Original Article

POMS

Production and Operations Management
1–20

DOI: 10.1177/10591478251367520
journals.sagepub.com/home/pao
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From Hidden Fees to Open Books: An Empirical Examination of the Impact of Hospital Price Transparency Rule on Costs and Quality of Medical Services

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Abstract

In the United States, the lack of competition within the healthcare market is notably influenced by the opacity of service pricing, leading to unchecked price increases without improvements in service quality. The hospital price transparency rule, implemented on January 1, 2021, seeks to address this by requiring the disclosure of prices, aiming to stimulate competition and lower costs. Yet, the policy's effect on hospital charges and consumer behavior remains largely unexplored. This study employs a difference-in-differences analysis of inpatient data from Florida hospitals to assess the impact of the Federal price transparency rule on hospital charges and patient decision-making, leveraging the phased compliance of hospitals with the rule. Our analysis reveals that while the price transparency rule does not broadly reduce hospital charges, it leads to lower charges for self-pay patients opting for elective procedures who are sensitive to price and can shop for better deals. This reduction is driven by both lower unit prices and decreased care complexity as hospitals compete to attract cost-conscious patients. Furthermore, our findings indicate that after the implementation of the policy, patients choose hospitals that not only comply with the rule but also charge below the market average, particularly benefiting those seeking elective services. This suggests that price transparency primarily aids cost-aware patients with the flexibility to choose more affordable providers. Our research underscores the nuanced impact of price transparency on healthcare costs and patient welfare, offering valuable insights for future healthcare policy development.

Keywords

Hospital Price Transparency, healthcare Cost, Healthcare Quality

Date received 21 July 2024; accepted 11 July 2025 after three revisions

Handling Editor: Sergei Savin

1 Introduction

Healthcare spending in the United States exceeded \$4.5 trillion in 2022, equating to an average of \$13,493 per person, making it the highest among countries worldwide (Hartman et al., 2024). The commercial health spending increased 21.8% from 2015 to 2019 with approximately two-thirds of this increase attributed to the surge in service prices (Brennan, 2019). The rising prices have increased the healthcare burden on individuals, with over half of all adults in the United States expressing trouble paying for healthcare services (Lopes et al., 2023).

Although not strictly regulated, competition in the US healthcare market is limited by the longstanding lack of price transparency. The limited market competition results in continuously escalating charges by healthcare providers, without any corresponding improvement in the quality of healthcare services (Gaynor et al., 2017).

Transparent pricing information, a fundamental element of free-market operations, can incite competition in the healthcare market. Market competition is expected to improve service quality and efficiency, foster innovation, and drive down prices in various markets, including healthcare (Dafny

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and Lee, 2016). The hospital price transparency rule was introduced as a solution to curb the rising healthcare costs, alleviate information asymmetry, and enhance the efficiency of healthcare markets (Chen and Miraldo, 2022). As of January 1, 2021, the nationwide *hospital price transparency rule* requires all hospitals operating in the United States to publish clear and easily understandable pricing information online, ensuring accessibility through two primary means; First, hospitals must present a comprehensive, machine-readable file encompassing all items and services offered. Second, they must display shoppable services in a consumer-friendly format. Shoppable services are defined as those that "can be scheduled by a healthcare consumer in advance,"[1] such as imaging and outpatient surgeries.

However, the effectiveness of this policy is debated. On the one hand, consumers will have access to cost information associated with their health care services so they will be able to shop around and choose the provider with lower charges (Singh, 2023). This is expected to increase competition (Wu et al., 2014), causing hospitals to lower their prices in order to attract more patients. On the other hand, others have cautioned that implementing such a policy may raise prices even more. This is because it might allow medical providers who currently receive lower payments to negotiate for higher rates on par with what insurance companies pay their counterparts (Glied, 2021). Prior research has shown that in such circumstances, providers with lower prices will be motivated to increase their prices to match their higher-priced peers in the market (Sinaiko and Rosenthal, 2011). Another nuanced issue here is that the ultimate effect of the policy depends not only on hospital behavior but also on patient reactions, particularly their capacity and willingness to incorporate price information when making decisions. Prior studies show patients rarely use price information to choose between healthcare providers (Desai et al., 2017). Previous studies on the effects of similar policies implemented at the state level have revealed minimal decreases in hospital charges (Christensen et al., 2020). The effect of such policy is therefore not yet known and requires careful examination, as it is unclear whether it will effectively lower hospital charges through increased competition, potentially exacerbate rising prices by enabling medical providers to negotiate higher rates, or have no effect at all due to the likelihood that patients may not utilize the available price information to make healthcare decisions.

We use the hospital inpatient discharge records provided by the Florida Agency for Healthcare Administration (AHCA) to investigate the impact of the hospital price transparency rule on both hospitals' pricing decisions and patients' responses. Specifically, we address two important research questions. (a) Does hospital price transparency rule effectively reduce healthcare costs? (b) Do patients use the newly available pricing data to choose hospitals?

The AHCA dataset includes bed-level information on individual patient admissions, such as the services provided, the billed prices that closely approximate actual payments, and patient's demographic data. Our empirical analysis employs a difference-in-differences design that leverages variations in the policy compliance timing among hospitals. Previous evaluations conducted by the Centers for Medicare & Medicaid Services (CMS) indicate that the level of compliance varies across hospitals (Kona, 2023), a sentiment echoed by researchers and reporters who have highlighted discrepancies in adherence status (Evans et al., 2021; Haque et al., 2022). We exploit the staggered compliance status of hospitals with the rule, identified through the Semi-Annual Hospital Price Transparency Compliance Report provided by the non-profit organization, PatientRightsAdvocate.org.[2] We note that hospitals make the decision regarding compliance with the policy, which raises concerns about endogeneity. We address this issue by utilizing time-dependent propensity score matching (TPSM) to minimize pre-treatment disparities between the treatment and control cohorts. To ensure robustness, we employ additional empirical methods, such as stabilized inverse probability weighting, and include an alternative control group comprising entities that achieved compliance in 2023.

We begin by demonstrating that the implementation of the price transparency rule does not result in significant changes in hospital charges across the entire market. Our analysis of heterogeneous treatment effects further reveals that hospitals tend to decrease charges for patients who are price sensitive. Specifically, hospitals reduce charges for self-pay patients by an average of 11.7%, whereas no reductions are observed for insured patients, likely due to their lower price sensitivity.

We further show that hospitals lower charges in competitive markets to attract price-sensitive patients. Our findings indicate that reductions in charges are more pronounced for self-pay patients opting for elective procedures, whereas there's no noticeable effect for those who seek urgent medical services. This could be attributed to the fact that, in an emergency, patients prioritize proximity and urgent care at the nearest hospital over price comparison. Furthermore, patients often face limitations in accessing price information for emergency services, as these do not fall under the category of "shoppable" services that the policy requires hospitals to disclose their price.

We then proceed to analyze patient behavior in response to the newly available price information from hospitals. We observe a shift in patient preferences toward hospitals adhering to the regulation. Our findings indicate that hospitals experience an average quarterly admission increase of 4.35% following compliance with the regulation, reflecting patients' preferences in their choices.

Furthermore, we explore the varying effects across different patient segments. Our findings suggest that the observed effects are primarily among self-pay, non-emergency patients who are both cost-conscious and capable of making informed decisions. Collectively, these findings support the conclusion that hospital price transparency has the potential to reduce healthcare spending, although the impact is limited and concentrated within a subset of self-paying patients who are primarily shopping for elective services.

This research contributes to three streams of literature. First and foremost, it speaks to existing literature on healthcare operations management which has long explored how policies and organizational strategies shape the efficiency (Berry Jaeker and Tucker, 2020; Dreyfus et al., 2020; Johnson et al., 2020), quality (Deore et al., 2023; Kc and Kim, 2022; Miedaner et al., 2024; Sharma and Goradia, 2023), and outcomes of healthcare delivery (Catena et al., 2020; Ding et al., 2020). Research in this domain has emphasized the critical role of operational decisions in improving patient care, optimizing resource utilization, and achieving organizational objectives under varying regulatory and market conditions (Adida and Bravo, 2023; Andritsos and Tang, 2014; Fredendall and Smith, 2020; Mishra et al., 2020). Our study extends this literature by examining the operational implications of price transparency policies—a growing area of interest in healthcare reform aimed at fostering competition and empowering patient decision-making. Specifically, we analyze how hospitals adjust their pricing strategies, service complexity, and operational outcomes in response to mandated price disclosure, and how these changes affect patient behavior and hospital performance. By bridging policy impact with operational responses, our research contributes to the understanding of how external regulatory pressures drive strategic and operational adjustments in healthcare organizations, providing insights for both policymakers and hospital managers.

Second, our paper adds insights to the literature on price transparency. The impact of price transparency on price reduction is debated in previous economic literature. While it is frequently claimed that price transparency will increase competition, reduce costs, and create consumer surplus (Schultz, 2014; Seim et al., 2017), it can also result in increased price levels. Boone and Pottersz (2006) suggest that in situations where goods are not perfect substitutes, an increase in price transparency will result in greater overall demand for various available products and subsequently lead to higher prices. Nishida and Remer (2018) show that price transparency can lead to competing firms setting higher average prices by lowering consumer search costs. Dewenter et al. (2017) empirically show that price transparency leads to information sharing between competitors in oligopolies, increasing the average price. Rossi and Chintagunta (2016) investigate the mandated posting of gas station prices in Italy. They discover that the policy reduces gas prices but has little effect on price dispersion, and that consumers do not use the posted price information effectively. Existing research on price transparency has inconsistent conclusions regarding the welfare improvement effect of price transparency, which underscores the necessity for additional empirical examination of the impact of price transparency policies. We fill this gap by investigating the pricing behavior of service providers and customer responses to pricing information in the context of medical services.

Finally, our paper adds to the discussion on price transparency in the healthcare market. Prior research highlights various mechanisms, including online platforms and government-mandated disclosures, showing that transparency can reduce prices (Linde and Siebert, 2021; Whaley, 2019) but has limited impact on heterogeneous services like office visits (Whaley, 2015). Christensen et al. (2020) find that the price transparency regulation leads to decreased listed prices for common services but has no effect on actual payment. From the patients' perspective, price-aware patients often switch to lower-cost providers (Lieber, 2017; Sinaiko et al., 2016; Wu et al., 2014). However, low adoption of transparency tools (Zhang et al., 2020) limits their effect on spending (Desai et al., 2017). The exact effects of price transparency in healthcare are still unclear for several reasons. First, existing research yields mixed findings on whether consumers actively use available pricing information to alter their healthcare decisions. Second, much of the prior research has concentrated on the prices listed in hospital chargemasters, which represent the standard charges for all patients but rarely reflect the actual amounts paid due to variations in insurance coverage and negotiated rates specific to each patient. Third, earlier studies have frequently focused exclusively on either hospitals or patients, neglecting to consider how the dynamics between hospital and patient behaviors might influence outcomes when analyzed collectively.

This paper provides several contributions: to the best of our knowledge, this is the first study that examines the impact of nationwide *hospital price transparency rule* which has a much broader impact compared to previous state-wide regulations. Compared with previous state legislature initiatives, this federal rule offers more accessible pricing information and has gained greater media attention, which could heighten patient awareness and encourage the usage. Second, we investigate the rule's impact on hospital billed prices which closely approximate the actual payment, providing insights into how the rule affects the actual healthcare spending. To ensure that the figures in the data represent the actual billed prices, we first confirmed with the AHCA authorities and then empirically investigated this by comparing the billed prices for patients with identical complaints but different insurances. An example is shown in Figure A1 in Appendix A1. Third, we access the changes in healthcare quality that are associated with the adjustments in pricing. Fourth, we examine the impact of this rule on the behavior of both hospitals and patients, and also explore the heterogeneous treatment effects on different market segments and patient groups, providing insights for policy evaluation.

2 Theoretical Background

In this section, we draw from existing literature to conceptualize the mechanism through which price transparency affects hospitals' and patients' behavior. We then formulate our hypotheses. In our theoretical framework, we identify the

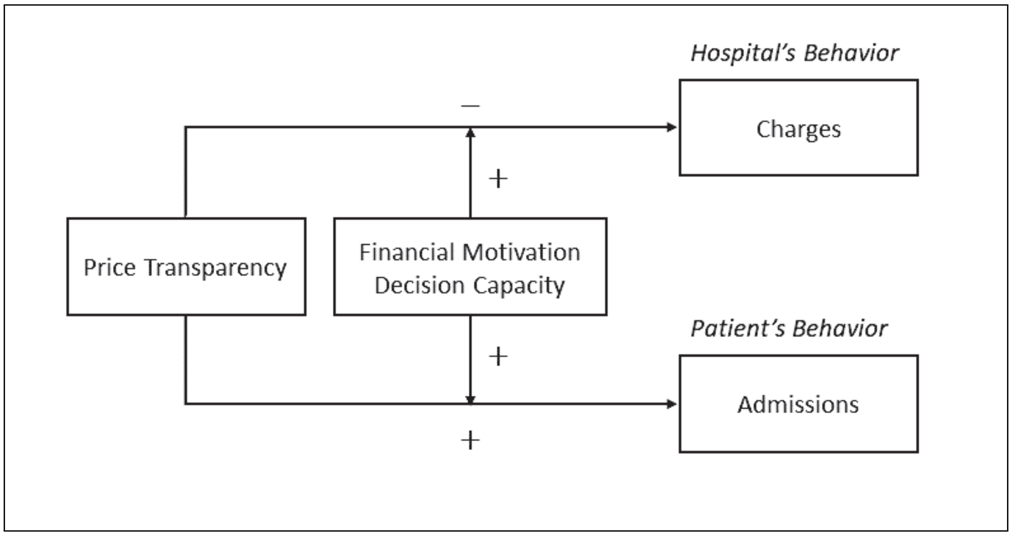

Figure 1. Conceptual framework.

implications of price transparency from both the perspective of hospitals (the supply side) and patients (the demand side). We propose that price transparency will exert downward pressure on charges from the supply side, driven by increased competition among hospitals vying to attract more patients while maintaining their social standing. On the demand side, we argue that patients, armed with pricing information, will make more informed choices, favoring hospitals offering lower prices.

To empirically validate our theoretical framework, we propose hypotheses that allow us to examine the *mechanisms of impact* on both supply and demand. These are designed and then tested based on the rational that the hypothesized mechanisms are more potent in contexts where the conditions conducive to their operation are more prevalent. Conversely, they will lead to weaker effects in situations where these conditions are lacking. These scenarios serve as moderators in our theoretical framework. By analyzing these moderators empirically, we aim to provide further empirical validation for the existence of the proposed impact mechanisms in our theory, thus bolstering the overall robustness of our framework. Figure 1 provides a conceptual representation of our theoretical framework.

2.1 Impact of Price Transparency Rule on Hospitals

Compliance with the hospital price transparency rule could lead to a reduction in hospital charges for two primary reasons. First, the disclosure of prices fosters market competition by empowering patients to factor price into their decision-making process (Schultz, 2014). Wu et al. (2014) discovered that price transparency encourages competition among healthcare providers. Armed with price information, consumers can compare costs across different providers and opt for the one offering the most value for their money. In anticipation of this competitive landscape, hospitals may adjust their charges downwards, expecting that patients will gravitate toward more affordable options.

Second, as noted by Christensen et al. (2020), the public disclosure of hospital charges may subject hospitals with comparatively high charges to reputational risks stemming from perceived overcharging. Considering the significance of social legitimacy for hospitals' effective operation (Krishnan and Yetman, 2011; Scott, 2000), hospitals may be motivated to lower their charges as a preemptive measure to evade such repercussions.

Hypothesis 1: Compliance with the hospital price transparency rule is associated with a reduction in hospital charges.

Importantly, total charges are determined by two components: (a) the unit prices assigned to each service, and (b) the complexity or intensity of services provided during the patient encounter. Hospitals may reduce total charges through either or both of these mechanisms. First, increased transparency may prompt hospitals to lower listed unit prices in order to appear more competitive and appeal to cost-conscious patients. Second, hospitals may reduce the complexity or intensity of care—such as reducing length of stay or minimizing non-essential services—to lower total charges without changing the price of individual services. Accordingly, we propose

Hypothesis 1.1: Compliance with the hospital price transparency rule is associated with a reduction in the unit prices of billed services.

Hypothesis 1.2: Compliance with the rule is associated with a reduction in the complexity or intensity of care.

The effects of the hospital price transparency rule are likely to be limited to self-pay patients and do not extend to insured patients. This limitation arises due to the nature of hospital insurance reimbursement rates, which are determined through complex negotiations between providers and insurers (Bernstein and Crowe, 2024; Jiang et al., 2023). These contracts are often fixed for several years, leaving little room for immediate price adjustments in response to transparency measures.

Moreover, insurers and hospitals already have access to extensive pricing data, both internally and from third-party sources (Chen and Miraldo, 2022). Consequently, the new rule is unlikely to have revealed significant new information to these stakeholders. As a result, insured patients, whose costs are largely covered by these pre-negotiated rates, have little financial incentive to alter their behavior based on publicly disclosed prices. In contrast, self-pay patients, who bear the full cost of healthcare services, are more directly impacted by price information. They have a greater motivation to consider price in their decision-making, making them the primary beneficiaries of the transparency rule. Given these dynamics, it is reasonable to expect that any observed effects of the policy would be concentrated within the self-pay population, with minimal or no impact on insured patients, particularly over a short time frame.

Hypotheses 1, 1.1, and 1.2 are predicated on two assumptions. First, it assumes that patients universally prioritize price when making healthcare decisions. However, this assumption may not hold true in all cases as highlighted by Schultz (2017). For instance, patients who are fully insured may not necessarily prioritize price when choosing healthcare providers, as their out-of-pocket expenses are typically covered by their insurance plans. In contrast, self-paying patients, who bear the full cost of healthcare services, are more likely to be sensitive to price. Second, it assumes that healthcare services exhibit elasticity, wherein patients' demand adjusts in response to charge changes. However, certain healthcare services demonstrate inelasticity, indicating that variations in charge have minimal impact on demand. This is particularly evident in emergency services, where patients often are in such dire need of medical services that they do not factor in price information and instead, seek care from the nearest hospital. The policy's focus on disclosing prices for shoppable services further complicates patients' access to pricing information for emergency services. In contrast, for elective procedures, patients not only have easier access to price data but also are able to factor that information into their decision-making process. Given that in elective procedures, price information holds greater significance and is more readily accessible to patients, we anticipate observing more noticeable reductions in charges for elective procedures compared to emergency services. Thus, we propose:

Hypothesis 1.3: The impact of hospital price transparency rule on reducing hospital charges is stronger for self-pay patients.

Hypothesis 1.4: The impact of hospital price transparency rule on reducing hospital charges is stronger for elective procedures.

Building on the rationale presented in the preceding hypotheses, we can expect that self-paying patients who need elective services possess not only the financial motivation but also the option to factor the cost of medical services into their decision-making process. Consequently, we propose the following:

Hypothesis 1.5: The impact of hospital price transparency rule on reducing hospital charges is stronger for self-pay patients who seek elective procedures.

Note that the relationship between healthcare costs and quality has been extensively debated in prior studies, such as Hussey et al. (2013), which show that higher healthcare spending does not necessarily result in better quality. The impact of price transparency on healthcare quality could manifest in two distinct ways. Price transparency might encourage hospitals to reduce charges through the elimination of superfluous and redundant services and the reduction of operational inefficiencies, potentially without adversely affecting the overall quality of care or patient health outcomes. Alternatively, to cut costs, hospitals might compromise on essential services and patient care, which could detrimentally affect the quality of healthcare services. Given the dual possibilities regarding the policy's impact on quality, this issue emerges as an empirical question. Therefore, we will provide preliminary empirical findings regarding the impact of the policy on quality of care in our subsequent analyses.

2.2 Impact of Price Transparency Rule on Patients

Hospital admissions reflect patient choice, and thus, ceteris paribus, an increase in a hospital's favorability among patients should be captured by a rise in the number of admissions it receives. Following the implementation of hospital price transparency rule, when patients become informed about the prices of medical services at different hospitals, they may take price into consideration when choosing a hospital. Schultz (2014) indicates that price transparency usually leads consumers to switch to less expensive providers. Within the healthcare sector, when price details are accessible online, there is a tendency for patients to shift toward providers with lower costs (Brown, 2019; Lieber, 2017).

The availability of pricing information, particularly when presented in a clear and comprehensive manner, tends to enhance patients' perception of hospitals. This increased transparency elevates patients' confidence in their judgments regarding prices. Consequently, patients are more inclined to view hospitals favorably and are thus more likely to choose them for their medical needs. This aligns with research suggesting that transparent processes and clear pricing information play a crucial role in influencing consumer decisions (Buell et al., 2017; Rossi and Chintagunta, 2016; Seim et al., 2017; Stamatopoulos et al., 2021; Zhang and Jiang, 2014). Therefore, the heightened confidence in judgment and the perceived accomplishment of information processing goals due to enhanced transparency can significantly influence patients' actual hospital selection behavior.

Hypothesis 2: Hospital price transparency rule increases hospital admissions.

Given the assumption that patients are utility maximizers and would opt for hospitals offering lower charges when all other factors are equal, we anticipate a shift in patient flow from hospitals with above-average charges to those with below-average charges. We hypothesize:

Hypothesis 2.1: The impact of hospital price transparency rule on hospital admissions increases with the extent to which hospital reduce their charges lower than market average.

However, not every patient is motivated to reduce their healthcare spending. The usage of price transparency tools remains low (Desai et al., 2016; Lieber, 2017; Zhang et al., 2020). Sinaiko et al. (2016) suggest that price-aware patients benefit more from the price transparency tool. Desai et al. (2017) suggest that only a minor fraction of insured people actively look for pricing information, which diminishes the likelihood of significant healthcare cost savings. Insured patients, shielded from immediate out-of-pocket costs, typically have fewer financial incentives to actively seek price information and opt for less expensive healthcare options. Conversely, self-pay patients, who bear the full financial responsibility themselves, tend to be more price-sensitive. In scenarios where patients have a direct stake and are more attuned to prices, the influence of price transparency policy on their choices is likely to be heightened. Furthermore, patient's ability to seek out providers with lower charges may be limited if they do not have the ability to make medical decisions. Recent research shows that online price transparency platforms are predominantly utilized by healthier individuals as they possess a greater ability to shop around for healthcare services (Sinaiko and Rosenthal, 2016). During emergencies, patients are typically directed to the nearest hospital for immediate care and may not have the opportunity to compare prices beforehand. While, for non-urgent, elective procedures where time is not pressing, patients can compare costs and make well-informed decisions before undergoing treatment. Thus, we propose:

Hypothesis 2.2: The impact of hospital price transparency rule on hospital admissions is stronger for self-pay patients.

Hypothesis 2.3: The impact of hospital price transparency rule on hospital admissions is stronger for patients who seek elective procedures.

Being aware of cost and having the capacity to decide are two important and necessary conditions for patients to search for more affordable healthcare options. When it comes to elective procedures, patients might consider price as a more important factor if they are fully responsible for direct out-of-pocket expenses. Even with price-awareness, patients are more capable to engage in price comparison for elective services when immediate care does not take precedence over financial considerations. Based on these arguments, we propose:

Hypothesis 2.4: The impact of hospital price transparency rule on hospital admissions is stronger for self-pay patients who seek elective procedures.

3 Model and Estimation

3.1 Data

Our main dataset comprises bed-level information of patients admitted to hospitals inpatient department in the state of Florida from January 2018 to December 2022, sourced from the Florida Agency for Healthcare Administration (AHCA). Each record details the hospital from which a patient was discharged during a specific quarter, along with comprehensive demographic details, such as sex and age, and insurance type—Medicare, Medicaid or commercial. These records also include detailed diagnosis and procedure ICD-10 codes, as well as the total cost incurred. The data consists of over 14 million patient visits across 321 hospitals during 5 years (or 20 quarters) in Florida.

We also utilized annual hospital financial data from 2018 to 2022, obtained from AHCA. Florida hospitals are required to submit fiscal year-end financial reports to AHCA each year. This dataset provides detailed financial information on hospitals, including short-term liabilities, long-term debt, and assets, which we leveraged to construct a matched sample for our empirical analysis.

To determine hospitals' compliance status with the price transparency rule, we refer to the semi-annual price transparency reports from PatientRightsAdvocate.org, a non-profit organization advocating for transparency in the healthcare system. They assess compliance by conducting a semi-annual progressive review of a random sample of hospital websites from the 6,002 hospitals subject to the rule. We determine the compliance status of hospitals using these review reports and focus on a subset of Florida hospitals that are evaluated by this NGO.[3]

As shown in Figure 2, hospitals are categorized into four distinct groups based on their compliance survey status. The first group consists of hospitals surveyed in the first time period (T1). Since the survey process is progressive—meaning that once a hospital is surveyed in one period, it continues to be surveyed in subsequent periods—there is no uncertainty regarding the compliance status of these hospitals across all time periods.

The second group includes hospitals that were not surveyed in T1 but were surveyed starting in the second period (T2) and onward. For these hospitals, compliance status is uncertain only for T1. Their compliance status in T1 is inferred based on their known status in T2. If a hospital did not comply in T2, it logically could not have complied in T1 either. If a hospital complied in T2, there is some ambiguity regarding its compliance in T1, as it may or may not have complied in that period. To address this uncertainty, we adopt a conservative approach

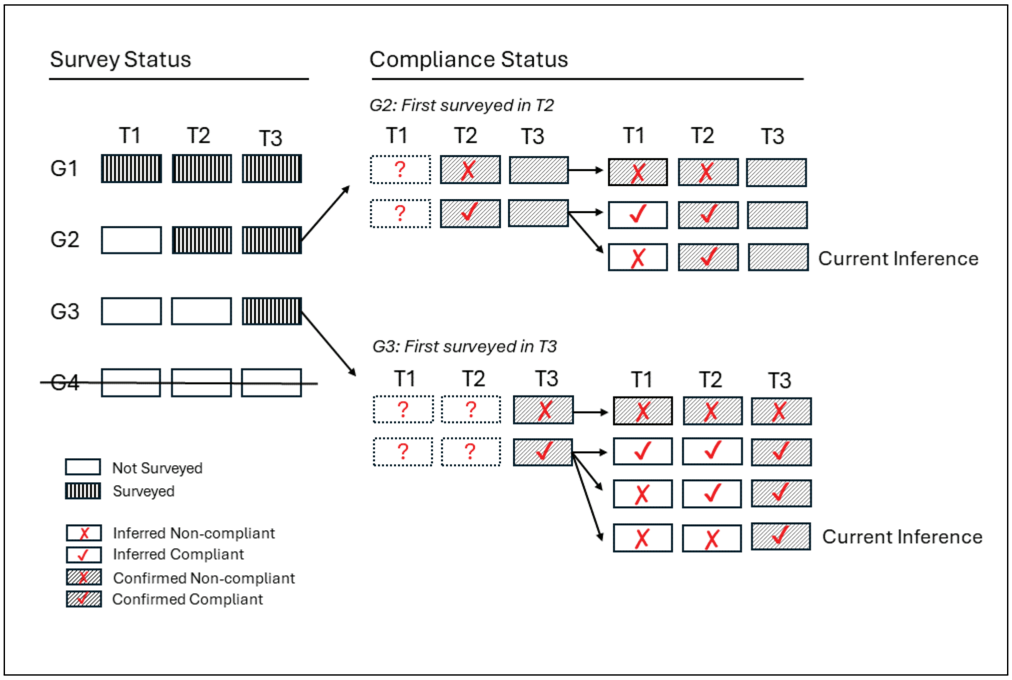

Figure 2. Hospital compliance status.

and assume non-compliance in T1. This conservative assumption works against our hypothesis and likely underestimates the policy's effect.

The third group comprises hospitals that were not surveyed in T1 or T2 but were surveyed starting in the third period (T3). For these hospitals, compliance status is unknown for T1 and T2, and their compliance history is inferred based on their status in T3. If a hospital did not comply in T3, it could not have complied in T1 or T2 either. However, if a hospital complied in T3, there are three possible scenarios: the hospital complied in both T1 and T2, complied only in T2, or did not comply in either T1 or T2. To ensure consistency, we again adopt the most conservative assumption and classify these hospitals as non-compliant in T1 and T2, which minimizes potential overestimation of the policy's effects.

Finally, the fourth group consists of hospitals for which compliance status is unknown even in the third time period (T3). These hospitals were excluded from our analysis due to the lack of sufficient information to reliably infer their compliance status. This categorization and conservative inference methodology ensure that uncertainties in compliance status are addressed in a way that biases our estimates downward, providing robust and cautious results while minimizing the risk of overstating the effects of the policy.

Our classification of compliance status assumes that once a hospital becomes compliant with the policy, its status remains stable across subsequent periods. While this assumption generally holds, the NGO reports indicate that a small fraction of hospitals—typically 1–2%—initially classified as compliant were later deemed non-compliant, often due to incomplete disclosure of negotiated rates. These reversals appear to be infrequent and may reflect technical or reporting errors rather than intentional withdrawal from compliance. In our dataset, only two hospitals that were compliant in T2 were later classified as non-compliant in T3. To assess the impact of these reversals, we conducted robustness checks reclassifying these hospitals accordingly. As reported in Appendix A2, our findings remain consistent, suggesting that our results are not sensitive to this issue.

3.2 *Empirical Strategy*

3.2.1 Specification. We employ a difference-in-differences (D-i-D) approach to test our hypothesis. The outcome variables of interest are described in Table 1. We begin with the analysis of changes in charges and service quality of hospitals as a result of the policy. Then we proceed to investigate admission which manifest the changes on patient decisions. We opted for the hospital level as our unit of analysis, rather than the patient level, for two main reasons. The treatment occurs at the hospital level, making it more appropriate to conduct our D-i-D analysis at the same level. This aligns the scope of our analysis with the level at which the policy changes are applied, ensuring that the effects we observe are directly attributable to these changes. Moreover, since admissions data are aggregated at the hospital level, conducting our analysis at the hospital-quarter level maintains consistency in the presentation of our results, thereby enhancing the interpretability

Table 1. Description of the outcome variables.

Notation	Description
$Admission_{it}$	Total number of admitted patients to hospital *i* at time *t*
$Log(Charges_{it})$	Logarithm of average cost per patient at hospital *i* at time *t*
$Length\ of\ Stay_{it}$	Average length of stay per patient at hospital *i* at time *t*, in days
$Mortality_{it}$	Total number of expired patients at hospital *i* at time *t*

of our findings and making it easier to draw meaningful conclusions about the policy's impact on hospital decisions and patients' responses.[4]

Control hospitals that do not comply with regulations serve as a baseline for understanding the potential changes in behavior of the treated group in a counterfactual situation where healthcare service pricing is not disclosed. We use the longitudinal variation in hospitals' regulatory compliance status to identify the treatment effect. In terms of timing, 2 hospitals complied with the rule in the third quarter of 2021, 7 in the first quarter of 2022, and 17 in the third quarter of 2022. The D-i-D specification is as follows.

$$Y_{it} = \alpha + \beta\ Compliant_{it} + \lambda_i + \mu_t + \epsilon_{it} \tag{1}$$

Where Y_{it} are the outcome variables of interest including total admission, logarithmic of average cost per patient, average length of stay and mortality rate, of hospital *i* at time *t*. $Compliant_{it}$ equals 1 if hospital *i* comply with the price transparency regulation at time *t*, and 0 otherwise. λ_i is hospital fixed effects which absorb the cross-sectional variation that could be due to unobserved characteristics of hospitals. μ_t is year fixed effect that captures the time-specific behavior variation. Given that hospitals' compliance with the regulation was staggered and reviewed by the NGO on a semi-annual basis, the treatment always occurred in either Quarter 1 or Quarter 3. Therefore, including quarter or year-quarter fixed effects would be collinear with the treatment status. Hence, we choose to include the year fixed effect in our two-way fixed effects (TWFE) model. The coefficient of interest, β, represents our estimate of the impact that a hospital's compliance with the mandate to disclose their pricing information has. We cluster standard error at hospital level to account for potential correlation within hospital.

Our D-i-D model rests on two important assumptions. First, the treatment assignment must be exogenous; however, the choice to adopt the price transparency regulation is inherently endogenous, as various factors may influence a hospital's decision to comply. Second, it is assumed that, without the treatment, the difference in outcomes between treated and control groups would stay consistent over time. We will describe our approach to addressing endogeneity issues in the following. In Section 6, we present several additional robustness checks.

3.2.2 Addressing Endogeneity. In order to ensure that differences in outcomes can be correctly attributed to the compliance with the hospital price transparency rule, we match treated units with similar control units based on a broad list of observable variables. Previous studies suggest that several factors, including peer compliance status, financial conditions, and IT readiness, affect hospitals' compliance decisions with the rule (Henderson and Mouslim, 2021; Jiang et al., 2022; Mittler et al., 2023; Nikpay et al., 2024). Among these, financial conditions play a key role, as the decision to comply hinges on the costs of compliance versus the penalties for noncompliance (a \$300 daily fine). As shown by Nikpay et al. (2024), hospitals facing higher estimated fines are more likely to comply with the rule. Since most of these factors are time-varying, we need to adjust for the self-selection bias that may arise due to such time-varying variables, using time-dependent propensity score matching (PSM) following Gong et al. (2023) and Lu (2005). Results are consistent with traditional PSM (in Appendix A4.3). Matching can help us efficiently remove sample imbalance and reduce systematic bias by eliminating observations that cannot be successfully matched (Dehejia and Wahba, 2002; Yılmaz et al., 2024). The time-dependent PSM can incorporate both time-invariant covariates, which might affect policy compliance decisions as suggested by previous research, and time-varying covariates, which may influence both whether a unit receives treatment and the timing of the treatment.

For each hospital *i* at time *t*, we estimate the propensity score $\widehat{ps_{it}}$, conditional on the set of attributes using a discrete time logit hazard model where in we regress the hospital compliant status on the covariates. The estimation results are shown in Table A18 in Appendix A4.1. The estimated hazard rates are used as propensity scores for matching. Sequential matching is then carried out in chronological order, based on the propensity score of each treated hospital at the time of treatment, and is done without replacement (Lu, 2005). Beginning with the first wave hospitals that comply with the rule, each treated hospital is matched with the two nearest control hospitals at the time of treatment, based on the estimated hazard rate. For instance, if Hospital A complied with the policy in July 2021 (Q3 2021), we estimate the propensity score for each hospital in Q3 2021 and then match this treated hospital with two control hospitals having the closest propensity scores in Q3 2021. We further enhance the precision of matching by using 1 on 1 matching, and we obtained consistent results, which are detailed in Appendix A4.2.

To address potential confounding effects from other policies, we considered the impact of the No Surprises Act, which went into effect on January 1, 2022, near the end of our observation period. This policy, designed to protect patients from unexpected medical bills, applies uniformly to all hospitals regardless of their compliance with the hospital price transparency rule. As a result, any potential effects of the No Surprises Act are evenly distributed between the treatment and

Table 2. Summary statistics.

	Min	25th Percentile	Mean	75th Percentile	Max	SD	Count
Admission	2.00	1,606.00	3,745.73	4,969.50	16,082.00	2,867.18	1,540
Average Charges per Patient	10,294.33	57,027.52	83,653.77	108,243.8	223,394.00	33,482.77	1,540
Average Length of Stay	1.83	3.98	4.57	4.97	12.46	1.06	1,540
Mortality	0.00	32	84.54	113	709.00	76.92	1,540

Notes: The table reports the summary statistics for the matched sample.

Table 3. Impact of price transparency rule on hospitals' behavior.

	(1) Log(Charges)	(2) Length of Stay	(3) Mortality
Compliant	−0.033	0.096	−1.028
	(0.024)	(0.086)	(5.036)
Constant	11.268***	4.586***	85.689***
	(0.001)	(0.004)	(0.242)
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
R-squared	0.839	0.746	0.852
Observations	1,540	1,540	1,540

Notes: Column (1) shows the result on testing Hypothesis 1. Column (2)–(3) shows the results on the changes in hospital service quality which estimated by using OLS. The results for Length of Stay are consistent by using Poisson regression. Standard error clustered at hospital level. Post-hoc power analysis for mortality shows 99% power, suggesting the insignificant results are not due to insufficient statistical power. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

control groups, minimizing the likelihood of bias in our estimates of the price transparency rule's impact. Furthermore, the timing of the No Surprises Act ensures that its influence on our findings is limited.

The initial sample includes 26 treated and 86 control hospitals. The matching procedures leave us 26 treated hospitals and 52 control hospitals. We iteratively check the data balance by comparing the covariates in the treatment and control groups. Table A19 in Appendix A4.1 presents the t-test results. Table 2 provides summary statistics of the matched dataset. The data spans from 2018 – 2022 (20 quarters in total). On average, a hospital admits 3,745.73 patients every quarter, with an average charge of $83,653.77 per patient and an average length of stay of 4.57 days. The average number of deceased patients per quarter is 84.54. The model-free evidence provided in Appendix A5 demonstrates that hospitals complying with the policy reduced their charges and experienced an increase in admissions. We further conduct lead and lag analysis following Agrawal and Goldfarb (2008). The results presented in Appendix A6 which shows that there is no pre-trend differences between treatment and control group.

4 Effects of Price Transparency Rule on Hospitals

4.1 Main Effect

We begin with the analysis on hospital behavior changes (testing Hypothesis 1). Table 3 presents the results of the ordinary least squares (OLS) estimation for equation (1) for several outcomes of interest. Column (1) examines the policy impact on the average charges. Despite the negative coefficient indicating a potential influence of the policy on reducing healthcare service costs, the effect is not statistically significant. Thus, our findings do not support Hypothesis 1. The reasons for the lack of support for Hypothesis 1 are discussed in detail in Section 4.2. Columns (2) and (3) assess hospital service quality through measurement of length of stay and mortality rates.[5] Longer hospital stays might imply enhanced care and lower chances of readmission (Thomas et al., 1997). Although negative, the length of stay does not exhibit any significant changes. Similarly, the mortality rate, which is an essential measure of healthcare quality, shows no significant changes, implying that the quality of hospital services has remained consistent at the market level following the implementation of the regulation.

4.2 Empirical Extensions: Exploring the Mechanisms of Impact

Our hypothesis suggests that the implementation of a price transparency policy will prompt hospitals to reduce charges through increased competition, as price-aware patients will explore their options and opt for more affordable hospitals. This hypothesis rests on two key premises: 1) demand shows price elasticity, and 2) substitutable competitors exists. Consequently, the extent of competition hospitals face can vary based on specific conditions. In this section, we examine these mechanisms through Hypothesis 1.3 – 1.5.

Table 4. Hospitals' behavior – treatment effect by insurance type.

	(1) Government-Funded Log(Charges)	(2) Commercial Log(Charges)	(3) Self-pay Log(Charges)
Compliant	−0.034	−0.021	−0.111***
	(0.022)	(0.027)	(0.038)
Constant	11.311***	11.228***	10.999***
	(0.001)	(0.001)	(0.002)
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
R-Squared	0.837	0.843	0.766
Observations	1,540	1,540	1,540

Notes: Columns (1)–(3) use a subsample of patients with different insurance types: Government-Funded, Commercial, and Self-pay, respectively. Columns (1)–(3) together show the results on testing Hypothesis 1.3. Standard errors clustered at hospital level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5. Hospitals' behavior – treatment effect by emergency vs. elective procedures.

	(1) Emergency Log(Charges)	(2) Elective Log(Charges)
Compliant	−0.033	−0.055
	(0.024)	(0.048)
Constant	11.249***	11.265***
	(0.001)	(0.002)
Year FE	Yes	Yes
Hospital FE	Yes	Yes
R-Squared	0.856	0.794
Observations	1,540	1,540

Notes: Columns (1) and (2) use the subsamples of patients who received treatment in the emergency department and those who did not, respectively. Columns (1) and (2) together show the results on testing Hypothesis 1.4. Standard errors clustered at hospital level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.2.1 Heterogeneous Effects by Insurance Type. First, we test Hypothesis 1.3 by investigating the varying changes in hospital charge for patients with different types of insurance, including Government-funded (Medicare and Medicaid), Commercial, and Self-pay. Individuals spending their own money on healthcare are expected to be more price sensitive and more inclined to utilize price information, compared with those with health insurance. Hospitals offering lower costs are likely to attract these cost-conscious patients. We divide the data into subgroups based on the principal payer responsible for each patient's services, and then estimate equation (1) on each subgroup separately. The results are presented in Table 4. The findings indicate that the price transparency policy results in hospitals reducing their charges for self-paying patients by 11. 7%, as shown in Column (3) of Table 4, while no significant price reduction is observed for patients with health insurance. This supports our Hypothesis 1.3.

4.2.2 Heterogeneous Effects by Procedure Type. We proceed to test Hypothesis 1.4 by investigating the heterogeneous effect of price transparency on emergency versus elective procedures. In terms of elective procedures, such as hip or knee replacements, where timing is less critical and the procedure could be delayed, patients are more likely to shop around for the best prices, thereby intensifying competition among hospitals. As a result, elective procedures tend to face more competition than emergency procedures. We determine the type of services a patient is seeking based on the department where they received treatment. If a patient was treated in the facility's emergency department, we classify him/her as seeking emergency procedures. Conversely, if a patient was not admitted through the emergency department, we classify him/her as seeking elective procedures. The estimation results are reported in Table 5. The findings for both emergency and elective procedures were insignificant, failing to provide adequate support for Hypothesis 1.4. These findings bolster our confidence in the estimation that hospitals lower prices due to the policy, given that emergency services, which are not part of the mandated price-disclosure for shoppable services, should not exhibit any effect.

4.2.3 Heterogeneous Effects by Insurance and Procedure Type. When patients are both mindful of costs and capable of making decisions, they tend to compare prices and shift toward providers offering lower costs. This behavior puts pressure on hospitals to lower their charges to attract these price-sensitive patients. We further investigate whether hospitals will reduce charges more for self-pay patients who seek elective procedures (Hypothesis 1.5), given that these patients are cost-conscious and capable of informed decision-making. We constructed a 2 (Emergency vs. Elective) × 3 (Government-funded, Commercial, and Self-pay) subsamples for analyzing heterogeneous price reduction effects. The estimated results are reported in Table 6. The findings reveal that the price transparency policy resulted in a 24.9% reduction in charges for elective self-pay patients and a 6% reduction for emergency self-pay patients. No significant charge changes were observed for other patient groups. Notably, the reduction for elective self-pay patients is substantially larger than the overall charge decrease for self-pay patients, which is 11.7%, as shown in Column 3 of Table 4. Thus, Hypothesis 1.5 is supported.

4.3 Mechanism Analysis: Decomposing Charge Reductions

In this section, we investigate the underlying mechanisms through which the hospital price transparency policy leads to reductions in total hospital charges. Focusing on elective-self patients, we aim to test the two mechanisms proposed in Hypotheses H1.1 and H1.2 – namely, whether the observed

Table 6. Hospitals' behavior – treatment effect by insurance type + emergency vs. elective procedures.

	Emergency			Elective		
	(1) Government-Funded Log(Charges)	(2) Commercial Log(Charges)	(3) Self-pay Log(Charges)	(4) Government-Funded Log(Charges)	(5) Commercial Log(Charges)	(6) Self-pay Log(Charges)
Compliant	−0.029	−0.033	-0.060^{**}	−0.051	−0.070	-0.223^{**}
	(0.023)	(0.027)	(0.028)	(0.048)	(0.050)	(0.090)
Constant	11.273^{***}	11.228^{***}	11.025^{***}	11.381^{***}	11.226^{***}	10.692^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.855	0.836	0.771	0.790	0.833	0.659
Observations	1,540	1,540	1,540	1,540	1,540	1,540

Notes: Columns (1)–(3) use subgroups of patients admitted through emergency department, divided by insurance type: Government-funded, Commercial, and Self-pay, respectively. Columns (4)–(6) use subgroups of patients not admitted through emergency department, divided by insurance type: Government-funded, Commercial, and Self-pay, respectively. Columns (1)–(6) together show the results on testing Hypothesis 1.5. Standard errors clustered at hospital level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Main	Emergency	Elective	Gov-funded	Commercial	Self-pay	Emergency Gov-funded	Emergency Commercial	Emergency Self-pay	Elective Gov-funded	Elective Commercial	Elective Self-pay
Length of Stay	0.096	0.093	0.239	0.143	0.008	-0.221	0.038	0.123	-0.108	-0.114	0.400	-1.151***
Mortality	-1.028	1.543	-2.666	1.375	1.112	0.315	0.879	0.481	0.316	0.230	0.808	-0.019

Figure 3. Summary of estimation results for length of stay and mortality. Notes: The figure presents the estimation results of β in equation (1) with length of stay and mortality as dependent variables. The brightness of the colors reflects the magnitude of the coefficients. Post hoc power analysis for mortality shows 99% power, suggesting the insignificant results are not due to insufficient statistical power.

reductions in charges are driven by decreases in unit prices, reductions in the care complexity/intensity, or both.

We begin by examining changes in length of stay as an indicator of service intensity. To do so, we estimate equation (1) with length of stay and mortality as the dependent variables across all samples. Figure 3 shows that, for elective self-pay patients, the average length of stay decreased by 1.151 days. Meanwhile, mortality rates remained stable across all samples, suggesting that the policy did not adversely impact healthcare quality.

To further isolate the relative contribution of each mechanism, we conducted a patient-level analysis by decomposing total charges into unit charges and procedure complexity. This decomposition allows us to separately estimate the effects of compliance on unit pricing versus care complexity while still capturing their combined impact on overall charges. Specifically, we modeled total charges (TC) as the product of unit charges (UC) and service complexity (SC):

$$TC = UC \times SC$$

Taking the natural logarithm of both sides, we transformed this into an additive form:

$$ln(TC) = ln(UC) + ln(SC)$$

To measure service complexity, we use Medicare Severity Diagnosis-Related Group (MS-DRG) weights, which reflect the average resources required to treat specific inpatient cases.[6] Each DRG weight represents the relative intensity and expected costliness of a hospital stay, allowing us to proxy the complexity of care delivered. For each patient, we observe both their total charges and corresponding DRG weight. We calculate unit price by dividing total charges by the DRG weight, which enables us to decompose the overall charges into unit pricing and service complexity components.

We estimate the effects of hospital compliance on each of these three components–ln(TC), ln(UC), and ln(SC)–using the following specification:

$$Y_{i(j)t} = \alpha + \beta\ Compliant_{i(j)t} + \lambda_j + \mu_t + \epsilon_{i(j)t} \tag{2}$$

Table 7. Decomposing the reduction in total charges among elective self-pay patients.

	ln(Total Charges)	ln(Complexity)	ln(Unit of Charges)
β (Coefficient of Compliant)	−0.109***	−0.076***	−0.029
Standard Error	(0.041)	(0.021)	(0.034)

Notes: This decomposition analysis focuses on elective self-pay patients, a group in which we observe a decline in total charges. The table reports the estimated coefficients for β from equation (2). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8. Impact of price transparency rule on patients' behavior.

	(1) Admission	(2) Admission
ΔCharge × Compliant		−1.241
		(1.251)
Compliant	116.169*	30.387
	(64.695)	(62.052)
ΔCharge		10.327***
		(1.954)
Constant	3788.726***	3946.825***
	(3.109)	(31.389)
Year FE	Yes	Yes
Hospital FE	Yes	Yes
R-Squared	0.973	0.973
Observations	1,540	1,463

Notes: Columns (1) and (2) report the estimation results of equation (1) and (2), respectively. Column (1) shows the results of testing Hypothesis 2. Column (2) shows the results of testing Hypothesis 2.1. Standard errors clustered at hospital level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

where $Y_{i(j)t}$ denotes the natural logarithm of total charges ($\ln(TC)$), unit charges ($\ln(UC)$), or service complexity ($\ln(SC)$) for patient i admitted to hospital j at time t. The variable $Compliant_{i(j)t}$ equals 1 if hospital j was compliant with the price transparency regulation at time t, and 0 otherwise. λ_j and μ_t represent hospital and year fixed effects, respectively. Standard errors are clustered at the hospital level to account for serial correlation.

This decomposition allowed us to separately estimate the effects of compliance on unit charges ($ln(UC)$) and complexity ($ln(SC)$), while still capturing their combined impact on total charges ($ln(TC)$). The results of this analysis are presented in Table 7. The findings suggest that the observed reductions in total charges are primarily driven by reductions in service complexity, while unit charges remain largely unaffected. This provides support for Hypothesis H1.2.

Taken together, these results suggest that hospitals respond to the transparency mandate through both price and operational adjustments. The reduction in total charges for self-pay elective patients, combined with evidence of shorter length of stay and lower service complexity, points to a dual mechanism through which transparency reduces hospital charges.

5 Effects of Price Transparency Rule on Patients

5.1 Main Effect

In this section, we aim to investigate the impact of price transparency rule on patient's choices. First, we estimate equation (1) with total admission as the dependent variable and present the results in Column (1) of Table 8. The results show that hospitals that comply with the price transparency policy experience an increase in patient admissions, indicating a 4.35% increase (116.16 ÷ 2665.98) in patient inflow compared to non-compliant hospitals. This provides support for Hypothesis 2. We explore the mechanism behind the increased admissions by focusing on patient's behavior changes. If patients truly utilize the posted price information and choose hospitals based on lower costs, we should expect to see an increase in their price sensitivity following the hospital's compliance to the price transparency regulation. We test our hypothesis 2.1 – 2.4 by introducing an interaction term to our specification:

$$\begin{aligned} Admission_{it} = {} & \beta_0 + \beta_1 Compliant_{it} + \beta_2 \Delta Charge_{i(t-1)} \\ & + \beta_3 Compliant_{it} \times \Delta Charge_{i(t-1)} \\ & + \lambda_i + \mu_t + \epsilon_{it} \end{aligned} \tag{3}$$

Where $Admission_{it}$ represents the total patients admitted to hospital i at time t. $\Delta Charge_{i(t-1)}$ represents relative price level for hospital i at time $t-1$, calculated by subtracting the average charge of hospital i at time $t-1$ from the average charge across all compliant hospitals. This variable captures the difference between a hospital's price and the average price of hospitals that eventually comply with the policy. It is calculated using prices from the pre-treatment period only, and the reference group is defined as hospitals that become compliant at any point during the study window. The purpose of this variable is to assess whether hospitals that were already low-priced experience greater increases in admissions after becoming transparent. In the pre-treatment period, such relative pricing is unobservable to patients, and therefore is not expected to affect behavior. However, after compliance, if prices are disclosed, we would expect relatively lower-priced hospitals to attract more admissions.

We use the average charge of all compliant hospitals as a proxy for the price benchmark that can be observed by patients. If the $\Delta Charge_{i(t-1)}$ is positive, it indicates that hospital i's price is relatively lower than the market average at time $t-1$. The lagged value is used here to alleviate the concern about reverse causality. $Compliant_{it}$ is the treatment indicator that takes 1 if hospital i comply with the policy at time t and 0 otherwise. λ_i and μ_t are hospital and year fixed effects, respectively. The patient's price sensitivity change is captured by β_3.

Column (2) in Table 8 presents the estimation results for equation (2). The coefficient of $Compliant_{it} \times \Delta Charge_{i(t-1)}$ is not significant, suggesting that the difference in charge does not have a notable influence on the patient's choice, lacking sufficient support for Hypothesis 2.1.

5.2 Empirical Extensions: Exploring Patients' Price Sensitivity

The main findings in Section 5.1 suggests that patients are not recognizing the reduced charges and are not taking this information into account when making decisions. However, patients are able to shop around for providers with lower charge only when they (a) are cost-conscious, and (b) have the capacity to make decisions. We test Hypothesis 2.2, 2.3, and 2.4 by investigating the heterogeneous treatment effect on patient's price sensitivity.

5.2.1 Heterogeneous Effects by Insurance Type. First, we examine patients with varying levels of cost-conscious, determined by their insurance type. We divided the data into four subsamples based on insurance type: Government-funded, Commercial, and Self-pay, and proceeded to estimate equation (3). Given that patients without healthcare coverage are responsible for their own payments, we anticipate observing greater price sensitivity among self-pay patients. The estimation results are presented in Table 9. The results shows that $\Delta Charge \times Compliant$ is insignificant regardless of insurance types.

Table 9. Patients' behavior – treatment effect by insurance type.

	(1) Government-Funded Admission	(2) Commerical Admission	(3) Self-pay Admission
ΔCharge × Compliant	−0.417	−0.218	0.188
	(1.084)	(0.360)	(0.220)
Compliant	12.863	−25.231	26.104**
	(43.106)	(21.668)	(10.121)
ΔCharge	6.556***	2.139***	0.792***
	(1.207)	(0.497)	(0.273)
Constant	2578.315***	854.613***	242.643***
	(19.581)	(8.200)	(4.342)
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
R-Squared	0.970	0.972	0.938
Observations	1,463	1,463	1,463

Notes: This table report the estimation results for equation (2). Columns (1)–(3) use a subsample of patients with different insurance types: Government-funded, Commercial, and Self-pay, respectively. Columns (1)–(3) together show the results on testing Hypothesis 2.2. Standard errors clustered at hospital level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

5.2.2 Heterogeneous Effects by Procedure Type. Then, we look at patients with varying decision-making capacity levels. Patients experiencing emergencies, where immediate intervention is imperative to prevent death or serious harm, typically lack decision-making capacity. We segmented the data into two subgroups based on whether patients are admitted through emergency department. The estimation results are reported in Table 10. The coefficients of $\Delta Charge \times Compliant$ are insignificant. Thus, Hypothesis 2.2 and Hypothesis 2.3 lack sufficient support.

5.2.3 Heterogeneous Effects by Insurance and Produce Type. In this section, we assess the various levels of patient price sensitivity by considering both cost-consciousness and decision-making capacity. We use the same 2 (Emergency vs. Elective) × 3 (Government-funded, Commercial, and Self-pay) matrix in Section 4.2.3 to construct different scenarios patient facing. We estimate the equation (3) by using the subsamples and the results are reported in Table 11. The findings show that the interaction term $Compliant \times \Delta Charge$ is significantly positive for elective-self-pay patients, suggesting that after the disclosure of price information, hospitals with relatively lower charges see an increase in patient admissions. This confirms that patients are actively involved in price comparison when they are both cost-conscious and possess decision-making capacity. Consequently, they tend to choose hospitals compliant with regulations, given their more competitive pricing. Conversely, for patients in emergency situations,

Table 10. Patients' behavior – treatment effect by emergency vs. elective procedures.

	(1) Emergency Admission	(2) Elective Admission
ΔCharge × Compliant	−0.660	−0.575
	(1.147)	(0.545)
Compliant	−1.050	27.600
	(60.441)	(29.529)
ΔCharge	7.798***	2.532***
	(1.524)	(0.621)
Constant	2841.871***	1105.918***
	(24.623)	(9.787)
Year FE	Yes	Yes
Hospital FE	Yes	Yes
R-Squared	0.960	0.968
Observations	1,463	1,463

Notes: This table reports heterogeneous treatment effect on patient's decision by emergency and elective conditions. Columns (1) and (2) use the subsamples of patients who received treatment in the emergency department and those who did not, respectively. Columns (1)–(2) together show the results of testing Hypothesis 2.3. Standard errors clustered at hospital level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the charge does not significantly affect their choice of hospital following the policy implementation. Thus, our Hypothesis 2.4 is supported.

6 Robustness Checks

In this section, we present robustness checks to support our observed effects. A summary of these tests is presented in Table 12.

6.1 Additional Analysis for Addressing Endogeneity

While time-dependent PSM helps to reduce pre-treatment differences between treatment and control groups using time-varying covariates, it still subject to some limitations, such as sample reduction and dependence on observable covariates. In this section, we present further analyses to address self-selection bias in compliance. The outcomes of each robustness check are summarized in Figure 4.

6.1.1 Alternative Control Group. In this section, we conduct a robustness test using hospitals that complied with the policy in 2023 as an alternative control group. By using non-compliant hospitals who will comply in the near future, we can account for time-invariant unobserved characteristics and minimize pre-treatment differences between groups (Bapna et al., 2018). Price transparency reports were collected from the same NGO in February and July 2023, identifying 24 compliant hospitals. The estimation results are summarized in Figure 4 and detailed in Appendix A7.1. The results for both hospital and patient behavior are consistent, except for Hypothesis 1.3, where the observed charge reduction for self-pay patients, though negative, is not significant.

6.1.2 Subsample Analysis. To further address concerns that unobserved covariates might affect hospital compliance, we conducted a subsample analysis by focusing on hospitals where endogeneity bias is likely to be smaller. Specifically, we examined hospitals with a higher share of Medicare admissions, as Medicare payments follow a fully transparent schedule. This makes these hospitals less sensitive to revenue changes resulting from compliance decisions, thereby reducing endogeneity concerns. Using 2018 data, we calculated the Medicare admission share for each hospital and selected the top 50% based on this metric.[7] This yielded a subsample of 19 treated hospitals and 49 control hospitals, all of which had at least 54.6% of admissions covered by Medicare. The estimation results are summarized in Figure 4 and detailed in Appendix A7.2. The findings are consistent across both hospital- and patient-level outcomes.

6.1.3 Stabilized Inverse Propensity Weighting. Matching methods often face the limitation of losing observations due to pruning. Inverse propensity weighting (IPW) is considered an alternative for balancing treatment and control groups without discarding data (Azoulay et al., 2009; Robins, 1986); however, it can suffer from issues related to extreme weights (Cole and Hernán, 2008). To address this, we conduct a robustness check using stabilized inverse propensity weighting (SIPW), which helps to reduce the variance of the effect estimates (Chesnaye et al., 2022; Xu et al., 2010). Weight stabilization is calculated by replacing the numerator (typically 1 in the IPW) with the crude probability of treatment, represented by the proportion of compliant hospitals.

First, we estimate the propensity score for each hospital using the same set of covariates employed in traditional PSM (as detailed in Appendix A4.3). The stabilized weights are then calculated as follows: (proportion of compliant hospitals)/ propensity score for treated hospitals, and (proportion of non-compliant hospitals)/(1−propensity score) for control hospitals. We re-estimate equations (1) and (3) with the stabilized weights. The estimation results are summarized in Figure 4 and detailed in Appendix A7.3. The results align with our main analysis, except that using SIPW provides additional support for Hypothesis 1.4, showing that the policy's impact on reducing hospital charges is more pronounced for elective procedures.

6.2 Alternative Estimators for Staggered DiD: Addressing Temporal Heterogeneity

Hospitals complied with the policy at different times during the study period, raising concerns about potential heterogeneity in treatment effects over time (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020). To address

Table 11. Patients' behavior – treatment effect by insurance type + emergency vs. elective procedures.

	Emergency			Elective		
	(1) Government-Funded Admission	(2) Commercial Admission	(3) Self-pay Admission	(4) Government-Funded Admission	(5) Commercial Admission	(6) Self-pay Admission
ΔCharge × Compliant	−0.265	−0.050	−0.008	−0.149	−0.167	0.196*
	(0.904)	(0.306)	(0.159)	(0.489)	(0.232)	(0.105)
Compliant	−9.791	−19.706	10.243	19.974	−6.275	15.357***
	(41.146)	(17.667)	(9.758)	(24.026)	(10.635)	(4.099)
ΔCharge	5.047***	1.360***	0.639***	1.511***	0.781***	0.149*
	(0.981)	(0.366)	(0.214)	(0.391)	(0.210)	(0.078)
Constant	1932.243***	517.253***	199.076***	646.745***	337.576***	43.753***
	(16.019)	(5.996)	(3.463)	(6.244)	(3.504)	(1.221)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.957	0.940	0.924	0.962	0.975	0.850
Observations	1,463	1,463	1,463	1,463	1,463	1,463

Notes: This table reports estimation results of equation (2). Columns (1)–(3) use subgroups of patients looking for emergency procedures, divided by insurance type: Government-funded, Commercial, and Self-pay, respectively. Columns (4)–(6) use subgroups of patients looking for elective procedures, divided by insurance type: Government-funded, Commercial, and Self-pay, respectively. Columns (1)–(6) together show the results on testing Hypothesis 2.4. Standard errors clustered at hospital level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12. Summary of robustness tests.

Concern	Test	Finding	Location
Endogeneity in compliance	Traditional PSM	H1.3, H1.5 and H2.4 are supported	See discussion on Section 3.2.2 and Online Table A29–A36
	Alternative control group	H1.5, H2 and H2.4 are supported	Online Table A38–A45
	Subsample Analysis	H1, H1.3, H1.4, H1.5, H2 and H2.4 are supported	Online Table A46–A53
	Stabilized Inverse Propensity Weighting	H1.3, H1.4,H1.5, H2 and H2.4 are supported	Online Table A54–A61
Heterogeneous Treatment Effect over Time	Estimator proposed by Borusyak et al. (2024)	H1, H1.3, H1.4, H1.5 are supported	Online Table A62–A65
	Estimator proposed by Wooldridge (2021)	H1, H1.3 H1.4 H1.5 are supported	Online Table A66–A69
Whether the changes in patients' behavior are driven by the policy	Falsification check using alternative dependent variables (e.g., patient's composition, admission of patients who is not sole decision maker)	There is no significant changes in the alternative dependent variables	Online Table A70

this, we conducted robustness tests using two alternative estimators to ensure that any heterogeneous treatment effects did not bias our analysis. First, we applied the estimator proposed by Borusyak et al. (2024), a robust method designed for staggered D-i-D settings with heterogeneous effects. It constructs counterfactual outcomes using never-treated and not-yet-treated units, reducing bias inherent in traditional two-way fixed effects models. The results, summarized in Figure 4 and detailed in Appendix A8.1, support all of our hypotheses and show treatment effects similar to those found using TWFE estimators.

Second, we used the estimator from Wooldridge (2021), which demonstrates that in staggered adoption contexts, when treatment effects differ by cohort and time, the TWFE estimator can be reformulated as a pooled OLS regression. In this approach, unit fixed effects are replaced by cohort fixed effects and the treatment effects to vary across both cohorts and time periods. The results, summarized in Figure 4 and detailed in Appendix A8.2 are numerically consistent with Borusyak et al. (2024)'s estimator.

		Main	Emergency	Elective	Gov-funded	Commercial	Self-pay	Emergency Gov-funded	Emergency Commercial	Emergency Self-pay	Elective Gov-funded	Elective Commercial	Elective Self-pay
Hospital's Behavior	***TWFE Model***												
	PSM	-0.028	-0.029	-0.045	-0.033	-0.023	-0.098**	-0.026	-0.037	-0.041	-0.051	-0.044	-0.317***
	SIPW	-0.043	-0.046*	-0.081*	-0.038	-0.036	-0.163***	-0.041	-0.052	-0.086***	-0.038	-0.080	-0.308***
	TPSM	-0.033	-0.033	-0.055	-0.034	-0.021	-0.111***	-0.029	-0.033	-0.060**	-0.051	-0.070	-0.223**
	Alternative Control	-0.029	-0.008	-0.054	-0.036	-0.004	-0.052	-0.007	0.010	-0.012	-0.052	-0.024	-0.195*
	Sub-sample Analysis	-0.105***	-0.088**	-0.181*	-0.112***	-0.085**	-0.119**	-0.089**	-0.091**	-0.059	-0.208**	-0.175**	-0.438***
	Borusyak et al. (2021)												
	TPSM	-0.049**	-0.048**	-0.080**	-0.049**	-0.042**	-0.149***	-0.042**	-0.055**	-0.099***	-0.072*	-0.101**	-0.202**
	Wooldridge (2021)												
	TPSM	-0.049**	-0.048**	-0.080**	-0.049**	-0.042**	-0.149***	-0.042**	-0.055**	-0.099***	-0.072	-0.101**	-0.202**
Patient's Behavior	***TWFE Model***												
	PSM	-0.748	-0.204	-0.544	-0.117	-0.139	0.239	-0.005	0.037	0.049	-0.112	-0.175	0.189*
	SIPW	-2.186**	-1.006	-1.177	-0.985	-0.527	0.548	-0.294	-0.029	0.098	-0.688	-0.498	0.452*
	TPSM	-1.241	-0.660	-0.575	-0.417	-0.218	0.188	-0.265	-0.050	-0.008	-0.149	-0.167	0.196*
	Alternative Control	-0.549	-0.044	-0.505	0.050	-0.036	0.182	0.136	0.090	-0.005	-0.085	-0.137	0.190*
	Sub-sample Analysis	-0.950	0.313	1.721	2.352	-0.915	1.357	1.076	-0.261	0.152	1.267	-0.656	1.208**

Figure 4. Summary of estimation results. Notes: The first panel of the figure presents the estimation results of β in equation (1).The second panel of the figure presents the estimation results of β_3 in equation (3). The brightness of the colors reflects the magnitude of the coefficients. Estimators of Borusyak et al. (2024) and Wooldridge (2021) do not support interaction terms, thus are not applied in the analysis of patient's behavior. PSM stands for propensity score matching. TPSM stands for time-dependent propensity score matching. SIPW stands for stabilized inverse probability weighting. Alternative Control stands for analysis by using hospitals complied with policy in 2023. Subsample analysis stands for analysis by using hospitals with higher Medicare admission share. Standard error clustered at hospital level.

6.3 Falsification Checks on Hospital Admissions

Our finding in the main analysis show that the hospital price transparency rule influences patients' hospital selection decisions. If we capture the policy's causal impact on patient behavior, we would expect no changes in the composition of patients, as the policy affects individuals uniformly, regardless of race or gender. To investigate this, we specifically analyze whether there are shifts in the percentage of male patients and the percentage of white patients.

In addition, another check to assess whether patients are actively reacting to the hospital price transparency rule by opting for compliant hospitals is to look at the behavior of patients who do not make choices by themselves. In particular, we focus on the origins of patient admissions and conduct analyses on two subsamples: patients who admitted from the prison and patients who transferred from physician's office. First, incarcerated patients who were transferred to hospitals from the prisons, do not have the ability to choose their hospital. Often, choices are constrained by factors such as the jurisdiction of the court and agreements between the court system and specific healthcare facilities. Second, previous research indicates that patients typically adhere to the guidance provided by their referring doctors, who may not be cognizant of the individual cost consequences associated with their recommendations (Glied, 2021). We therefore should not expect to observe any changes in the behaviors of these two patient groups. The results in Table A70 in Appendix A9 give us confidence in our estimates by showing that we do not observe effects that we are not supposed to see.

Furthermore, to assess whether the observed reduction in MS-DRG weights among elective self-pay patients reflects changes in underlying clinical severity, we analyzed the impact of compliance on the Charlson comorbidity index (CCI), aggregated at the hospital level. Table A71 in Appendix A9.1 reports the results of this analysis. We find that compliance with the price transparency rule does not lead to a statistically significant decrease in patient mix. This suggests that hospitals did not experience a meaningful shift in the clinical severity of patients following compliance. Therefore, the observed reduction in treatment complexity, as captured by MS-DRG weights, is unlikely to be driven by broad changes in patient health status and may instead reflect other behavioral or operational responses.

7 Discussion and Conclusion

7.1 Summary and Discussion

In this research, we examine the effects of mandatory price disclosure policies on the pricing tactics employed by hospitals and the subsequent reactions of patients, by focusing on three research questions.

First, we explore *whether hospital transparency regulations effectively lower healthcare costs*. Our findings reveal that while hospitals do not significantly reduce charges across the board after complying with the price transparency mandate, thereby providing no support for Hypothesis 1, they do lower charges for patient who are sensitive to price and are able to shop around, supporting Hypotheses 1.3 and 1.5. Hospitals lack the incentive to reduce charges when patients are indifferent to costs or when hospitals are the predominant choice, such as in emergency situations where the nearest facility is the preferred option. This rationale could also apply to scenarios where patients with severe illnesses have limited options, relying on hospitals that offer the necessary services, or hospitals providing specialized services that may not be motivated to reduce charges.

Second, we examine *whether patients utilize pricing data to make informed decisions*. Our main results show that hospitals adhering to the regulation see an increase in patient admissions. This analysis is predicated on two essential assumptions: patients must be both aware of costs and capable of making informed choices. When patients are not directly responsible for costs, their likelihood of seeking price comparisons diminishes. Furthermore, even cost-sensitive patients find price information irrelevant if unable to compare costs prior to treatment. Our results indicate that the hospital price transparency rule exerts a more pronounced influence on self-pay patients who are seeking elective procedures. This group of patients are motivated to minimize their expenses and can make decisions, making them more inclined to choose hospitals with lower charges following the policy implementation, as proposed in Hypothesis 2.4. An interesting observation from our research is the compounding effect of both patients' will and choice. Our results indicate that the hospital price transparency rule manifests significant effects only if patients are both willing to reduce their costs (self-paying patients with price sensitivity) and have the choice to do so (through searching for lower prices for elective procedures). The utility of price information in promoting cost-effective decision-making depends on patients' awareness of costs and their capacity to make choices. Collectively, these findings imply that the presence of financial incentives is crucial for the policy's effectiveness, and its impact on patient behavior is heightened when patients are both conscious of costs and equipped with the ability to make decisions.

Third, our findings reveal nuanced consequences of the hospital price transparency policy, suggesting potential trade-offs between reduced prices and service quality. Specifically, for self-pay patients undergoing elective procedures, we observed a reduction in both the length of stay and the complexity of services, as measured by MS-DRG codes. While the reduction in complexity could be interpreted as hospitals shifting toward less resource-intensive services, it also raises concerns about potential declines in quality. These findings align with the idea that hospitals may adjust operational practices to lower costs in response to the policy. Importantly, while no changes in mortality rates were observed, the reduction in length of stay and complexity highlights the need for further examination of the policy's implications for quality outcomes. Future research should explore more granular indicators of quality, such as readmissions, to better understand the broader impact of price transparency on healthcare delivery.

7.2 Policy Recommendations

Our research offers important implications for policymakers, revealing that while price transparency has the capacity to foster market competition and reduce healthcare service costs, its impact is most pronounced for patients with "skin in the game." Self-paying patients seeking elective medical services have direct financial stakes in their healthcare choices and benefit significantly as hospitals adjust their pricing strategies to cater to consumers who actively make healthcare decisions based on price information. These findings emphasize the need for nuanced policy implementation, suggesting that to fully leverage the advantages of price transparency, policies should specifically support and encourage informed decision-making among patients who have a direct financial investment in their healthcare choices.

First, hospital price transparency policies prove to be significantly more effective in lowering costs for self-paying patients seeking elective medical services. This underscores the critical role of patient agency in efforts to manage the escalating costs of healthcare. Given this insight, we recommend that policymakers devise financial incentives for insured patients to encourage them to consider pricing as a key factor in their decision-making process when selecting a hospital for elective procedures. Such measures could broaden the impact of price transparency policies, ensuring they benefit a wider patient demographic by promoting cost-conscious choices across the healthcare spectrum.

Second, given the observed effects of price transparency, we advise policymakers to enhance its impact by broadening its availability and encouraging its more frequent use among patients. This objective could be achieved through various strategies, such as developing standardized, user-friendly templates for hospitals to use, thereby simplifying the process for patients to compare and contrast prices. Additionally, actively promoting the existence of these tools can significantly raise awareness among patients about their availability. Such initiatives would not only empower patients with the information needed to make informed decisions but also foster a more competitive healthcare market where transparency leads to better and more cost-effective patient choices.

Third, we recommend that policymakers closely monitor changes in patient outcomes following the implementation of the policy. Our findings indicate that hospitals may respond to reduced charges by reducing the length of stay and favoring less complex procedures.

Finally, policy efforts should extend to physicians who play an important role in shaping healthcare consumption decisions. To this end, policy initiatives could focus on providing physicians with enhanced tools that integrate cost considerations into clinical decision-making processes.

7.3 Limitations and Future Research

Our study is subject to certain limitations. First, we determine each hospital's compliance timeline with the price transparency policy using semi-annual reports from a non-governmental organization. This approach may not capture the exact timing of compliance, potentially affecting the precision of our analysis. Future research could benefit from more granular data sources or methodologies that pinpoint compliance more accurately, possibly through data with more frequent reporting periods, to gain a nuanced understanding of hospital compliance behaviors.

Second, our study is limited by the inability to fully address potential endogeneity in hospital compliance decisions. While we explored several approaches to mitigate this issue, including PSM, SIPW, and the use of future-compliant hospitals as an alternative control group, these methods rely on observed covariates and may not completely account for unobserved factors. As a result, the possibility of unobserved confounding remains a limitation of our study, which should be considered when interpreting our findings. One promising strategy for addressing this concern is to leverage policy heterogeneity across states. For example, states such as California (2006), Massachusetts (2012), and New Hampshire (2007) implemented their own price transparency rules well before the federal mandate took effect. In these contexts, compliance with the federal rule may have been driven by exogenous factors—such as existing infrastructure or regulatory alignment—rather than endogenous financial or operational considerations. Expanding the geographic scope of our analysis to include such states could both reduce concerns about selection bias and create opportunities to use state policy variation as an instrumental variable. However, our current dataset includes only Florida hospitals, which limits our ability to implement this approach. We view this as a promising direction for future research that could strengthen causal inference and improve external validity.

Third, given the modest overall compliance rate, our analysis is confined to a subset of Florida hospitals adhering to the regulation. Expanding the scope of research to include a broader array of hospitals as compliance rates increase would offer a more comprehensive view of the policy's impact across diverse healthcare settings. Incorporating alternative data sources could also extend the applicability of our findings to wider geographical areas, enhancing the generalizability of insights regarding the policy's effectiveness and its variability across different markets and hospital types.

Fourth, our estimation of patient price sensitivity and decision-making capacity is based on insurance type and medical urgency, respectively. Future investigations might employ more nuanced measures of price sensitivity, such as variations in insurance coverage, and refine assessments of decision-making ability by considering factors like chronic conditions.

Lastly, our study is limited by the inability to analyze readmissions, a key operational outcome closely monitored by hospital managers and regulators. Due to the lack of unique patient identifiers in our dataset, we are unable to track individual patients over time and identify readmission events. This limitation restricts our ability to explore an important indicator of healthcare quality, highlighting an area for future research if more granular patient-level data becomes available.

Acknowledgments

The authors sincerely thank the senior editor and the two anonymous reviewers for their constructive and thoughtful comments, which greatly improved the quality of this paper.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

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Supplemental Material

Supplemental material for this article is available online (doi: 10.1177/10591478251367520).

Notes

1. The definition of shoppable services from Centers for Medicare & Medicaid Services: https://www.cms.gov/files/document/steps-making-public-standard-charges-shoppable-services.pdf
2. The website of PatientRightsAvocate.org: https://www.patientrightsadvocate.org/
3. Our data collection encompasses the reports from July 2021, February 2022, and July 2022, which reviewed 500, 1,000, and 2,000 hospitals, respectively. The first report reviewed 49 hospitals in Florida, which accounted for 15.26% of the state's total hospitals. In the second report, 105 hospitals were reviewed, making up 32.71% of Florida's hospitals. By the third report, 127 hospitals had been reviewed, representing 39.56% of the total hospitals in Florida.
4. We recognize that using aggregate data at the hospital level may overlook variations in the number of observations across hospitals. Therefore, we have conducted additional robustness checks, detailed in Appendix A3.
5. Note that in our analysis, mortality is measured at the hospital-quarter level. Due to the extended observation period and the large size of the hospitals included, mortality is not a rare event in our dataset. Specifically, only 1.2% of the hospital-quarter observations report zero mortality, indicating that most hospitals experience at least one death within a three-month period. This distribution suggests that our dataset is adequately equipped to detect meaningful differences in mortality outcomes, should they exist.
6. MS-DRG Classifications and Software, CMS, https://www.cms.gov/medicare/payment/prospective-payment-systems/acute-inpatient-pps/ms-drg-classifications-and-software
7. We also implemented a more restrictive version of this approach by selecting the top 30% of hospitals based on Medicare share, in

which all hospitals had at least 62.0% Medicare admissions. The results are consistent.

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How to cite this article

Pan X and Yaraghi N (2025) From Hidden Fees to Open Books: An Empirical Examination of the Impact of Hospital Price Transparency Rule on Costs and Quality of Medical Services. *Production and Operations Management* xx(x): 1–20.