance of accounting for multiple margins when evaluating labor market regulations in healthcare.

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.

References

Acemoglu, D. (2003, 3). Labor- and capital-augmenting technical change. *Journal of the European Economic Association 1*, 1–37.

Acemoglu, D. (2010). When does labor scarcity encourage innovation? *Journal of Political Economy 118*(6), 1037–1078.

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. Volume 4 of *Handbook of Labor Economics*, pp. 1043–1171. Elsevier.

Acemoglu, D. and A. Finkelstein (2008, 10). Input and technology choices in regulated industries: Evidence from the health care sector. *Journal of Political Economy 116*, 837–880.

Acemoglu, D. and P. Restrepo (2021, 06). Demographics and automation. *The Review of Economic Studies 89*(1), 1–44.

Aiken, L. H., S. P. Clarke, D. M. Sloane, J. Sochalski, and J. H. Silber (2002, 10). Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *JAMA 288*(16), 1987–1993.

American Hospital Association (AHA) (2000-2002). Aha annual survey database. https://www.ahadata.com/aha-annual-survey-database. (accessed Mar 2023).

Aneja, A., M. Luca, and O. Reshef (2025). The benefits of revealing race: Evidence from minority-owned local businesses. *American Economic Review 115*(2), 660–689.

Arkhangelsky, D., S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager (2021, December). Synthetic difference-in-differences. *American Economic Review 111*(12), 4088–4118.

Ashenfelter, O. and v. Jurajda (2022). Minimum wages, wages, and price pass-through: The case of mcdonald's restaurants. *Journal of Labor Economics 40*(S1), S179–S201.

Atasoy, H., B. N. Greenwood, and J. S. McCullough (2019). The digitization of patient care: A review of the effects of electronic health records on health care quality and utilization. *Annual Review of Public Health 40*(Volume 40, 2019), 487–500.

Autor, D. H., F. Levy, and R. J. Murnane (2003, 11). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*, 1279–1333.

Bessen, J., M. Goos, A. Salomons, and W. Van den Berge (2025). What happens to workers at firms that automate? *Review of Economics and Statistics 107*(1), 125–141.

Blau, D. M. (2007). Unintended consequences of child care regulations. *Labour Economics 14*(3), 513–538.

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

Buntin, M. B., M. F. Burke, M. C. Hoaglin, and D. Blumenthal (2011). The benefits of health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs 30*(3), 464–471. PMID: 21383365.

Bureau of Labor Statistics (2020). Registered nurses made up 30 percent of hospital employment in may 2019. The Economics Daily.

California Department of Health Services (2003). Final Statement of Reasons, R-37-01: Sacramento (CA).

Campello, M., J. R. Graham, and C. R. Harvey (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics 97*(3), 470–487. The 2007-8 financial crisis: Lessons from corporate finance.

Centers for Medicare and Medicaid Services (CMS) (1996-2008). Cost reports. https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/Cost-Reports-by-Fiscal-Year. (accessed Oct 2022).

Chen, M. M. and D. C. Grabowski (2015). Intended and unintended consequences of minimum staffing standards for nursing homes. *Health Economics 24*(7), 822–839.

Clarke, D., D. Pailañir, S. Athey, and G. Imbens (2024). On synthetic difference-in-differences and related estimation methods in stata. *The Stata Journal 24*(4), 557–598.

Congressional Budget Office (2008). Evidence on the costs and benefits of healthcare information technology.

Cook, A., M. Gaynor, M. Stephens, and L. Taylor (2012, 3). The effect of a hospital nurse staffing mandate on patient health outcomes: Evidence from california's minimum staffing regulation. *Journal of Health Economics 31*, 340–348.

Dierkes, A. M., L. H. Aiken, D. M. Sloane, J. P. Cimiotti, K. A. Riman, and M. D. McHugh (2022). Hospital nurse staffing and sepsis protocol compliance and outcomes among patients with sepsis in the usa: a multistate cross-sectional analysis. *BMJ Open 12*(3).

Donaldson, N., L. B. Bolton, C. Aydin, D. Brown, J. D. Elashoff, and M. Sandhu (2005). Impact of california's licensed nurse-patient ratios on unit-level nurse staffing and patient outcomes. *Policy, Politics, & Nursing Practice 6*, 198–210.

Dranove, D., C. Forman, A. Goldfarb, and S. Greenstein (2014, November). The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy 6*(4), 239–70.

Duggan, M., A. Gupta, and E. Jackson (2022). The impact of the affordable care act: evidence from california's hospital sector. *American Economic Journal: Economic Policy 14*(1), 111–151.

Fan, H., Y. Hu, and L. Tang (2021). Labor costs and the adoption of robots in china. *Journal of Economic Behavior & Organization 186*, 608–631.

Furukawa, M. F., T. Raghu, and B. B. Shao (2010). Electronic medical records, nurse staffing, and nurse-sensitive patient outcomes: Evidence from california hospitals, 1998–2007. *Health Services Research 45*(4), 941–962.

Griffiths, P., C. Saville, J. Ball, J. Jones, N. Pattison, T. Monks, S. N. C. S. Group, et al. (2020). Nursing workload, nurse staffing methodologies and tools: A systematic scoping review and discussion. *International journal of nursing studies 103*, 103487.

Gumpert, A., H. Steimer, and M. Antoni (2022). Firm organization with multiple establishments. *The Quarterly Journal of Economics 137*(2), 1091–1138.

Harless, D. W. (2019, 10). Reassessing the labor market effects of california's minimum nurse staffing regulations. *Health Economics 28*, 1226–1231.

Healthcare Information and Management Systems Society (HIMSS) Analytics (1998-2008). Himss analytics database (deprived from the dorenfest ihds+ database). https://www.himss.org/. (accessed Sep 2023).

Hotz, V. J. and M. Xiao (2011, 8). The impact of regulations on the supply and quality of care in child care markets. *American Economic Review 101*, 1775–1805.

Iacus, S. M., G. King, and G. Porro (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis 20*(1), 1–24.

Katz, L. F. and K. M. Murphy (1992, 2). Changes in relative wages, 1963-1987: Supply and demand factors. *The Quarterly Journal of Economics 107*, 35–78.

Lasater, K. B., D. M. Sloane, M. D. McHugh, J. P. Cimiotti, K. A. Riman, B. Martin, M. Alexander, and L. H. Aiken (2021). Evaluation of hospital nurse-to-patient staffing ratios and sepsis bundles on patient outcomes. *American Journal of Infection Control 49*(7), 868–873.

Lewis, E. (2011, 05). Immigration, skill mix, and capital skill complementarity. *The Quarterly Journal of Economics 126*(2), 1029–1069.

Lin, H. (2014). Revisiting the relationship between nurse staffing and quality of care in nursing homes: An instrumental variables approach. *Journal of Health Economics 37*, 13–24.

Mark, B., D. W. Harless, and J. Spetz (2009, 3). Market watch: California's minimum-nurse-staffing legislation and nurses' wages. *Health Affairs 28*.

Matsudaira, J. D. (2014). Government regulation and the quality of healthcare. *Journal of Human Resources 49*(1), 32–72.

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

McHugh, M. D., L. H. Aiken, D. M. Sloane, C. Windsor, C. Douglas, and P. Yates (2021). Effects of nurse-to-patient ratio legislation on nurse staffing and patient mortality, readmissions, and length of stay: a prospective study in a panel of hospitals. *The Lancet 397*(10288), 1905–1913.

Medicare Payment Advisory Commission (2005). REPORT TO THE CONGRESS: Medicare Payment Policy.

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

Morse, L., H. Duncan, L. V. Apen, K. Reese, and C. L. Crawford (2024). Centralized scheduling of nursing staff: A rapid review of the literature. *Nursing Administration Quarterly 48*(4), 347–358.

Munnich, E. L. (2014). The labor market effects of california's minimum nurse staffing law. *Health Economics 23*, 935–950.

Raja, C. (2023, 12). How do hospitals respond to input regulation? evidence from the california nurse staffing mandate. *Journal of Health Economics 92*.

Rauh, J. D. (2006). Investment and financing constraints: Evidence from the funding of corporate pension plans. *The Journal of Finance 61*(1), 33–71.

Richards, M. R., M. Shi, and C. M. Whaley (2025). Economic shocks and healthcare capital investments. Technical report, National Bureau of Economic Research.

Sabet, L. (2005). Adopting online nurse scheduling and staffing systems. *California HealthCare Foundation*.

Tong, P. K. (2011). The effects of california minimum nurse staffing laws on nurse labor and patient mortality in skilled nursing facilities. *Health Economics 20*(7), 802–816.

Tuominen, O. (2020). Rescheduling sudden absences of nursing staff in hospital settings. *Turun Yliopiston Julkaisuja, Sarja D, Osa 1464*.

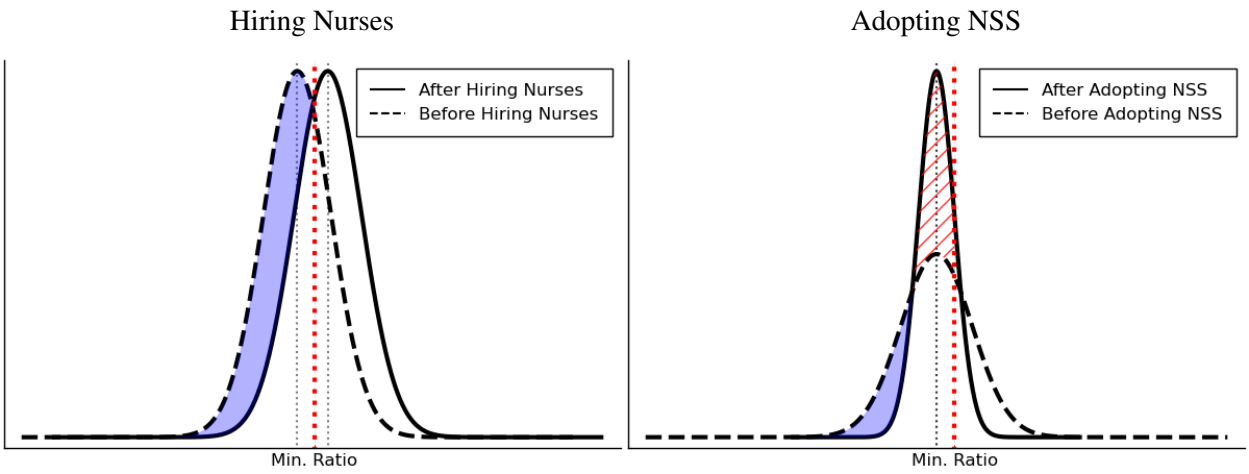
Tuominen, O. A., H. Lundgren-Laine, W. Kauppila, M. Hupli, and S. Salanterä (2016). A real-time excel-based scheduling solution for nursing staff reallocation. *Nursing Management 23*(6).

Wright, A. and D. F. Sittig (2008). Sands: a service-oriented architecture for clinical decision support in a national health information network. *Journal of Biomedical Informatics 41*(6), 962–981.

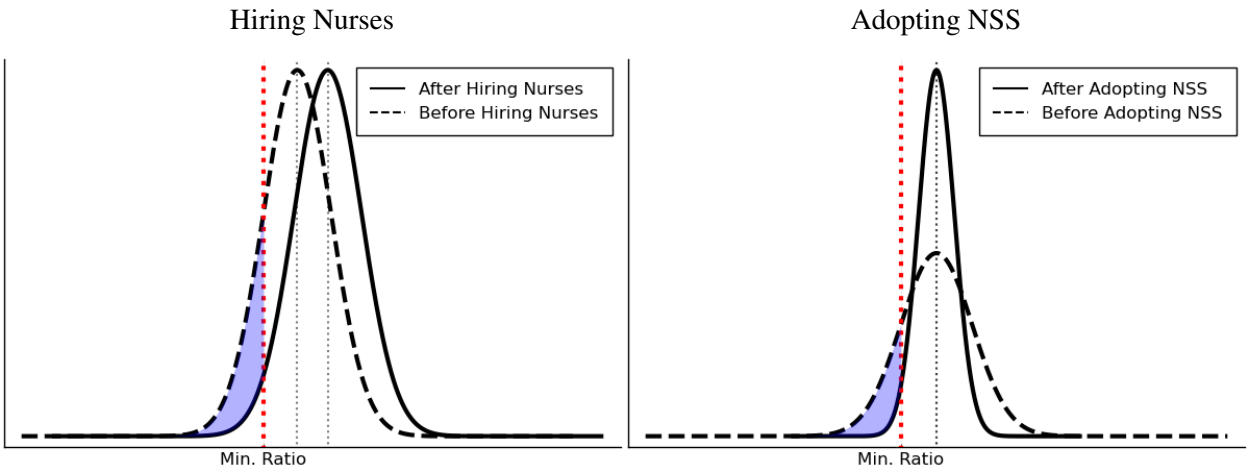
Figures and Tables

Figure 1: Compliance Risk in Real-Time Staffing

(a) Lower Baseline NPRs

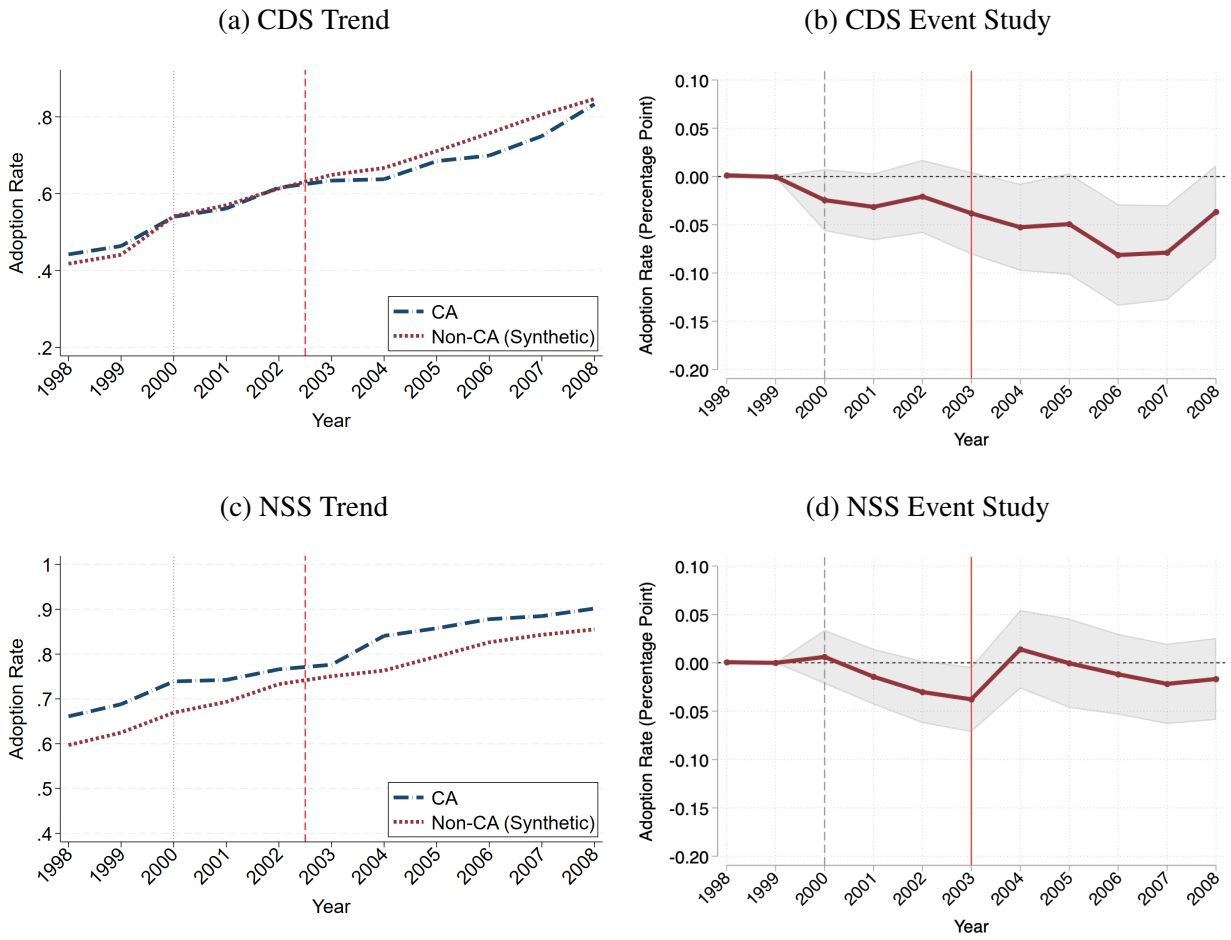


(b) Higher Baseline NPRs



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.

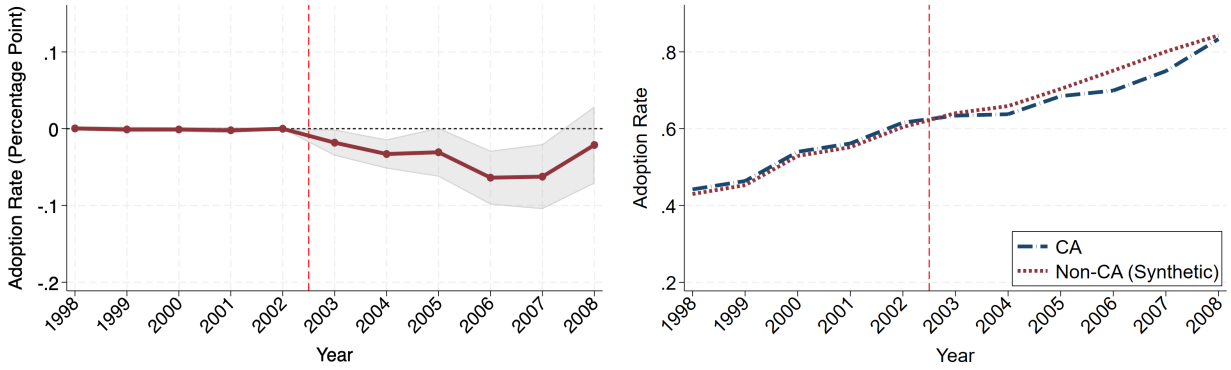
Figure 2: SDID Trained with 1998–1999



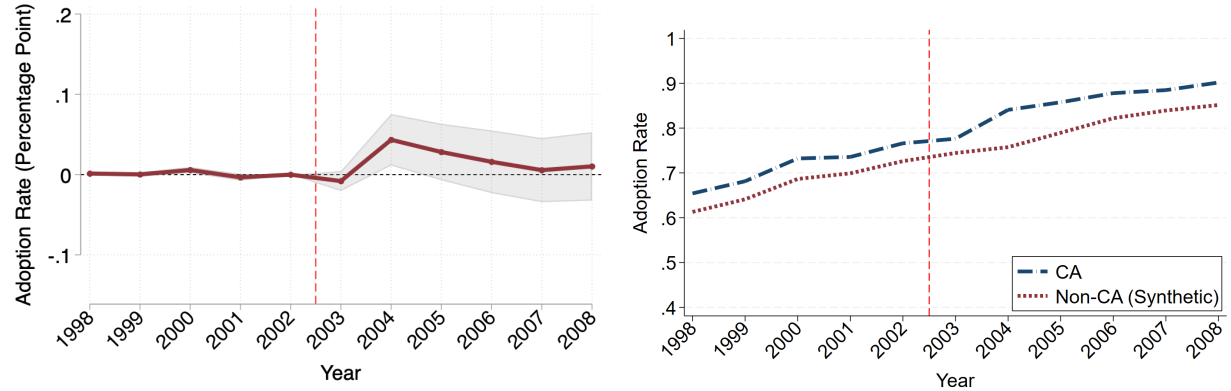
Notes: This figure reports results from synthetic difference-in-differences (SDID) with weights estimated using only the 1998–1999 training period. The top row shows the results of Clinical Decision Support (CDS); the bottom row shows the results of Nurse Staffing Software (NSS). The left column shows adoption trends for California hospitals and their synthetic controls, while the right column reports the corresponding event study estimates.

Figure 3: SDID Event Study

(a) Clinical Decision Support



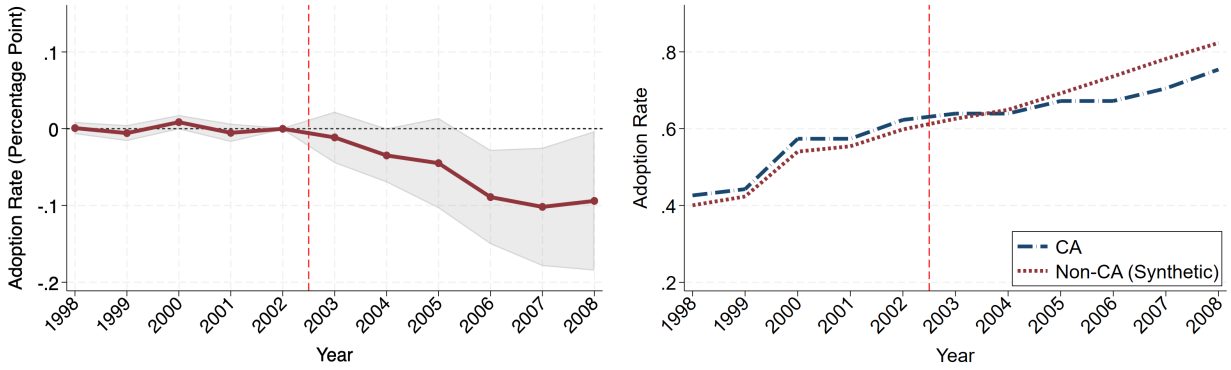
(b) Nurse Staffing Software



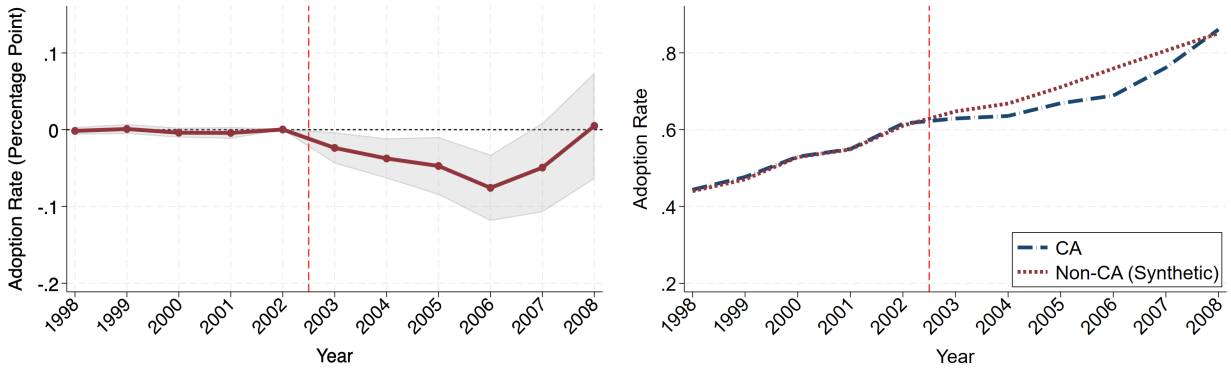
Notes: The left panel presents the results of event study using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (4). Each coefficient shows the difference between treated and synthetic 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, Clinical Decision Support

(a) High-need Hospitals



(b) Moderate-need Hospitals



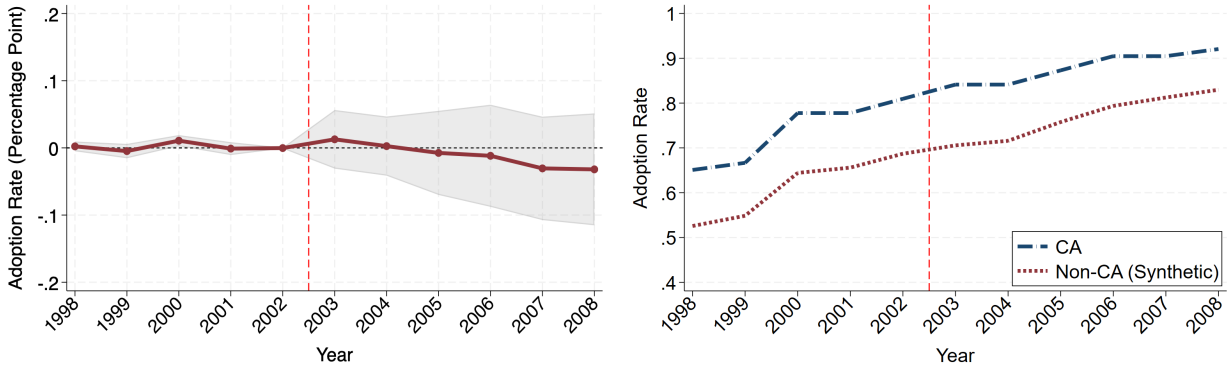
(c) Low-need Hospitals



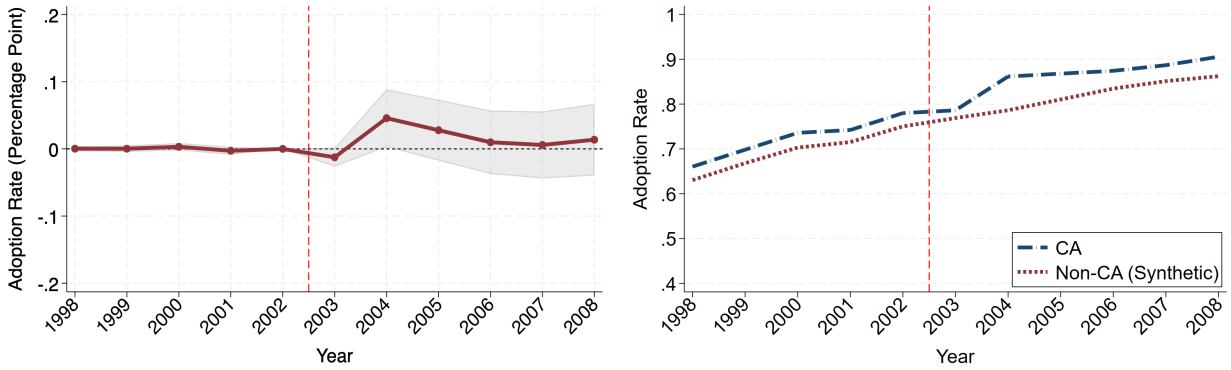
Notes: The left panel presents the results of event study on Clinical Decision Support (CDS) using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (4). Hospitals are grouped by pre-policy 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 Pre-policy Staffing Levels, Nurse Staffing Software

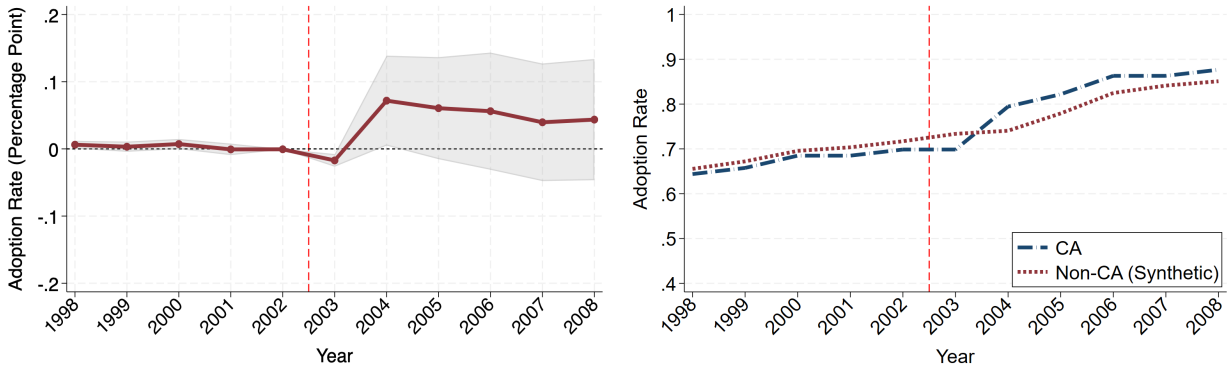
(a) High-need Hospitals



(b) Moderate-need Hospitals



(c) Low-need Hospitals



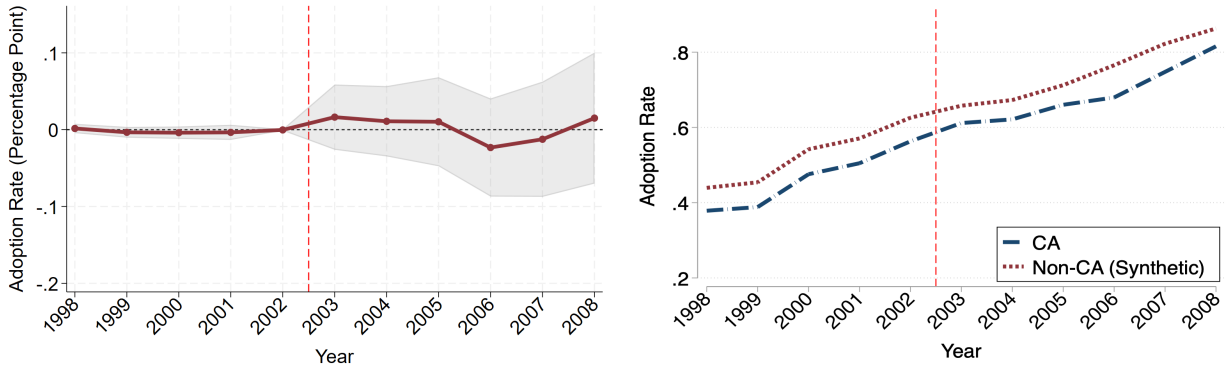
Notes: The left panel presents the results of event study on Nurse Staffing technologies using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (4). Hospitals are grouped by pre-policy 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 6: SDID Event Study by Financial Conditions, Clinical Decision Support

(a) Constrained Hospitals



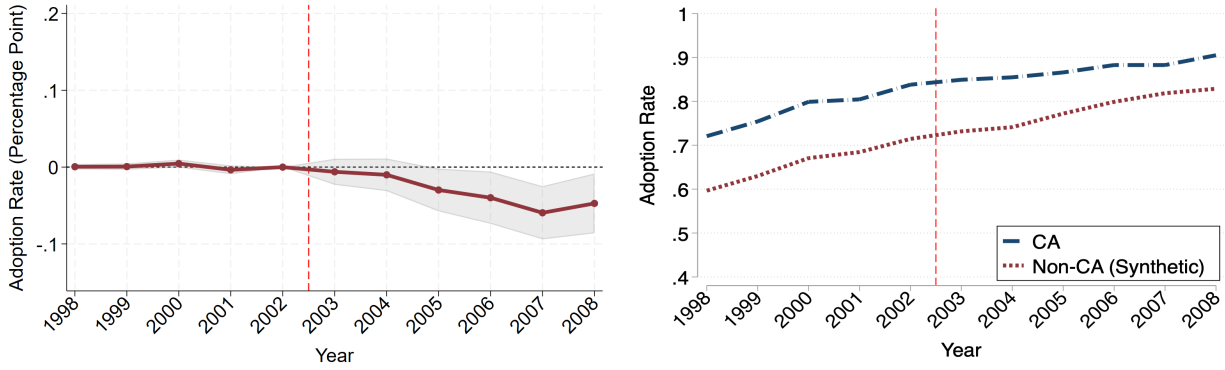
(b) Unconstrained Hospitals



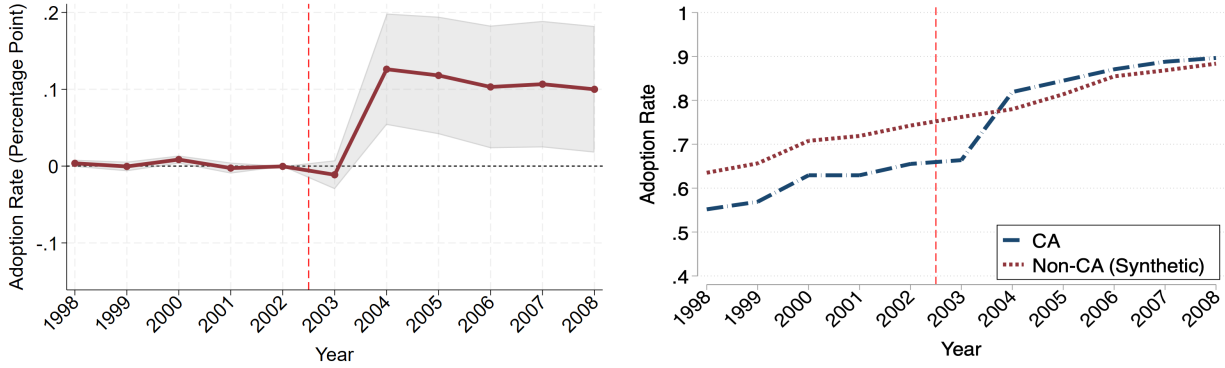
Notes: The left panel presents the results of event study on Clinical Decision Support (CDS) using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024). The estimation specification is presented in equation (4). Hospitals are classified as 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 7: SDID Event Study by Financial Conditions, Nurse Staffing Software

(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 (4). 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	0.62	0.00	0.77	0.73	0.04
NPR	0.32	0.31	0.01	0.32	0.31	0.01*
RN-LVN ratio	0.86	0.84	0.02***	0.86	0.83	0.03***
For-Profit	0.19	0.19	0.00	0.25	0.18	0.07***
Urban	0.57	0.51	0.06*	0.59	0.51	0.08***
% 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	5.2	5.07	0.13**	5.16	5.08	0.08
Log Patient Days	10.31	10.01	0.30***	10.26	10	0.26***
Log FTEs	6.51	6.41	0.10*	6.46	6.4	0.06
Log Hourly Wage	3.45	3.24	0.21***	3.45	3.24	0.21***
Log Revenue	17.52	16.6	0.92***	17.5	16.59	0.91***
N	276	3014		295	2949	

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***	-0.063***	-0.003	0.016	0.010
	(0.017)	(0.014)	(0.023)	(0.016)	(0.015)	(0.022)
Baseline Mean	0.63	0.62	0.63	0.76	0.79	0.77
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
N	38,720	36,190	17,356	38,691	35,728	15,908

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***	-0.063***	-0.003	0.016	0.010
	(0.017)	(0.014)	(0.023)	(0.016)	(0.015)	(0.022)
Panel B: Excluding Implementation Transition Years						
$CA_i \times Post_t$	-0.044**	-0.038*	-0.069***	-0.008	-0.001	0.007
	(0.022)	(0.021)	(0.025)	(0.021)	(0.020)	(0.022)
Panel C: Excluding Nearby States from Control Group						
$CA_i \times Post_t$	-0.038**	-0.039***	-0.066***	-0.004	0.015	0.016
	(0.017)	(0.014)	(0.023)	(0.016)	(0.015)	(0.021)
Panel D: Stricter Technology Adoption Definition						
$CA_i \times Post_t$	-0.033**	-0.025*	-0.080***	-0.008	0.011	0.005
	(0.017)	(0.014)	(0.024)	(0.016)	(0.015)	(0.021)

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: A Model of Compliance with Minimum Nurse-to-Patient Ratios

This appendix formalizes the discussion in Section 3.2. Hospitals subject to the mandate have two margins along which they can reduce the expected cost of noncompliance: hiring additional nurses or adopting nurse staffing software (NSS). We take the penalty for violation and the probability of inspection conditional on noncompliance as constant, so that the hospital's objective reduces to minimizing the probability that the real-time nurse-to-patient ratio (NPR) falls below the mandated minimum.

A.1 Setting

Let the real-time NPR, r, be the average NPR subject to a multiplicative shock,

$$r \;=\; \frac{L}{D}\, e^{\sigma\varepsilon}, \qquad \varepsilon \sim F(0,1), \tag{A.1}$$

where L is the average number of nurses across shifts, D is expected patient demand, and F is a mean-zero scale-family distribution with density f. The term $e^{\sigma\varepsilon}$ captures fluctuations in staffing relative to demand at a point in time.

The multiplicative structure follows from the primitives. The real-time NPR is the number of nurses on duty, L_t, divided by the number of patients present, D_t, both of which fluctuate around their averages: $L_t = Le^{\nu_t}$ and $D_t = De^{u_t}$. The shock in (A.1) is then $\sigma\varepsilon = \nu_t - u_t$, and we suppress the time subscript throughout. Since L, D, and $e^{\sigma\varepsilon}$ are all positive, $r > 0$. Let $\bar{r}$ denote the mandated minimum ratio.

Taking logs yields a location-scale structure,

$$\log r \;=\; \mu + \sigma\varepsilon, \qquad \mu \equiv \log(L/D), \tag{A.2}$$

in which the two compliance margins map into the two parameters. Hiring nurses raises L and hence the location parameter μ. Adopting NSS improves the allocation of a given stock of nurses across shifts and units in response to realized fluctuations, which compresses the dispersion of r around its mean and is therefore represented as a reduction in the scale parameter σ.

A.2 Violation Probability

Because the log transformation is monotone, the probability of violating the mandated minimum is

$$V(\mu,\sigma) \;=\; \Pr[\,r<\bar{r}\mid\mu,\sigma\,] \;=\; \Pr[\,\log r<\log\bar{r}\mid\mu,\sigma\,] \;=\; \Pr\left[\varepsilon<\frac{\log\bar{r}-\mu}{\sigma}\right] \;=\; F\left(\frac{\log\bar{r}-\mu}{\sigma}\right). \tag{A.3}$$

Define the standardized threshold

$$\bar{z} \;\equiv\; \frac{\log\bar{r}-\mu}{\sigma}. \tag{A.4}$$

Then $\bar{z}>0$ if and only if $\mu<\log\bar{r}$: the hospital's average NPR lies below the mandated minimum, corresponding to high-need hospitals. Conversely, $\bar{z}<0$ if and only if $\mu>\log\bar{r}$, corresponding to moderate- and low-need hospitals, whose average staffing already meets or exceeds the requirement but which may still violate the mandate at particular times.

A.3 Marginal Effects of the Two Margins

Differentiating (A.3) with respect to the location parameter gives

$$\frac{\partial V}{\partial\mu} \;=\; f(\bar{z})\left(-\frac{1}{\sigma}\right) \;<\; 0, \tag{A.5}$$

so hiring nurses reduces the violation probability for every hospital, regardless of baseline staffing. Differentiating with respect to the scale parameter gives

$$\frac{\partial V}{\partial\sigma} \;=\; f(\bar{z})\left(-\frac{\log\bar{r}-\mu}{\sigma^2}\right) \;=\; f(\bar{z})\left(-\frac{1}{\sigma}\right)\bar{z}. \tag{A.6}$$

Since $f(\bar{z})>0$ and $\sigma>0$, the sign of (A.6) is the opposite of the sign of $\bar{z}$. A reduction in σ therefore lowers the violation probability if and only if $\bar{z}<0$, that is, if and only if $\mu>\log\bar{r}$. For a hospital staffed below the mandated ratio on average, compressing the distribution of r around a mean that already lies below $\bar{r}$ concentrates mass on the wrong side of the threshold and raises the violation probability.

Taking the ratio of the two marginal effects yields the benefit of reducing dispersion relative to the benefit of raising average staffing,

$$\frac{-\,\partial V/\partial\sigma}{\partial V/\partial\mu} \;=\; -\bar{z} \;=\; \frac{\mu-\log\bar{r}}{\sigma}. \tag{A.7}$$

Among hospitals for which NSS is beneficial at all, the relative value of NSS is increasing in the

baseline average NPR and decreasing in the baseline dispersion of real-time NPRs.

A.4 Implications

Proposition 1. *Let $r = e^{\mu+\sigma\varepsilon}$, where ε has distribution F and density f, and let $V(\mu,\sigma) = \Pr[\, r < \bar{r}\,]$. Then:*

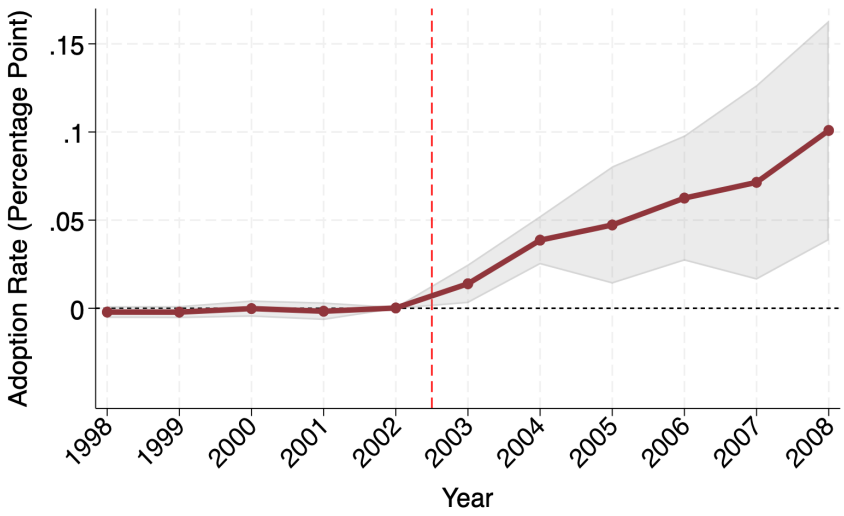
1. (Hiring always helps.) $\dfrac{\partial V}{\partial \mu} < 0$ *for any density* f.
2. (NSS helps only better-staffed hospitals.) *A reduction in σ lowers V if and only if $\mu > \log \bar{r}$.*
3. (Ordering among better-staffed hospitals.) *Conditional on $\mu > \log \bar{r}$, the benefit of reducing σ relative to that of raising μ, given by* (A.7)*, is increasing in μ and decreasing in σ.*

The three parts map directly into the empirical predictions discussed in Section 3.2. First, by part 1, hiring nurses improves compliance for every hospital. Second, by part 2, NSS improves compliance only for hospitals already staffed above the mandated ratio on average; for high-need hospitals, hiring therefore dominates NSS as a compliance strategy. Third, by part 3, among hospitals that do benefit from NSS, the relative value of adoption rises with baseline average staffing and falls with baseline volatility, so low-need hospitals are more likely to adopt NSS than moderate-need hospitals.

These results require only that the real-time fluctuations enter multiplicatively and that their distribution belong to a scale family. In particular, they do not depend on the shape of F, and hold for any density f.

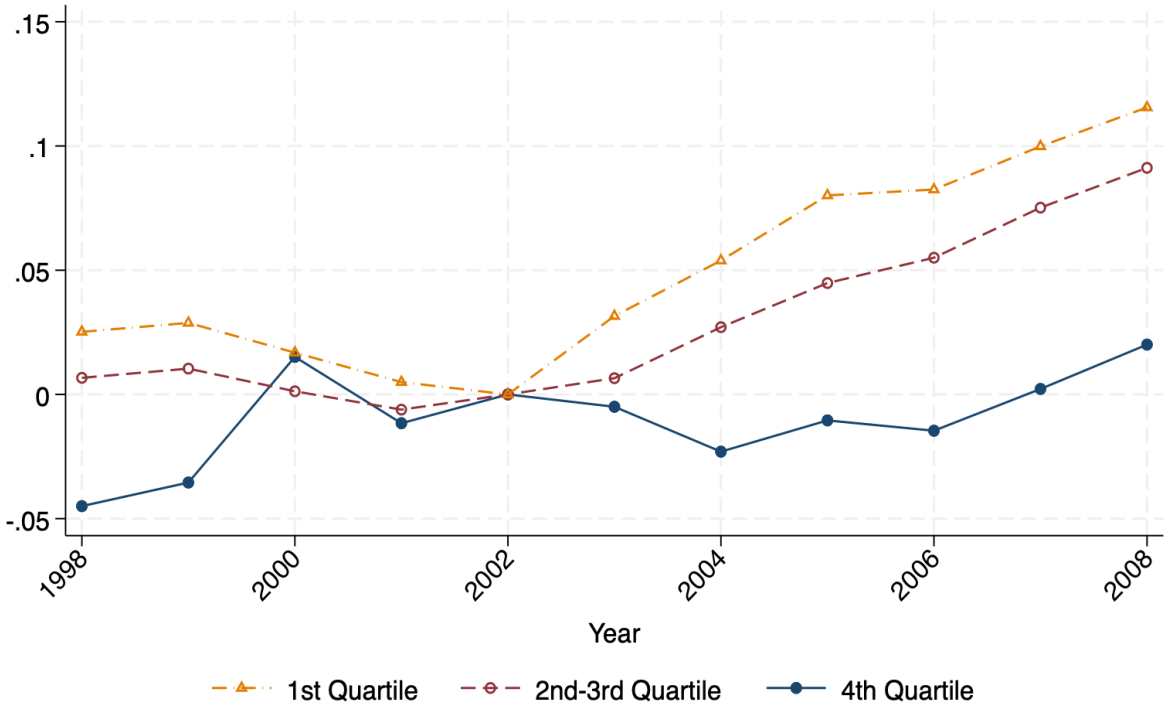
B Online Appendix: Additional Figures and Tables

Figure B1: SDID Event Study: Total Hours Worked



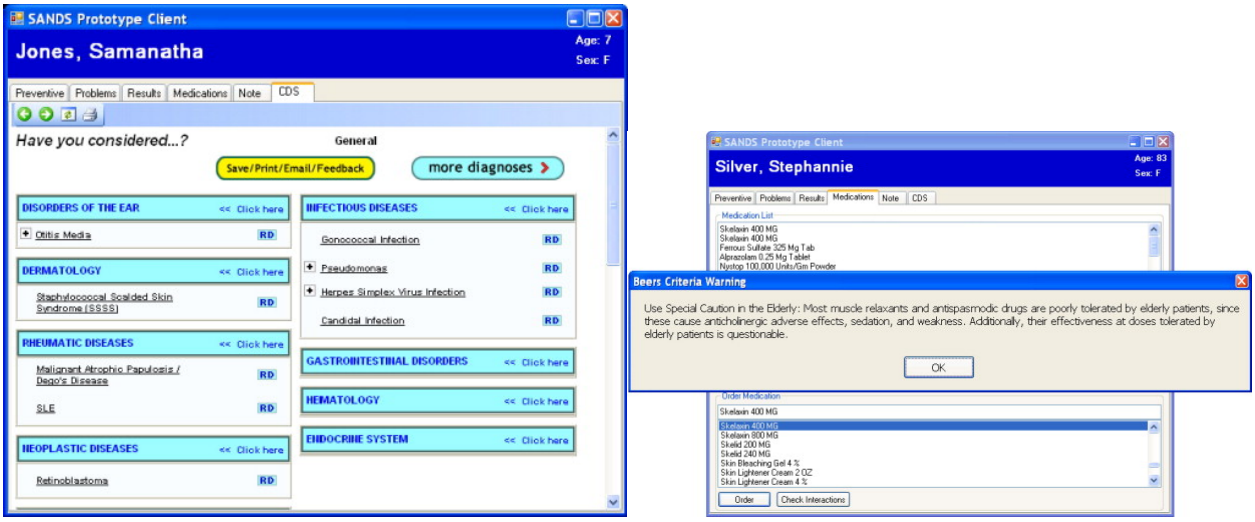
Notes: This figure presents the results of event study using the synthetic difference-in-differences estimation suggested by Arkhangelsky et al. (2021) and Clarke et al. (2024) on total hours worked across all hospital employees. The estimation specification is presented in equation (4). Each coefficient 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 B2: Change in Nurse-to-Patient Ratios (Base Year = 2002)



Notes: Sources are California's Office of Statewide Healthcare Planning and Development (OSHPD) 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).

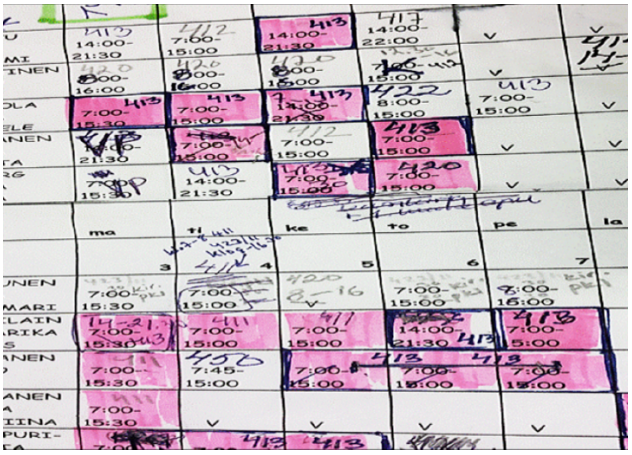
Figure B3: Examples of Clinical Decision Support in Practice



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 B4: Comparison of Nurse Staffing Systems Before and After IT Adoption

(a) Paper-based Scheduling System



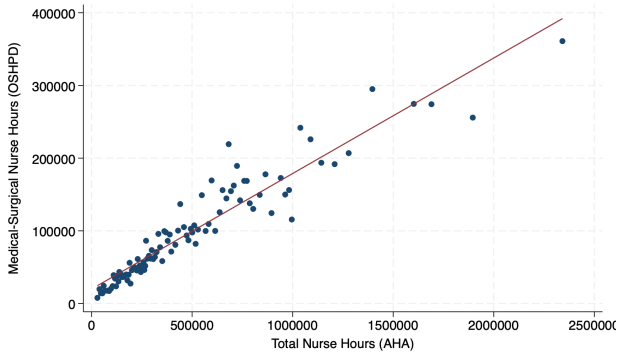
(b) IT-based Scheduling System



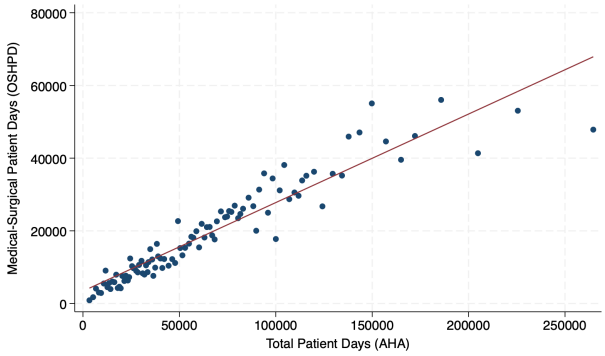
Notes: Panel (a) is adapted from Tuominen (2020), while (b) screenshots are from the MedRez.net Scheduling Tool, circa 2009 (https://www.medrez.net/index.php). Panel (a) illustrates the manual reservation of float pool nurse shifts via printed lists. Left figure of panel (b) shows a digital scheduling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

Figure B5: Comparison of OSHPD and AHA Measures: Nurse Hours and Patient Days

(a) Nurse Hours

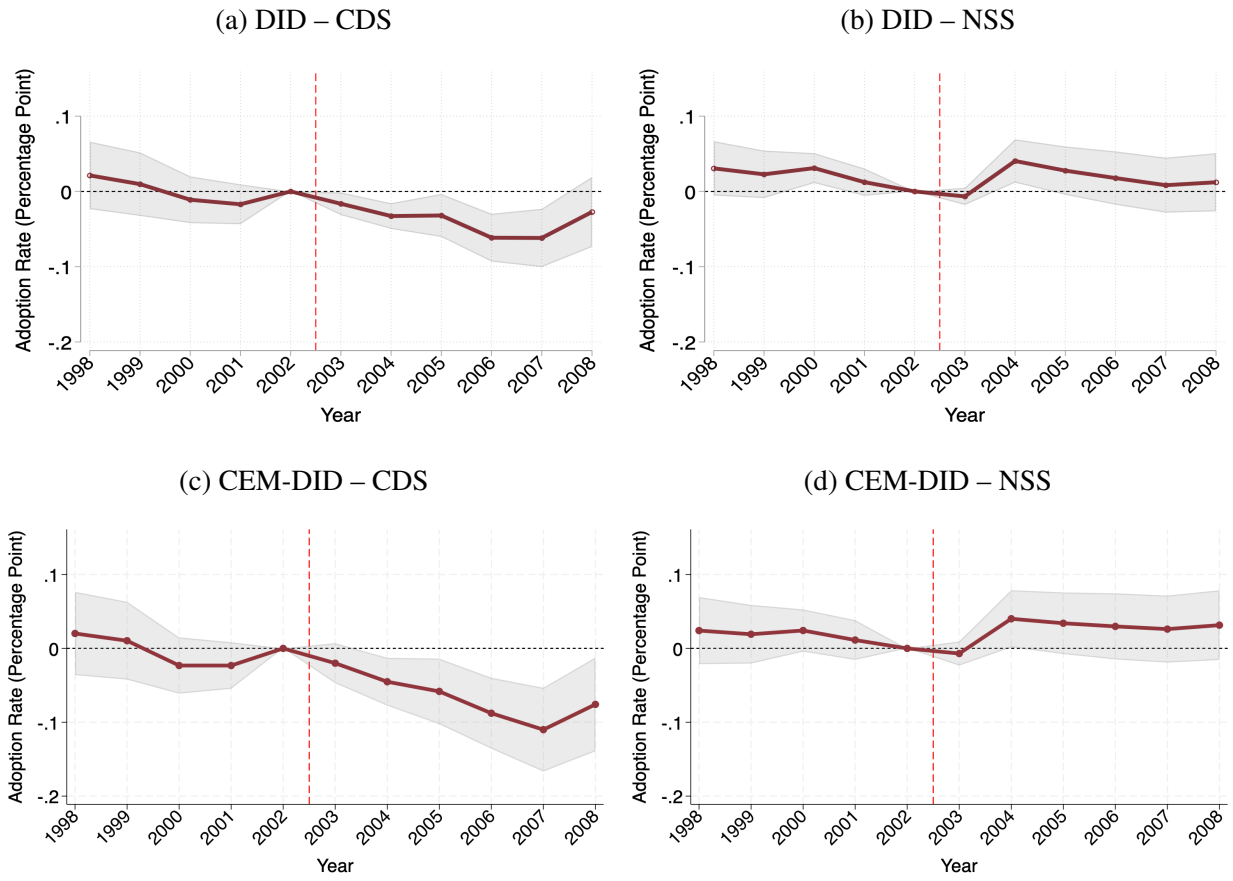


(b) Patient Days



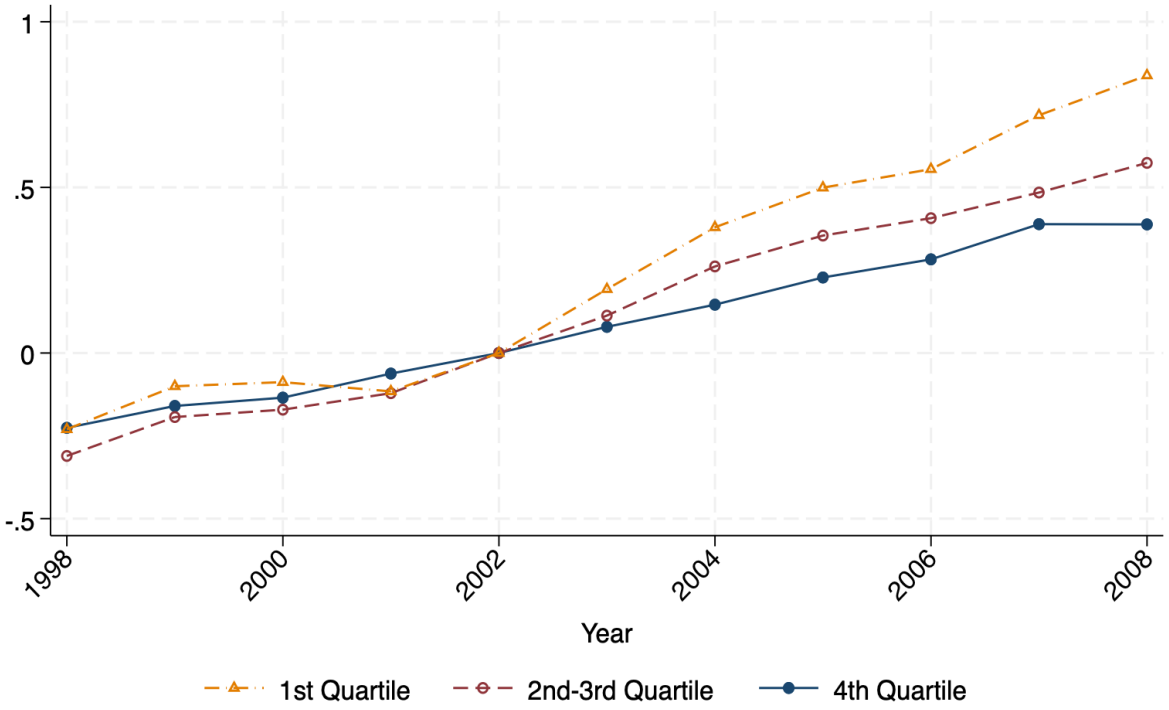
Notes: This figure compares hospital-level nurse staffing and patient volume across two datasets for California hospitals observed in both OSHPD general medical-surgical units and AHA during the 2000–2002 pre-policy period. The left panel shows a binned scatterplot of total nurse hours, and the right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

Figure B6: Alternative Event Study Estimates: DID and CEM-DID



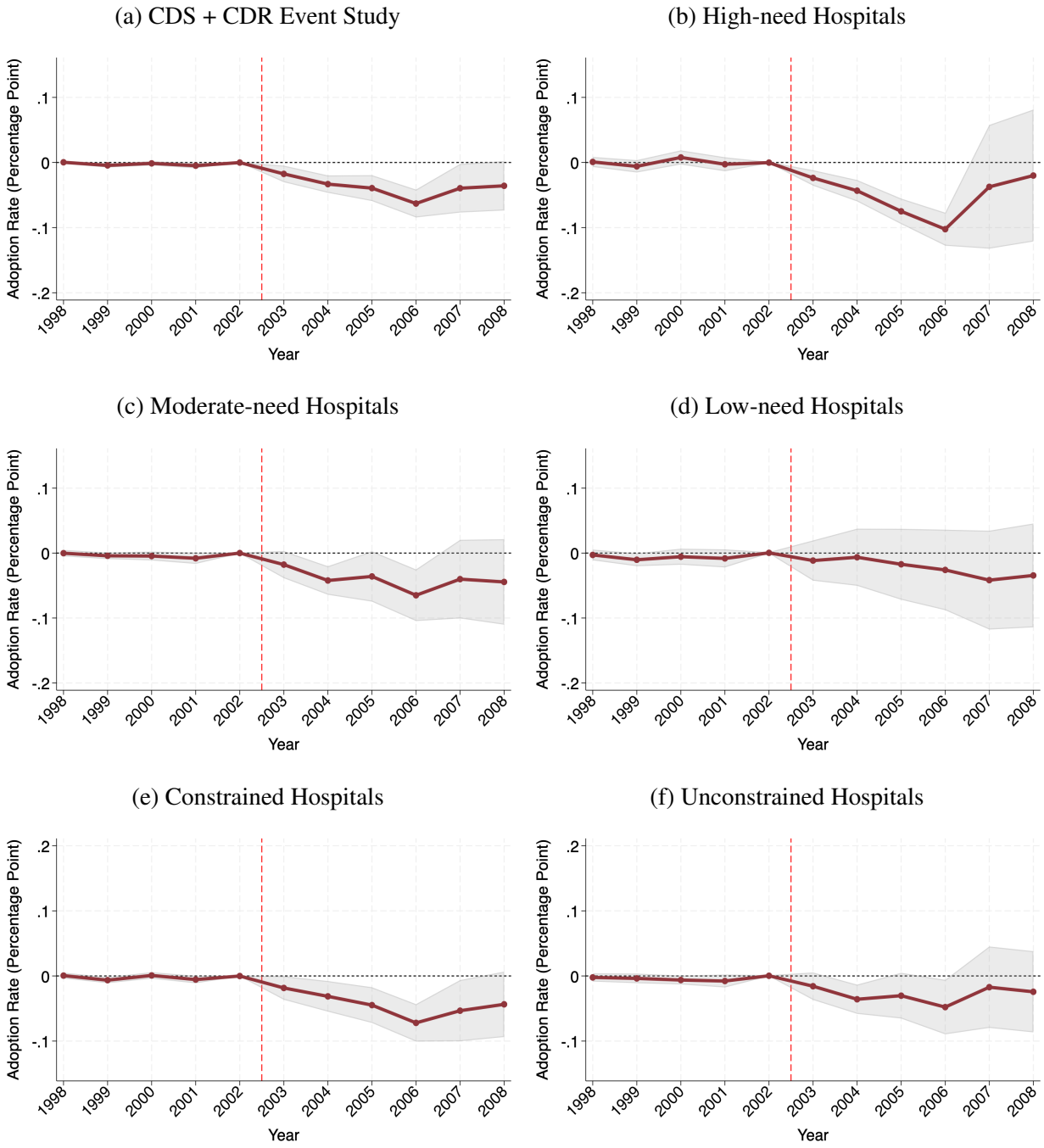
Notes: This figure reports event study estimates from alternative estimators comparing California hospitals to hospitals in other states. The top row shows standard difference-in-differences (DID) estimates; the bottom row shows estimates using Coarsened Exact Matching (CEM) with DID. The left column 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 B7: Change in Log Total Salaries for Nurses (Base Year = 2002)



Notes: Sources are California's Office of Statewide Healthcare Planning and Development (OSHPD) 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 B8: SDID for CDS or CDR Adoption



Notes: This figure reports trends of adoption rates of California and synthetic control group from Synthetic Difference-in-Differences (SDID) using a broader measure of clinical IT adoption equal to one if a hospital has adopted either Clinical Decision Support (CDS) or a Clinical Data Repository (CDR). Panel (a) reports estimates for the full sample. Panels (b)–(d) report estimates separately for hospitals with high, moderate, and low pre-policy staffing need, respectively. Panels (e)–(f) report estimates separately for hospitals classified as financially constrained and unconstrained based on their pre-policy operating margins.

Table B1: Hospital Characteristics in Balanced and Excluded Samples

	Clinical Decision Support			Nurse Staffing Software		
	Balanced	Excluded	Δ	Balanced	Excluded	Δ
Technology 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**
Urban	0.52	0.56	-0.04	0.52	0.52	0.00
% 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 B2: Summary Statistics by Pre-Policy Staffing Levels

	High need		Moderate need		Low need	
	CA	Non-CA	CA	Non-CA	CA	Non-CA
Panel A. CDS						
Technology Adoption	0.62	0.59	0.62	0.63	0.61	0.62
NPR	0.18	0.16	0.31	0.31	0.45	0.44
RN-LVN ratio	0.83	0.80	0.87	0.85	0.88	0.84
For-Profit	0.20	0.11	0.17	0.21	0.21	0.22
Urban	0.62	0.38	0.58	0.55	0.49	0.56
% Medicare	0.37	0.56	0.34	0.51	0.30	0.47
% Medicaid	0.18	0.13	0.20	0.13	0.19	0.14
Log Beds	4.84	4.66	5.29	5.19	5.33	5.22
Log Patient Days	9.75	9.48	10.47	10.18	10.46	10.13
Log FTEs	6.10	6.03	6.59	6.50	6.76	6.55
Log Hourly Wage	3.38	3.16	3.47	3.25	3.47	3.27
Log Revenue	16.75	15.93	17.74	16.80	17.74	16.78
N	61	711	151	1490	64	813
Panel B. NSS						
Technology Adoption	0.81	0.68	0.78	0.75	0.70	0.74
NPR	0.18	0.16	0.31	0.31	0.46	0.45
RN-LVN ratio	0.84	0.80	0.86	0.85	0.88	0.84
For-Profit	0.19	0.11	0.24	0.21	0.32	0.21
Urban	0.63	0.39	0.61	0.55	0.53	0.55
% Medicare	0.36	0.56	0.34	0.51	0.31	0.47
% Medicaid	0.18	0.13	0.20	0.13	0.19	0.14
Log Beds	4.84	4.69	5.22	5.19	5.30	5.22
Log Patient Days	9.75	9.46	10.39	10.18	10.43	10.13
Log FTEs	6.09	6.03	6.51	6.49	6.69	6.54
Log Hourly Wage	3.38	3.16	3.47	3.25	3.49	3.27
Log Revenue	16.75	15.91	17.68	16.79	17.78	16.79
N	63	688	159	1458	73	803

Note.–This table reports hospital characteristics measured in 2002 for hospitals in the balanced samples used in the Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) analyses. 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. Within each group, the table reports mean characteristics separately for California (CA) and non-California (Non-CA) hospitals.

Table B3: Summary Statistics by Financial Conditions

	Constrained		Unconstrained	
	CA	Non-CA	CA	Non-CA
Panel A. CDS				
Technology Adoption	0.64	0.60	0.56	0.64
NPR	0.30	0.30	0.33	0.32
RN-LVN ratio	0.86	0.83	0.86	0.85
For-Profit	0.16	0.14	0.26	0.26
Urban	0.53	0.51	0.54	0.51
% Medicare	0.35	0.51	0.37	0.51
% Medicaid	0.23	0.14	0.18	0.13
Log Beds	5.20	5.04	5.13	5.10
Log Patient Days	10.23	9.93	10.30	10.11
Log FTEs	6.52	6.37	6.47	6.46
Log Hourly Wage	3.40	3.23	3.48	3.25
Log Revenue	17.39	16.49	17.69	16.73
N	150	1727	103	1251
Panel B. NSS				
Technology Adoption	0.82	0.72	0.66	0.76
NPR	0.30	0.30	0.34	0.32
RN-LVN ratio	0.85	0.83	0.87	0.85
For-Profit	0.18	0.14	0.39	0.25
Urban	0.55	0.51	0.58	0.51
% Medicare	0.35	0.51	0.36	0.51
% Medicaid	0.22	0.14	0.18	0.13
Log Beds	5.15	5.05	5.12	5.10
Log Patient Days	10.13	9.91	10.32	10.12
Log FTEs	6.44	6.35	6.45	6.46
Log Hourly Wage	3.40	3.23	3.49	3.25
Log Revenue	17.31	16.46	17.76	16.73
N	156	1673	116	1240

Note.–This table reports hospital characteristics measured in 2002 for hospitals in the balanced samples used in the Clinical Decision Support (CDS) and Nurse Staffing Software (NSS) analyses. Hospitals are classified as financially constrained if their average operating margin over the pre-policy period (2000–2002) is negative, and financially unconstrained otherwise. Within each financial group, columns report mean characteristics separately for California (CA) and non-California (Non-CA) hospitals.

Table B4: Summary Statistics for Matched Sample

	CDS Sample			NSS Sample		
	CA	Non-CA	Δ	CA	Non-CA	Δ
Technology Adoption	0.64	0.57	0.07*	0.77	0.79	-0.02
NPR	0.33	0.32	0.01	0.33	0.32	0.01
RN-LVN ratio	0.86	0.87	-0.01*	0.86	0.87	-0.01
For-Profit	0.21	0.21	0.00	0.22	0.22	0.00
Urban	0.68	0.68	0.00	0.68	0.69	-0.01
% Medicare	0.34	0.39	-0.05***	0.34	0.39	-0.05***
% Medicaid	0.19	0.18	0.01	0.19	0.17	0.02
Log Beds	5.18	5.33	-0.15**	5.18	5.31	-0.13**
Log Patient Days	10.28	10.35	-0.07	10.28	10.32	-0.04
Log FTEs	6.49	6.67	-0.18***	6.49	6.64	-0.15**
Log Hourly Wage	3.46	3.32	0.14***	3.46	3.32	0.14***
Log Revenue	17.55	17.12	0.43***	17.55	17.1	0.45***
N	292	1322		298	1169	

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 technology, using baseline technology adoption status, for-profit ownership, urban status, bed-size terciles, separate terciles of Medicare and Medicaid patient shares, and staffing-exposure categories. Patient days are excluded from the revised specification because they are highly correlated with bed size. 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 B5: Robustness to Alternative Specifications by Pre-Policy Staffing Levels

	Clinical Decision Support			Nurse Staffing Software		
	High need	Moderate need	Low need	High need	Moderate need	Low need
Panel A: 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)	(0.03)
Panel B: Excluding Implementation Transition Years						
$CA_i \times Post_t$	-0.078*	-0.027	-0.027	-0.031	0.007	0.012
	(0.041)	(0.029)	(0.046)	(0.041)	(0.027)	(0.044)
Panel C: Excluding Nearby States from Control Group						
$CA_i \times Post_t$	-0.064***	-0.039**	-0.015	-0.012	0.014	0.040
	(0.024)	(0.018)	(0.034)	(0.029)	(0.020)	(0.034)
Panel D: Stricter Technology Adoption Definition						
$CA_i \times Post_t$	-0.034	-0.016	-0.041	-0.010	0.014	0.040
	(0.026)	(0.021)	(0.028)	(0.029)	(0.019)	(0.032)

Note.–This table presents robustness checks for the heterogeneity analysis by pre-policy staffing levels using synthetic difference-in-differences (SDID). Hospitals are grouped into high-, moderate-, and low-need categories based on their pre-policy nurse-to-patient ratios. 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 block bootstrapping with 1,000 replications. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B6: Robustness to Alternative Specifications by Financial Conditions

	Clinical Decision Support		Nurse Staffing Software	
	Constrained	Unconstrained	Constrained	Unconstrained
Panel A: Baseline				
$CA_i \times Post_t$	-0.064***	0.003	-0.032**	0.090***
	(0.014)	(0.027)	(0.013)	(0.031)
Panel B: Excluding Implementation Transition Years				
$CA_i \times Post_t$	-0.067**	0.008	-0.051**	0.079**
	(0.026)	(0.039)	(0.020)	(0.040)
Panel C: Excluding Nearby States from Control Group				
$CA_i \times Post_t$	-0.064***	0.003	-0.033**	0.089***
	(0.014)	(0.026)	(0.013)	(0.031)
Panel D: Stricter Technology Adoption Definition				
$CA_i \times Post_t$	-0.053***	0.019	-0.033***	0.090***
	(0.015)	(0.027)	(0.013)	(0.029)

Note.–This table presents robustness checks for the heterogeneity analysis by pre-policy financial conditions using synthetic difference-in-differences (SDID). Hospitals are classified as financially constrained or unconstrained based on their pre-policy operating margins. 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 block bootstrapping with 1,000 replications. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B7: SDID with Alternative Pre-Policy Staffing Levels

	Clinical Decision Support			Nurse Staffing Software		
	High-need	Mod-need	Low-need	High-need	Mod-need	Low-need
Panel A: NPRs over 2000-2002 (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: NPRs over 2000-2001						
$CA_i \times Post_t$	-0.063**	-0.043***	-0.008	-0.010	0.006	0.052
	(0.029)	(0.016)	(0.033)	(0.032)	(0.019)	(0.032)
Panel C: NPRs in 2000						
$CA_i \times Post_t$	-0.067***	-0.036*	-0.022	-0.006	-0.000	0.053*
	(0.021)	(0.019)	(0.028)	(0.032)	(0.018)	(0.031)

Note.–This table presents coefficient estimates on the interaction between a California indicator and a post-policy indicator by hospital groups based on pre-policy nurse-to-patient ratios (NPRs). Panel A reports the baseline estimates where pre-policy NPRs are defined using NPRs over 2000-2002. Panel B reports the estimates where pre-policy NPRs are defined using NPRs over 2000-2001. Panel C reports the estimates where pre-policy NPRs are defined using NPRs in 2000. 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. All specifications include hospital and year fixed effects. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps for SDID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B8: SDID with Alternative Financial Constraints

	Clinical Decision Support		Nurse Staffing Software	
	Constrained	Unconstrained	Constrained	Unconstrained
Panel A: Negative Operating Margin over 2000-2002 (Baseline)				
$CA_i \times Post_t$	-0.064***	0.003	-0.032**	0.090***
	(0.014)	(0.027)	(0.013)	(0.031)
Panel B: Negative Operating Margin over 2000-2001				
$CA_i \times Post_t$	-0.077***	-0.007	-0.037***	0.056**
	(0.013)	(0.020)	(0.012)	(0.024)
Panel C: Negative Operating Margin in 2000				
$CA_i \times Post_t$	-0.071***	0.004	-0.024*	0.064**
	(0.012)	(0.027)	(0.013)	(0.028)

Note.–This table presents coefficient estimates on the interaction between a California indicator and a post-policy indicator by hospital groups based on pre-policy financial status. Panel A reports the baseline estimates where pre-policy financial status is defined using operating margins over 2000-2002. Panel B reports the estimates where pre-policy financial status is defined using operating margins over 2000-2001. Panel C reports the estimates where pre-policy financial status is defined using operating margins in 2000. Hospitals are classified financially constrained if pre-policy financial status is negative. All specifications include hospital and year fixed effects. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps for SDID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B9: SDID with Alternative Pre-Policy Staffing Cutoffs

	Clinical Decision Support			Nurse Staffing Software		
	High-need	Mod-need	Low-need	High-need	Mod-need	Low-need
Panel A: 25-75 percentiles of pre-policy NPRs (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: 20-80 percentiles of pre-policy NPRs						
$CA_i \times Post_t$	-0.056*	-0.041***	-0.018	0.007	0.010	0.038
	(0.032)	(0.015)	(0.035)	(0.039)	(0.018)	(0.035)
Panel C: 30-70 percentiles of pre-policy NPRs						
$CA_i \times Post_t$	-0.065***	-0.030	-0.028	-0.026	0.025	0.037
	(0.022)	(0.021)	(0.027)	(0.026)	(0.023)	(0.029)

Note.–This table presents coefficient estimates on the interaction between a California indicator and a post-policy indicator by hospital groups based on pre-policy nurse-to-patient ratios (NPRs). Panel A reports the baseline estimates with 25 and 75 percentiles as hospital group thresholds. Panel B reports the estimates with 20 and 80 percentiles as the thresholds. Panel C reports the estimates with 30 and 70 percentiles as the thresholds. All specifications include hospital and year fixed effects. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps for SDID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B10: Alternative Specifications 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: SDID (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: DID						
$CA_i \times Post_t$	-0.060*	-0.036	-0.029	-0.014	0.007	-0.008
	(0.034)	(0.023)	(0.035)	(0.035)	(0.022)	(0.032)
Panel C: CEM						
$CA_i \times Post_t$	-0.069**	-0.039*	-0.049	-0.020	0.012	-0.007
	(0.034)	(0.023)	(0.037)	(0.037)	(0.023)	(0.034)

Note.–This table presents coefficient estimates on the interaction between a California indicator and a post-policy indicator by hospital groups based on 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. Panel A reports the baseline estimates from synthetic difference-in-differences (SDID). Panel B reports the estimates from standard difference-in-differences (DID). Panel C reports the DID estimates with Coarsened Exact Matching (CEM). 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 B11: Alternative Specifications by Financial Conditions

	Clinical Decision Support		Nurse Staffing Software	
	Constrained	Unconstrained	Constrained	Unconstrained
Panel A: SDID (Baseline)				
$CA_i \times Post_t$	-0.064***	0.003	-0.032**	0.090***
	(0.014)	(0.027)	(0.013)	(0.031)
Panel B: DID				
$CA_i \times Post_t$	-0.074***	-0.001	-0.046**	0.009
	(0.027)	(0.025)	(0.022)	(0.026)
Panel C: CEM				
$CA_i \times Post_t$	-0.118***	-0.029	-0.050**	-0.012
	(0.034)	(0.027)	(0.025)	(0.032)

Note.–This table presents coefficient estimates on the interaction between a California indicator and a post-policy indicator by hospital groups based on pre-policy financial status. Hospitals are classified financially constrained if their average operating margin over 2000-2002 is negative. Panel A reports the baseline estimates from synthetic difference-in-differences (SDID). Panel B reports the estimates from standard difference-in-differences (DID). Panel C reports the DID estimates with Coarsened Exact Matching (CEM). 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 B12: Heterogeneity by Financial Conditions with Alternative Balance Sheet Measures

	Clinical Decision Support		Nurse Staffing Software	
	Constrained	Unconstrained	Constrained	Unconstrained
Panel A: High liabilities-to-assets				
$CA_i \times Post_t$	-0.075***	-0.017	-0.035**	0.104***
	(0.013)	(0.029)	(0.015)	(0.033)
Panel B: Low fund-balance-to-assets				
$CA_i \times Post_t$	-0.074***	-0.018	-0.036**	0.104***
	(0.013)	(0.028)	(0.015)	(0.032)
Panel C: Low working-capital-to-assets				
$CA_i \times Post_t$	-0.061***	-0.044**	-0.001	0.047*
	(0.015)	(0.022)	(0.017)	(0.027)

Note.–This table reports SDID estimates by alternative pre-policy balance-sheet measures of financial constraints. Liabilities-to-assets is total liabilities divided by total assets. Fund-balance-to-assets is total fund balance divided by total assets. Working-capital-to-assets is current assets minus current liabilities, divided by total assets. Each measure is averaged over 2000–2002. Hospitals are classified as financially constrained if they have above-median liabilities-to-assets, below-median fund-balance-to-assets, or below-median working-capital-to-assets. Observation counts vary slightly across panels; they range from 17,776–17,985 for constrained CDS samples, 17,787–17,974 for unconstrained CDS samples, 17,457–17,545 for constrained NSS samples, and 17,721–17,798 for unconstrained NSS samples. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B13: 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 middle two quartiles, and low-need hospitals in the highest quartile. All columns control hospital fixed effects and year fixed effects. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B14: 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 parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B15: SDID with Alternative Technologies

	Emergency Room	Intensive Care	Radiology	Lab Info System	Patient Schedule	OR Schedule
$CA_i \times Post_t$	-0.018	0.011	-0.012	-0.014**	0.037**	0.143***
	(0.017)	(0.019)	(0.013)	(0.005)	(0.017)	(0.023)

Note.–This table presents synthetic difference-in-differences (SDID) estimates for alternative technologies. All specifications include hospital and year fixed effects. Standard errors in parentheses are obtained by block bootstrapping with 1000 bootstraps. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$