Exploring the Heterogeneous Effects of State Price Transparency Laws on Charge Prices, Negotiated Prices, and Operating Costs

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Abstract

To limit the strong growth of U.S. health care expenditures, some states have mandated that medical providers publicly report their charge prices. Our study evaluates the heterogeneous effects of this price transparency policy. We use a comprehensive database that covers more than 2,000 hospitals nationwide from 1996 to 2017. We employ a flexible generalized synthetic control method that allows for heterogeneous treatment effects. We find that the price transparency policy not only reduced charge prices by 3.9% (which corresponds to savings of $1,164 per hospital stay) but also diminished negotiated prices by 15.9% and hospital costs by 4.7%. Our estimation results show that the transparency laws have a shorter-(longer-)lasting impact on charge (negotiated) prices. We also find large heterogeneous responses across hospitals that depend on: (1) hospitals' past charge prices prior to adopting the price transparency law, that is, high-price hospitals reduce charge and negotiated prices, while low-price hospitals increase charges; (2) hospital characteristics such as ownership, case mix, and payer mix; and (3) hospital size and market competition. We also conduct counterfactuals to predict price changes of non-treated states and find large reductions in negotiated prices.
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1 Introduction

The United States has experienced a strong growth in health care expenditures and increasing charges for medical services (see Anderson et al. (2003), Cox and Kamal (2017), Papanicolas et al. (2018), Aouada, Brown, and Whaley (2019), and Christensen et al. (2020)).[1] Studies report that different hospitals charge substantially different prices, which are indicative of price dispersion and are often explained by a lack of hospital price disclosures.[2] To curb hospital prices, many states introduced transparency policies that mandate hospitals to publicly disclose charge prices. The aim is to provide opportunities for more effective competition and to steer patients toward lower-priced medical providers.[3]

While most research in this area evaluates the effects of charge price transparency policies on charge prices, relatively little is known about their effect on negotiated prices and hospital efficiency. Ongoing policy debates in this area confirm that we need further insight on this important topic. Our study puts special emphasis on the heterogeneous effects that charge price transparency policies exert on charge prices, negotiated prices, and hospital costs.

The drastic surge in health expenditures is concerning since it represents a large fraction of consumers' incomes and may, therefore, affect individuals' access to care—a concern that spans both uninsured as well as insured populations in the U.S. (see Berchick, Hood, and Barnett (2018)). Seminal studies report large price differences for comparable medical services, providing evidence of price dispersions. Medical charges to insurers and patients can differ across hospitals for several reasons. Hospitals provide different quality and they differ in their costs, their patients, and their mix of care, which can imply price differences (see Sorensen (2000), Jin and Leslie (2003), Hendricks et al. (2012), and Bronnenberg et al. (2015)). Moreover, hospital prices differ depending on market size and competition. For example, hospitals in more concentrated markets can negotiate higher prices with insurers (Dranove, Shanley, and White (1993)).

[1]Health care expenditures account for about 17% of gross domestic product.

[2]See, for example, Robinson (2011), Baker et al. (2013), Hsia et al. (2014), Pasalic et al. (2015), Whaley (2015a), Cooper et al. (2018), and White and Whaley (2019).

[3]In 2019, federal laws enforced by the Affordable Care Act pursue the same mandate (see Christensen et al. (2020)).

The topic of high charge prices and negotiated prices has received wide attention by policy makers, scholars, and politicians. These individuals have discussed various alternative policies (such as deductible controls, price controls, rationed care, etc.) to reform America's health care system and to reduce health care expenditures. Several states enacted charge price transparency policies starting in 2005. These policies mandate that medical providers report price information to state authorities. The intent behind these regulations is that information disclosures could help increase competition and market efficiency, leading to a reduction in prices and overall health expenditures. While most states adopted these information transparency policies, they are still controversially debated in public, and their effects are still widely unknown.

We empirically investigate heterogeneous effects of charge price transparency policies on charge and negotiated prices and on hospital costs. We use a large database covering U.S. hospital charges from 1996 to 2017. Our dataset includes more than 2,000 hospitals and more than 30 state-level charge price transparency policies. The data show that charge prices, negotiated prices, and qualities for the same medical services vary largely across insurers and health providers, locations, etc.

We employ a flexible generalized synthetic control method that estimates heterogeneous treatment effects across treated hospitals. Allowing hospitals to have heterogeneous treatment responses is critically important in our study, as our data show a large variation in prices. Using control group information from a flexible interactive fixed effects model allows for accommodating potentially endogenous treatments, multiple treated units, and treatment periods.

Our results provide evidence that price transparency laws have large heterogeneous effects on charge prices, negotiated prices, and operating costs across hospitals. Our estimation results show that charge price transparency laws reduce charge prices by 3.9% for a limited period of time. We find that government owned and not-for-profit hospitals reduce charge prices, which is similar to the results by Christensen et al. (2020). Charge prices also become more responsive to competition and decline further in more competitive local markets. After transparency laws are enacted, competition becomes effective and puts downward pressure on prices. So the policies provide greater clarity about competitor pricing.

We also find that charge prices can increase (relative to the average effect) for hospitals that are located in urban areas, that operate in more concentrated markets, and that are characterized by a larger capacity and a higher case mix index (CMI).

Interestingly, our results show that charge price reductions last only for around six years and then return to their original levels. The finding that negative charge price trends fade away after six years could be explained by two effects that work in opposite directions. In the shorter run, transparency laws could predominantly enforce competition, which puts downward pressure on charge prices. Over time, however, hospitals learn to diminish competitive pressure (and reestablish their tacitly collusive outcome), which brings charge prices back to their original levels.

Our results show even larger and longer-lasting impacts on negotiated prices paid by insurers to hospitals. We find that negotiated prices went down by 15.9%. The large price reductions apply especially to government and not-for-profit hospitals as well as to hospitals serving Medicare and Medicaid patients. Hence, transparency laws enable insurers to drastically reduce negotiated prices and to achieve savings in medical expenses.

Noteworthy is the fact that the charge price transparency law has a longer lasting impact on negotiated prices compared with the impact on charge prices themselves. This could be explained by the fact that hospitals engage with insurers in bilateral negotiations when determining negotiated prices. Hence, reverting negotiated prices to their original levels is more difficult for medical providers since these prices also depend on insurers and they have an interest to keep negotiated prices at lower levels. The large and long-lasting effects of transparency laws on negotiated prices result in large savings for payers (here, insurers), while they diminish reimbursements and revenues collected by hospitals.

The transparency laws also have a long-lasting impact on hospitals' operating costs, which decline by 4.7%. The cost reductions especially apply to system affiliated hospitals. Not-for-profit and teaching hospitals realize fewer cost reductions; the same applies to hospitals with larger stocks of Medicaid patients.

One interesting finding is that those hospitals that priced within the lower (higher) quantile of the price distribution prior to enacting price transparency laws increase (reduce) prices relative to the counterfactual of not adopting a price transparency policy. Hence, price dispersions become smaller. More specifically, we find that price and cost changes are dependent on whether hospitals originally priced high or low. In this regard, hospitals in the top quantile (that is, hospitals that originally charged high prices in 2004) reduce prices by 14.3% and 12.8% (relative to middle-distribution hospitals) for charge prices and negotiated prices, respectively. In contrast, hospitals in the bottom quantile (that is, hospitals that originally charged low prices) increase charge and negotiated prices (relative to middle-distribution hospitals) by 11% and 9%, respectively. It is interesting to note that more inexpensive hospitals would increase charge prices and negotiated prices. This finding may be explained by the earlier argument that price transparency can serve as a focal point for low-cost providers to match prices charged by high-price competitors. In general, it is a remarkable finding that hospitals react differently to the transparency law and change charge and negotiated prices depending on their location in the original price distribution.

Finally, we conduct counterfactuals and examine what impact the price transparency policy would have if it were adopted in states that have not adopted it yet. We find that the law would realize negotiated price reductions of up to 21%, suggesting large gains for insurers.

The paper is structured as follows: Section 2 provides information on transparency policies and related literature. Section 3 presents the data sources and descriptives. Section 4 outlines our empirical approach. Section 5 shows our results, while Section 6 concludes.

2 Transparency Policy and Literature Review

The charge price transparency policies initiated many debates that centered around the question of whether these policies are an appropriate instrument for reducing health expenditures. Proponents of the charge price transparency policy argue that competition in hospital markets is not effective, as undisclosed prices would not provide an opportunity to compare prices. The transparency policy publicizes prices and allows for price comparisons, which enforces competition. The transparency policy also asks medical providers to reveal hospital quality. Currently, there is incomplete information on the quality of medical treatments, which makes it difficult to compare services. In fact, patients may use price as a proxy for quality and, believing they will receive better treatment, choose a more expensive provider (see Hussey, Wertheimer, and Mehrotra (2013)). Moreover, hospitals have an opportunity to mimic high-quality providers and charge high prices. Overall, proponents argue that imperfect information on prices and quality result in large price dispersions, while price transparency policies provide opportunities to reduce prices and price dispersions (see Salop and Stiglitz (1977), Burdett and Judd (1983), and Siebert (2021)).

Opponents of the charge price transparency policy raise concerns that they could have the unintended consequence of facilitating tacit collusion between providers and, therefore, increase prices (see Cutler and Dafny (2011)). A related concern is that public prices would serve as reference prices that allow low-price hospitals to raise prices (similar to what happened when cement prices were published in Denmark, see Aouada, Brown, and Whaley (2019) and Albaek, Moellgaard, and Overgaard (1997) for further information). Disclosed charge prices could reveal proprietary information about privately negotiated contracts to competitors (see Roy (2012)). A further fundamental criticism is that charge prices are rarely used (by consumers, government, and insurers) for health payments; nearly all private medical claims are paid using negotiated prices. Negotiated prices are determined in private negotiations between hospitals and insurers and they can be very different from charge prices.[4] Aouada, Brown, and Whaley (2019) find that negotiated prices are set up to 60% below charge prices. Recognizing the limitations of the charge disclosure policies, interest groups have raised doubts about the usefulness and efficacy of these laws (see Iowa Hospital Charges (2014)).

In finding a consensus on the price transparency policies, interest groups have called for the publishing of charge prices rather than negotiated prices (see Reinhardt (2006)). Many

[4]Involved parties are often contractually forbidden from disclosing negotiated rates (see Whaley (2015b)).

parties consider the charge price transparency law a good starting point, and they also expect a reduction of negotiated transaction prices for several reasons. Most importantly, several studies have shown that negotiated prices are not necessarily independent of charge prices (see Cooper et al. (2018)). Along these lines, industry experts state that negotiated prices can be closely related to charge prices. Negotiated prices are considered negotiated discounts from charge prices that provide the initial, nondiscriminatory basis of all patient billings. Hence, charge prices can often serve as a reference price when hospitals and insurers determine negotiated prices.

In contrast, other parties would not expect charge price transparency to have an impact on negotiated prices, they believe that charge and negotiated prices are independent and hospitals can decouple charge prices from negotiated payments. Given that most medical services are effectively paid based on negotiated prices rather than charge prices, the question of whether the charge price transparency policy effectively reduced health care costs and payments appears to be of great policy significance.

There is a large literature showing that there can be significant price variations in markets such as health care (Brown (2019), Cooper et al. (2019)), automobiles (Goldberg and Verboven (2001)), and retail (Hitsch et al. (2019) and DellaVigna and Gentzkow (2019)). Theoretical studies have shown that large price dispersions can result from imperfect information on prices (see Stigler (1961), Diamond (1971), Rothschild (1974), and Salop and Stiglitz (1977)).

Several empirical studies examine the effect of price revelations via the internet and find that markets become more competitive and reduce prices (see Brown and Goolsbee (2002)). Other empirical studies focus on charge prices for hospital services (see Brill (2013), Bai and Anderson (2015), and Hsia et al. (2014)). Barrette and Kennedy (2016) and Whaley (2018) show that quality differences do not contribute much to explaining charge price variations.

Our study is most closely related to studies that investigate the effect of transparency laws. Whaley (2015a and 2015b) and Lieber (2017) found some evidence on payments (from transparency) and show that revelation policies allow some individuals to shop around for lower costs, while Whaley et al. (2014) and Desai et al. (2016) found rather negligible effects. Christensen et al. (2020) focused on five common medical procedures and found that price transarency laws (PTLs) cause hospitals to reduce charge prices by 5%. Charge price reductions are explained by reputational arguments—that is, nonprofit, state-owned, and church-affiliated hospitals face reputational costs from perceived overcharging, and this imposes institutional pressure to maintain fair pricing.

Only few studies evaluate the effects of transparency policies on negotiated prices. Christensen et al. (2020) found no impact on negotiated prices between providers and insurers. Whaley (2015b) focused on prices for laboratory tests and found that providers competitively respond to the price transparency and reduce negotiated prices by 3.4%. Brown (2019) focused on medical imaging procedures and evaluated the impact of transparency policies in New Hampshire. He distinguished between demand effects (customers) and supply effects (providers) and found that supply-side effects reduce price dispersion. He also found that the policy reduces patients' out-of-pocket costs by 5%. Overall, little (if not negligible) evidence is found that transparency policies result in significant payment reductions.

Several empirical studies in bargaining contexts consider negotiated prices between insurers and hospitals. Those studies highlight merger effects (Gowrisankaran et al. (2015)), hospital systems (Lewis and Pum (2015)), tiered hospital networks (Prager (2016)), and insurer competition (Ho and Lee (2017)). Most studies show that providers operating in concentrated markets may be able to negotiate higher prices with insurers (see Town and Vistnes (2001) and Gowrisankaran et al. (2015)).

Our study differs from prior studies in an important way. We evaluate the price transparency effect on charge prices, negotiated prices, and costs. Pertaining to the effect on negotiated prices and costs, prior research has provided very little insight. In comparison to other studies, we cover more states and more time periods, and we go beyond the focus of specific treatment areas. We also use a wide set of hospitals across the entire United States. We also utilize a different methodology versus earlier studies, which allows us to consider heterogeneous treatment responses across hospitals. This enables us to provide insights into which hospital and market determinants result in price reductions and price increases.

3 Data and Descriptives

We study the effect of state-level price transparency laws using a comprehensive panel dataset that contains information on acute care hospitals in the U.S. from 1996 to 2017. During the sample period, 31 states adopted the price transparency law, while 19 states were unaffected by the policy. (Around 62% of the hospitals have been affected by the law, while 38% were not.) Our unbalanced panel dataset includes about 2,000-2,500 hospitals each year. The hospital data is sourced from the Center for Medicare and Medicaid Services (CMS) and reflects hospital cost report information as reported to the Healthcare Cost Report Information System (HCRIS) by Medicare Administrative Contractors.[5]

We collected additional information on hospital-specific treatments using CMI information taken from Medicare impact files that are available for hospitals using the prospective payment system (PPS).[6]

We sourced hospital quality data for the years 2010-2017 from the Hospital Compare database. The data are especially useful when we control for price variations and decompose heterogeneous price responses by hospitals. Appendix A provides detailed information and explanations on the collection and cleaning of the data.

Our data shows considerable variation in states adopting the price transparency law and the time when states adopted price transparencies (also referred to as treatment). Figure 1 shows the states that adopted price transparency laws in dark blue and state that did not adopt the law in light blue.[7] Figure 2 highlights states' different price transparency law adoption times. We note that states adopted the price transparency law from 2005 to

[5] For additional information on our data collection, see: https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/?redirect=/CostReports/. Note that our data period covers two different Medicare cost reports: CMS-2552-1996 and CMS-2552-2010. We use CMS crosswalks to combine information from both reports.

[6] See also: https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Historical-Impact-Files-for-FY-1994-through-Present.html.

[7] Maryland is excluded from our analysis due to specific hospital pricing regulations, see Maryland Health Services (2019).

2013—mainly in 2007.

Table 1 presents summary statistics on prices, costs, and further hospital and market characteristics. Looking at the outcome variables of interest, the average inpatient charge price per discharge (referred to as charge price from now onward) is $28,128. The average non-Medicare payment as paid by the payers to the hospitals (referred to as the negotiated price) amounts to $9,208. The negotiated price is much lower than the charge price and explained by bargaining between medical providers and payers. This is a well-established institutional fact and consistent with previous studies. The associated standard deviations for the charge and negotiated prices ($19,341 and $4,892, respectively) are large and emphasize large price variations that could possibly result from price discrimination as well as heterogeneous hospital characteristics (such as quality differences) and market characteristics (such as differing concentration levels). The average total costs or expenditures of a hospital are around $218 million which corresponds to a daily cost of $5,733 per patient. The large standard deviation of the costs ($265 million) across hospitals is remarkable.

In order to provide further insights into price variations within local markets (as defined at the Hospital Referral Regions (HRRs)), we report standard deviations for charge and negotiated prices within HRRs, which are $10,822 and $3,844, respectively. Both price variations remain relatively high at the local market level. This provides support that price variations are prevalent in local markets, which could result from nontransparent price policies and heterogeneous hospital characteristics.

Turning to the hospital characteristics, Table 1 shows that 48% of hospitals are involved in teaching, 20% are for-profit hospitals, 65% are not-for-profit hospitals, and 15% are government owned. On average, a hospital uses 54% of its capacity, and 59% of the charges are related to Medicare and Medicaid.

Regarding market competition, the average Herfindahl-Hirschman Index (as measured in beds within a range of 20 miles) is 0.14. We also provide descriptives of hospital quality measures across (1) patient satisfaction, (2) readmissions, and (3) mortality rates. The readmission and mortality rates are assessed across cases with heart attacks, heart failures, and pneumonia.

Figure 3 shows the evolution of charge and negotiated prices over time for treated and untreated (control) states. Figure 3a shows that the average charge prices for treated and untreated hospitals have been increasing steadily over time, where the average charge prices of hospitals in treated states are higher than the ones located in untreated states. The figure also shows that the price variation of treated and untreated hospitals has increased dramatically over time. The price variation of treated hospitals is more pronounced compared to untreated hospitals, and it also increases more strongly over time.

Turning to the evolution of negotiated prices (see Figure 3b), the average negotiated prices are increasing over time for treated hospitals, though the negotiated prices increase only modestly after 2004. It is noteworthy that the spread between average prices of treated and untreated hospitals is much smaller compared to the spread of charge prices. The variation of negotiated prices is large but remains stable after 2004. The price variation (in comparison to the averages) is much smaller compared to the variation of charge prices.

Figure 4 shows hospital cost trends. Similar to charge prices, we see a trend of increasing average costs and cost dispersions over time. The average costs of treated hospitals are above those of untreated hospitals, while the difference in averages is relatively small. The overall cost variation is quite large for both groups, which is also shown in Table 1.

Next, we outline our empirical strategy for evaluating the effect of charge price transparency regulations on prices and costs.

4 Empirical Framework

Consider a hospital $i \in I$, in state $s \in S$, and period $t \in T$, with an average inpatient charge price per discharge given by P_{ist}. Each hospital has associated with it a binary indicator for treatment denoted by $W_{ist} \in \{0, 1\}$, where $W_{ist} = 0$ indicates that i is not treated (with a charge-price transparency regulation) in period t, while $W_{ist} = 1$ indicates that hospital i is treated in period t. Following the potential outcomes framework (see Neyman (1923), Rubin

(1974), and Rosenbaum and Rubin (1983)) the causal effect of treatment for hospital i is:

$$\tau_{ist} = P_{ist}(1) - P_{ist}(0), \tag{1}$$

where identification of the treatment effect follows from the treatment assignment, W_{ist}, being independent of the potential outcomes, $P_{ist}(W_{ist})$, when we condition on hospital specific observables X_{ist} along with a set of latent factor components, $\gamma_i^{'}\mathbf{f}_t$.[8] This is the standard unconfoundedness assumption of Rosenbaum and Rubin (1983), with the added easing of this assumption through the inclusion of unit and time specific factor components. Stated formally, our identifying assumption is:

$$\{P_{ist}(1), P_{ist}(0)\} \perp W_{ist} \mid X_{ist}, \gamma_i^{'}\mathbf{f}_t. \tag{2}$$

The problem that we are confronted with in equation (1) is that we only observe the realized prices $P_{ist}(W_{ist})$ when states are treated or not treated, but we do not observe the counterfactual prices if a treated state were not treated. As such, we need a procedure for estimating the counterfactual charge-price, $\hat{P}_{ist}(0)$.

We employ the generalized synthetic control method as proposed by Xu (2017). This method has a number of desirable features. First, unlike the traditional difference in difference method, this method does not require any parallel trends assumption. Second, it can accommodate multiple treated units and varying treatment periods, which is a characteristic of our dataset. Moreover, this approach employs the Bai (2009) interactive fixed effects (IFE) specification, which provides added flexibility in terms of its specification, its amelioration of the unconfoudnedness assumption (as noted above), and its ability to accommodate cross-sectional dependence within the data – a particularly important concern in our application.

The generalized synthetic control method brings together the synthetic control method by Abadie, Diamond, and Hainmueller (2010, 2015) with the linear IFE model of Bai (2009).

[8]It should be noted that the factor components, $\gamma_i^{'}\mathbf{f}_t$, nest traditional fixed effects as a special case (see Bai (2009)).

Eberhardt et al. (2013) show that including factor structures help ameliorate concerns related to endogeneity issues caused by omitted variables, accommodate serial and cross-sectional correlations in the residuals, and reduce concerns about possible biases from mis-measurement of control variables.

On an additional note regarding potential endogeneity issues (on the price transparency dummy), it seems unlikely that endogeneity issues enter the regression equation since prices are related to the hospital level, while decisions on the transparency laws are made at the state level. Nevertheless, we provide data descriptives on observables to see if there are fundamental and systematic differences between treated and untreated states, which our data do not confirm. There certainly is a remaining concern that unobservables exert direct impacts on prices and the treatment decisions. We, therefore, adopt the generalized synthetic control method and allow for hospital and time fixed effects that are interacted with each other. Those interacted fixed effects will absorb any remaining unobserved correlations between prices and the dummy variable.

Our IFE specification is given by:

$$P_{ist} = \delta_{ist} PTL_{st} + \beta x_{ist} + \gamma_i^{'} \mathbf{f}_t + \epsilon_{ist}, \tag{3}$$

where PTL is a dummy variable that takes on a vale of one if a state was treated and the price transparency regulation was adopted, x denotes other controls and $\gamma_i^{'} \mathbf{f}_t$ represents the interacted factor components. It is worth noting that the current model nests standard time and unit fixed effects as a special case. We now turn to explaining the estimation of the parameters and factor components as shown in equation (3), along with details on the imputation of counterfactuals for treated units.

4.1 Estimation Implementation

We adopt the generalized synthetic control approached by Xu (2017) using an IFE specification as suggested by Bai (2009) to estimate the treatment effects on the treated hospitals ($\hat{\tau}_{ist} = P_{ist}(1) - \hat{P}_{ist}(0)$) from equation (3). As such, we proceed in four steps to obtain an estimate for the average treatment effect on the treated (ATT), where the first three steps explain how we obtain an estimate for each treated hospital's counterfactual outcome ($\hat{P}_{ist}(0)$).

First, we estimate the IFE model using only the hospitals in the control group (co) denoted by the set $\mathcal{C}$:

$$(\hat{\beta}, \hat{F}, \hat{\Lambda}_{co}) = \underset{\hat{\beta}, \hat{\mathrm{F}}, \hat{\Lambda}_{\mathrm{co}}}{\operatorname{argmin}} \sum_{i \in \mathcal{C}} \left(P_i - X_i \tilde{\beta} - \tilde{F} \tilde{\lambda}_i \right)' \left(P_i - X_i \tilde{\beta} - \tilde{F} \tilde{\lambda}_i \right) \tag{4}$$

$$\text{s.t.} \qquad \tilde{\mathrm{F}}' \tilde{\mathrm{F}} / \mathrm{T} = \mathrm{I_r} \text{ and } \tilde{\Lambda}'_{co} \tilde{\Lambda}_{co} = \text{diagonal}, \tag{5}$$

where F and Λ_{co} (and λ) contain the latent factor components $\mathbf{f}_t$ and γ_i, respectively, as their elements. P_i and X_i are matrices that contain P_{ist} and x_{ist}, respectively. I and *diagonal* refer to unity and diagonal matrices and r refers to the number of factors.

Given estimates for $(\hat{\beta}, \hat{F}, \hat{\Lambda}_{co})$, we next estimate factor loadings for each treated unit by minimizing the mean squared error of the predicated treated outcome in the pretreatment periods:

$$\tilde{\lambda}_i = \underset{\tilde{\lambda}_{\mathrm{i}}}{\operatorname{argmin}} \left(\mathrm{P_i^0} - \mathrm{X_i^0} \hat{\beta} - \hat{\mathrm{F}}^0 \tilde{\lambda}_{\mathrm{i}} \right)' \left(\mathrm{P_i^0} - \mathrm{X_i^0} \hat{\beta} - \hat{\mathrm{F}}^0 \tilde{\lambda}_{\mathrm{i}} \right) \tag{6}$$

$$= - \left(\hat{F}^{0'} \hat{F}^0 \right)^{-1} \hat{F}^{0\prime} \left(P_i^0 - X_i^0 \hat{\beta} \right), \quad \forall i \in \mathcal{T},$$

where the zero superscript denotes pre-treatment period data, and $\mathcal{T}$ is the set of all treated units.

Third, we compute counterfactuals for the treated hospitals using the estimates $(\hat{\beta}, \hat{F})$ from the first step, and $(\tilde{\lambda}_i)$ from the second step, that is,

$$\hat{P}_{ist}(0) = \delta_{ist} PTL_{st} + \beta x_{ist} + \hat{\lambda}_i' \hat{\mathbf{f}}_t. \tag{7}$$

Given the counterfactuals for the treated hospitals, we obtain the treatment effect on the treated as:

$$\hat{\tau}_{ist} = P_{ist}(1) - \hat{P}_{ist}(0), \quad \forall t > T_0, \tag{8}$$

where T_0 denotes the period of treatment. Average treatment effects on the treated at a state level are calculated by averaging across hospitals within a state s:

$$\widehat{ATT}_{ts} = \left(\frac{1}{N_s^{tr}}\right) \sum_{i \in \mathcal{T}_s} \left(\hat{P}_{ist}(1) - \hat{P}_{ist}(0)\right), \quad \forall t > T_0, \tag{9}$$

where N_s^{tr} denotes the number of treated units within the state, and $\mathcal{T}_s$ is the set of all such treated units.

Similarly, the average treatment on the treated at the national level is calculated by averaging across states:

$$\widehat{ATT}_{t} = \left(\frac{1}{N^{tr}}\right) \sum_{i \in \mathcal{T}} \left(\hat{P}_{ist}(1) - \hat{P}_{ist}(0)\right), \quad \forall t > T_0. \tag{10}$$

4.2 Factor Model Selection

The formulation of equation (3) assumes the researcher knows the number of factors to include within their model specification. In practice, however, we do not know the optimal number of factors. Hence, we determine the number of factors employing the leave-one-out-cross-validation approach used by Xu (2017). This approach builds on determining a set of candidates for the factors and looping through pre-treatment periods while at each iteration one data period is being dropped. At each iteration, the omitted (or left-out) outcome is then predicted. Once the loop is completed, the mean squared prediction error (MSPE) is computed for the entire model. This procedure is repeated for different choices of factors and ends with the selection of factors that yield the lowest MSPE.

The procedure is summarized by the following steps:

Step 1 For a predetermined number of factors r, we estimate an IFE model using control group data $\{P_i, X_i\}_{i \in \mathcal{C}}$. This yields the coefficient estimates $(\hat{\beta}, \hat{F})$.

Step 2 We perform a cross-validation loop for each of the pretreatment periods $t < T_0$ using the treated sample. For each pretreatment period, we hold back the pretreatment data that belong to the period and predict the outcome for the period (e.g. charge price) for each hospital ($\forall i \in \mathcal{T}$). Using the prediction, we compute the prediction error.

Step 3 Given all prediction errors that result from each of the cross-validation iterations, we compute $MSPE(r) = \sum_{k=1}^{T_0} \sum_{i \in \mathcal{T}} e_{ik}^2 / T_0$.

Step 4 We repeat steps 1-3 for each set of factors (r) and select the optimal number of factors based on: $r^* = \underset{\text{r}}{\text{argmin}}\ MSPE(r)$.

4.3 Decomposition of Average Treatment Effects on the Treated

In order to learn more about which characteristics drive hospitals' treatment responses, we run the following regression:

$$\widehat{ATT}_{ist} = \alpha + \beta x_{ist} + \phi_s + \gamma_t + \epsilon_{ist}, \tag{11}$$

where x_{ist} again captures hospital characteristics, ϕ_s denotes state fixed effects and γ_t captures year fixed effects. Hence, we evaluate how the treatment effects vary with hospital characteristics, such as ownership type, location (urban vs. rural), teaching status, payer status, capacity, quality, and competition. Remember, we measure competition at the market level using the Herfindahl-Hirschman Index (HHI) defined at a 20-mile radius.[9] We also control for potential differential treatment responses based on each hospital's price prior to being treated. We are especially interested in testing for asymmetric price adjustments after treatment depending on whether hospitals originally charged high or low prices. Hence, we control for higher (lower) priced hospitals that charged prices in the top (bottom) quantile of the local price distribution prior to being treated.

5 Estimation Results

This section is structured as follows: Subsection 4.1 presents the main estimation results, that is, the average treatment effects on the treated considering hospital charge prices, negotiated prices, and their total expenditures or costs. The results for the cross-validation approaches

[9] The HHI is constructed using market shares based on hospital bed counts.

and the factor loadings are relegated to Appendix B. Subsection 4.2 provides estimation results for heterogeneous treatment effects along hospital, quality, and competition measures. Subsection 4.3 reports the counterfactual results that relate to the estimation of treatment effects across untreated states.

5.1 Average Treatment Effects on the Treated

The average treatment effects on the treated at the national level and across all post-treatment periods are shown in Table 2. The upper entry of Panel A in Table 2 reports a charge price reduction by 3.9%, which corresponds to a savings of $1,164 per hospital stay. This effect is significant at the 90% level. The lower entry of Panel A shows that the charge price dispersion contracted by 4.3% within local hospital referral regions. This effect is also significant at the 90% level. The estimation results provide evidence that the charge price transparency regulation has a modest price reducing effect at the national level and also diminishes price variations in local markets.

Figures 5a and b illustrate the corresponding evolution of the Average Treatment Effects on the Treated over time, where zero refers to the period when the policy was enacted. The upper Figure 5a shows that the ATT turns negative in the year leading up to the treatment, suggesting that hospitals preemptively adjust their charge prices prior to when the price transparency law becomes effective. The negative ATT persists (significantly at the 95% level) for about 6 years. During these 6 years, the realized average charge prices are consistently between 4% and 5% lower than the estimated counterfactual charge prices. The negative impact is discontinues after 6 years when charge prices return to pretreatment levels. The fact that the negative charge price trends fade away after six years could be explained by the two contrasting theories introduced earlier: Remember, the one theory suggests that transparency laws enhance competition and reduce prices, while the other theory suggests that the transparency laws facilitate tacit collusion and increase prices. Our result—price reductions fade away after some time—could be explained by an initial predominant impact of price transparency on charge prices that enhances competition. Over time, however, hospitals learn to diminish competitive pressure (and reestablish their tacitly collusive outcome), which brings charge prices back to their original levels.

Figure 5b shows similar trends for the ATT on the local charge price dispersion. Standard deviations of average charge prices were reduced by between 5% to 10% in the first 4 years post treatment. After 4 years, the price dispersion returns to the pretreatment levels.

Panel B of Table 2 shows the estimation results pertaining to negotiated prices. The transparency regulation has a much larger effect and reduces negotiated prices on average by 15.9%. Hence, charge price transparency regulations imply higher bargaining power to insurers and away from hospitals, which would explain the large reduction in negotiated prices. The regulation also diminishes the dispersion of negotiated prices by 11.9%. Noteworthy is the fact that the charge price transparency law exerts a larger and longer lasting impact on negotiated prices compared to charge prices themselves. This could be explained by the fact that hospitals are engaged in bilateral negotiations with insurers when determining negotiated prices. Hence, reverting negotiated prices to their original levels is more difficult here since insurers have an incentive to keep negotiated prices at lower levels. The large and long-lasting effect on transparency laws on negotiated prices is especially relevant since those are primarily used for payments for hospital treatments. Therefore, transparency laws can result in large savings for payers (here, insurers) and diminish reimbursements and revenues collected by hospitals.

Figures 6a and b show that the level and dispersion of the negotiated prices decline over time. Remarkable is the finding that the negative effect on negotiated prices lasts throughout the entire time period and does not revert to pretreatment levels. Hence, post-treatment effects on negotiated prices have a long-lasting impact. The long-lasting downward pressure on negotiated prices exerts high pressure on hospitals as diminished negotiated prices result in lower revenues. This suggests that hospitals experience high pressure to become more efficient and to reduce their costs. Therefore, we also explore the effect that charge price transparency regulations exert on hospital costs.

Panel C of Table 2 shows that charge price transparency laws have a cost saving effect on hospitals, as average costs decline by 4.7%. The cost savings could be explained by the large reduction in reimbursements (negotiated prices) that forced hospitals to become more efficient in order to compensate for revenues losses. Figure 7 depicts a persistent downward trend in terms of total costs after the transparency law. It is worth nothing that that these downward trends persist 8 to 10 years after treatment, and show no indication of a reversal trend to pretreatment levels. Hence, post-treatment efficiency gains generated by hospitals are longer lasting.

5.2 Decomposition of Average Treatment Effects on the Treated: Heterogeneous Treatment Responses

Having estimated considerable price and cost changes, we now decompose these changes to gain more insights about heterogeneous treatment effects across hospitals and markets. We estimate equation (11) while controlling for several characteristics that may exert an impact on the treatment effect. More specifically, we control for the hospitals' past charge prices along the charge price distribution in the hospital referral region prior to enacting the price transparency law (that is, in 2004). We also control for several hospital characteristics, competition, factor inputs, and quality.

Table 3 presents the results. Column (1) reports the heterogeneous effects on charge prices. The results show that hospitals' past price (that is, their original position within their local market price distribution) has a strong effect on explaining price changes after enacting the price transparency law. In particular, hospitals that original priced high (in the top quantile of the price distribution) reduced their charge prices by an additional 14.3% compared to other hospitals that priced in the middle of the price distribution. This could be explained that transparency laws reveal to these medical providers that they charge relatively high prices compared to their competitors, which could motivate a price reduction.

In contrast, hospitals that originally chose low charge prices (in the bottom quantile of the price distribution) increase their charge prices by 10.7% relative to other hospitals that priced in the middle of the price distribution. Hence, low charging hospitals use the transparency law as an opportunity to adjust their prices to a higher level. Hence, transparency laws reveal to these providers that they can charge more. This result is interesting and somewhat surprising, as one would expect that price transparency would impose downward pressure on prices such that prices adjust to a minimum. However, this is not the case here where low price hospitals are able to increase prices. The ability to adjust price could be explained by the fact that efficient hospitals recognize that they could charge a larger markup. The price increase could also be explained by the fact that quality is difficult to observe and low quality hospitals use the transparency policy as an opportunity to increase price relying on quality being imperfectly observed.

Interesting is also the fact that the price adjustment from the upper and lower quantile is asymmetric, that is, hospitals that price high further reduce prices compared to hospitals that price low and react with a price increase.

Turning to the impact of hospital characteristics on the charge price effects (still column (1) of Table 3), our results provide evidence for several hospital characteristics having a significant impact on explaining heterogeneous treatment effects. First, government owned and not-for-profit hospitals further reduce charge prices, which is similar to the result by Christensen et al. (2020). Second, hospitals in urban areas, hospitals characterized by higher case mix indices, and larger hospital (as measured by beds) further increase charge prices. Third, higher market concentration (defined on the basis of a hospital specific 20 mile radius) is associated with significantly higher charges. Hence, hospitals operating in more competitive markets further reduce charge prices as a response to the price transparency law. Finally, hospitals with higher patient quality ratings further reduce charge prices. However, the effects pertaining to hospital quality (as measured by readmission rates across AMI, HF and PN) are economically weak and inconclusive.

We turn to reporting the heterogeneous treatment effects on negotiated prices as shown in column (2) of Table 3. The estimation results show that past prices (prior to enacting the transparency law) significantly explain the changes of negotiated prices post treatment. Hospitals that charged higher prices in the past (located in the top quantile of the local price distribution) reduce negotiated prices by an additional 12.8% relative to hospitals that priced in the middle of the price distribution. Those hospitals that originally priced low increase their prices by 8.8% (compared to hospitals that priced in the middle of the price distribution). The asymmetric price reactions is similar to the heterogeneous effects on charge prices, although the overall effect is here to reduce prices (across all hospitals), albeit in heterogeneous ways. Moreover, hospitals in the upper part of the distribution further reduce charge and negotiated prices when compared to those hospitals in the lower part of the price distribution that increase charge and negotiated prices. Remember, however, that the average treatment effect on negotiated prices was much higher than the impact on charge prices (15.9% versus 3.9%) and longer lasting as mentioned in the earlier section.

Government owned and not-for-profit hospitals further reduce negotiated prices, while hospitals with a higher CMI increase negotiated price (similar to the results on charge prices). We find that hospitals with larger populations on Medicare and Medicaid patients further reduce negotiated prices. Hence, hospitals with a larger public patient makeup (in terms of Medicare and Medicaid patients) respond to transparency regulation with a relatively larger price reduction than other hospitals, a result that is in line with Christensen et al. (2020). Note that competition has no significant effect on explaining heterogeneous responses in negotiated prices.

Turning to the decomposition of the ATTs on total costs (see column (3)), we do not find evidence that past prices have an impact on explaining cost changes post treatment. This result sounds reasonable since a dominant strategy for every hospital, independent of its location in the price distribution, should be the reduction of costs. We also find larger cost reductions (post transparency law) for system affiliated hospitals. This finding could be explained by system affiliated hospitals benefiting from more efficient administrative procedures and larger bargaining power when purchasing capital and material inputs. Finally, we find lower (overall) cost responses by not-for-profit and teaching hospitals, as well as hospitals with higher populations of Medicaid patients. Again, we note that competition has no significant effect on explaining differential cost responses.

We applied further robustness checks and conduct separate regressions for hospitals that price high and low prior to the transparency law. These regressions would provide a test for differential behavioral responses by hospitals. The estimation results (shown in Table 4) very closely replicate our results from Table 3.

5.3 Counterfactual: Average Treatment Effects of Untreated

As part of a secondary counterfactual analysis, we are interested in assessing the potential impact of the charge price transparency regulation on untreated states.

Optimal Policies For Treatment Allocation

We formulate a policy function, π, that maps hospital characteristics, X_i, into a treatment decision, W_i, as described by the following equation:

$$\pi : X_i \rightarrow W \in \{0, 1\}. \tag{12}$$

Given a set of such policies, Π, the optimal policy function π^* maximizes the expected payoff of the policy:

$$\pi^* = \underset{\pi \in \Pi}{\arg\max} E\left[P_i\left(\pi\left(X_i\right)\right)\right]. \tag{13}$$

The policy function, $\pi\left(X_i\right)$, assigns treatment based on the hospital characteristics X_i. The treatment decision whether or not to enact price transparency regulation is operationalized by finding the $\pi \in \Pi$ that maximizes the function $V(\pi)$, where:

$$V\left(\pi\right) = \frac{1}{n}\sum_{i \in N}\left(2\pi\left(X_i\right) - 1\right)(-1)\hat{\tau}_i. \tag{14}$$

where $\hat{\tau}_i$ denotes our estimated hospital specific treatment effect from the price transparency law. Using this payoff, we assign treatments to hospitals and average the effects over all hospitals within a state in order to assess the average counterfactual state-level policy effect. This allows us to evaluate states that would (and would not) benefit from charge price transparency regulations, assuming the objective is to reduce prices.

Counterfactual Treatment Effects

Using the heterogeneous treatment effects model (see Subsection 5.2), we predict counterfactual treatment effects for the untreated states within our sample in 2014.[10] Therefore, we use the following regression model:

$$\widehat{ATT}_{ist} = \alpha + \beta x_{ist} + \epsilon_{ist}, \tag{15}$$

to estimate the parameters $\hat{\theta} = (\hat{\alpha},\ b\hat{e}ta)$ using data on the treated states. We next use these parameters to impute hospital specific treatment effects within the untreated group as:

$$\widehat{ATU}_{jst} = \hat{\alpha} + \hat{\beta} x_{jst}. \tag{16}$$

Having obtained the predicted $\widehat{ATU}_{jst}$ values for the untreated hospitals, we average over all hospitals within a given state in order to obtain the state level average treatment effect on the untreated,

$$\widehat{ATU}_{ts} = \left(\frac{1}{N_s^U}\right) \sum_{j \in \mathcal{U}_s} \left(\widehat{ATU}_{jst}\right), \quad t = 2014. \tag{17}$$

where U_s stands for the set of untreated hospitals in a state.

The resulting state specific estimates are displayed in Figure 8.[11] The figure shows that charge price transparencies result in higher, rather than lower, average charges if enforced upon untreated states. The state-specific treatment effects reflect average charge price increases between 6% and 23%. These predictions suggest that universal application of price transparency may not be favored if the end goal of such transparency is to put downward pressure on existing charge prices.

Lastly, Figure 9 presents the counterfactual treatment effects for untreated states with regard to negotiated payments. Here, the counterfactual treatment predictions range between no change all the way to a potential 21% reduction in average negotiating prices. These findings seem to align with our main results, suggesting broad potential gains on negotiated

[10] We focus on 2014 as that is the first full year when all treated states have been treated, however, we find similar results using other years instead (e.g., 2015, etc.).

[11] These results naturally rest on the strong assumption that $ATT = ATE = ATU$.

prices for insurers in the presence of price transparency.

6 Conclusion

Price transparency laws aim at reducing prices and health expenditures. The introduction of price transparency laws was considered controversial and several concerns have been raised. First, opponents were concerned that transparency laws could result in price increases since they provide opportunities to collude and serve as an instrument to set reference prices (or anchor prices) that other providers would adjust to. Second, price transparency laws focus on publicizing charge prices only. However, medical treatments are usually reimbursed on the basis of negotiated prices. Those negotiated prices are the result from bargaining processes between medical providers and payers. They usually lie below charge prices and are kept confidential. The question arises if price transparency laws have any impact at all on negotiated prices and health expenditures.

We empirically investigate heterogeneous effects of charge price transparency policies on charge and negotiated prices and costs. Based on a large database that encompasses U.S. hospital charges from 1996 to 2017, we find large variations of charge prices, negotiated prices, qualities, and competition across hospitals. We employ a flexible generalized synthetic control method that allows for flexible interactive fixed effects. Our estimation results provide evidence that price transparency laws can have large average effects on charge prices, negotiated prices, and total costs. The effects on charge prices are smaller compared to the ones on negotiated prices. Moreover, the effects on negotiated prices and total costs last longer than the effects on charge prices. This finding suggests that insurers can use price transparency laws to their advantage in price negotiations with hospitals. Overall, transparency laws cause price reductions (especially for negotiated prices)

We also find that past prices (before the transparency law was enacted), hospital characteristics and competition can strongly contribute to explaining heterogeneous treatment effects. Those hospitals that charged higher prices (prior to the transparency law) further reduce charge and negotiated prices. Interestingly, hospitals that charged lower prices increase charge prices. This finding is contrary to the expectation that transparency laws would impose downward pressure on price throughout and result in a minimum price (and possibly a uniform price). Instead, price transparency laws can provide opportunities for hospitals to match competitors and increase prices charged. This could be explained by quality being imperfectly observed and some low-quality hospitals seeing the price transparency law as an opportunity to match other prices.

We also find large heterogeneous price and cost reductions that depend on hospital and market characteristics. For example, public and not-for-profit hospitals are found to further reduce charge and negotiated prices, while not-for-profit and teaching hospitals experience a lower cost reduction.

For future research, it would be interesting to further explore price adjustments from the upper and lower quantile of the price distribution prior to adopting the transparency law. Especially remarkable were the heterogeneous price responses, that is, hospitals in the upper quantile reduced prices charged while hospitals in the lower quantile were able to increase prices charged. It would be interesting to explore the reasons why more inexpensive hospitals increased charge prices. Potential arguments could be that those hospitals collude or those hospitals provide low quality, which is imperfectly observed while price transparency provides opportunities to match average prices.

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Figures

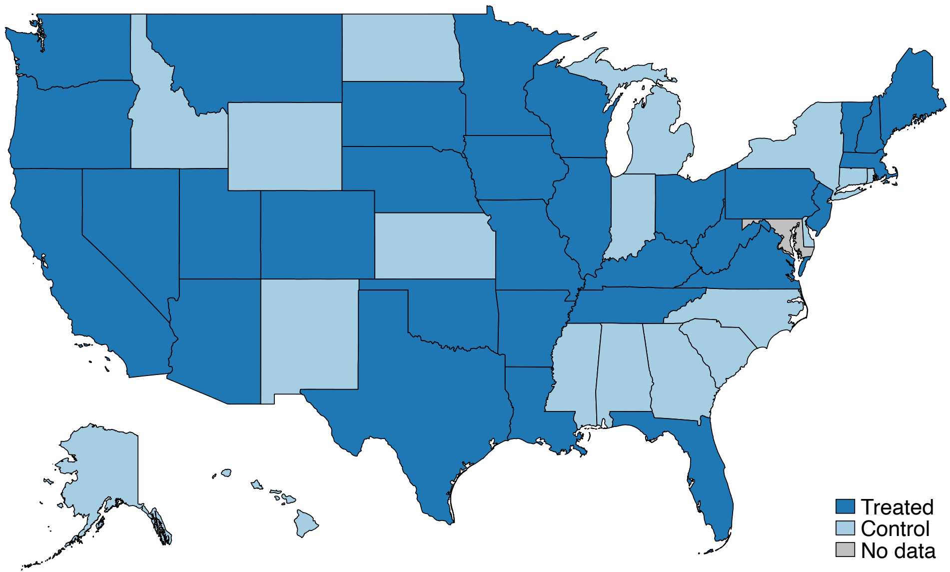


Figure 1: Adoption of Price Transparency Laws: Treated Vs. Untreated States

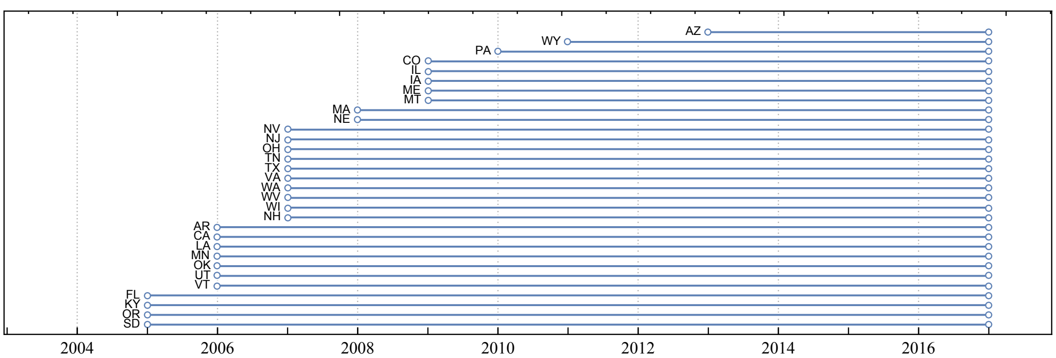
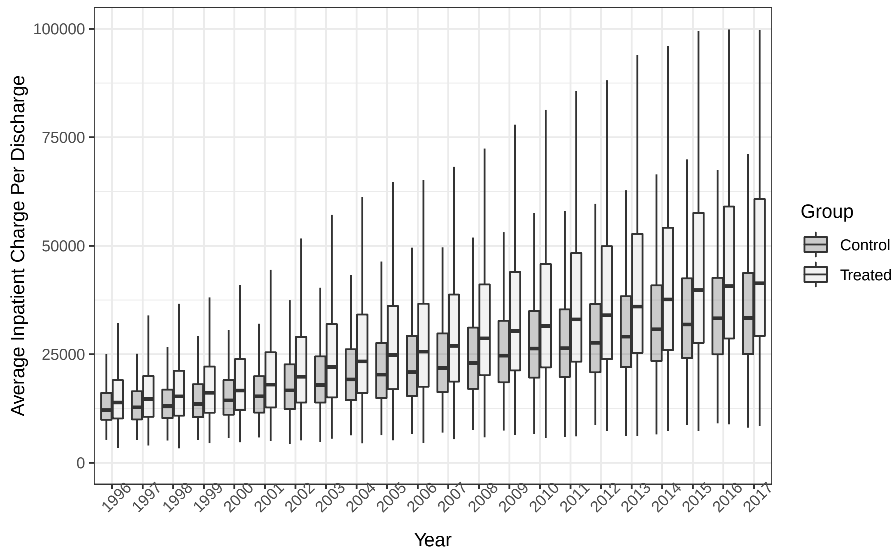
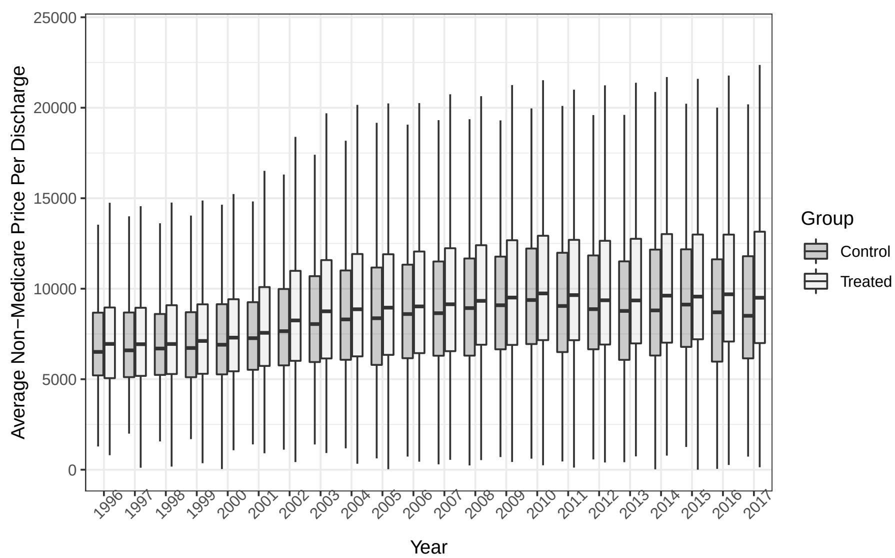


Figure 2: Adoption of Price Transparency Law For Treated States.



(a) Average Charge Prices



(b) Average Negotiated Prices

Figure 3: Box-Plot Time Trends of Charge and Negotiated Prices

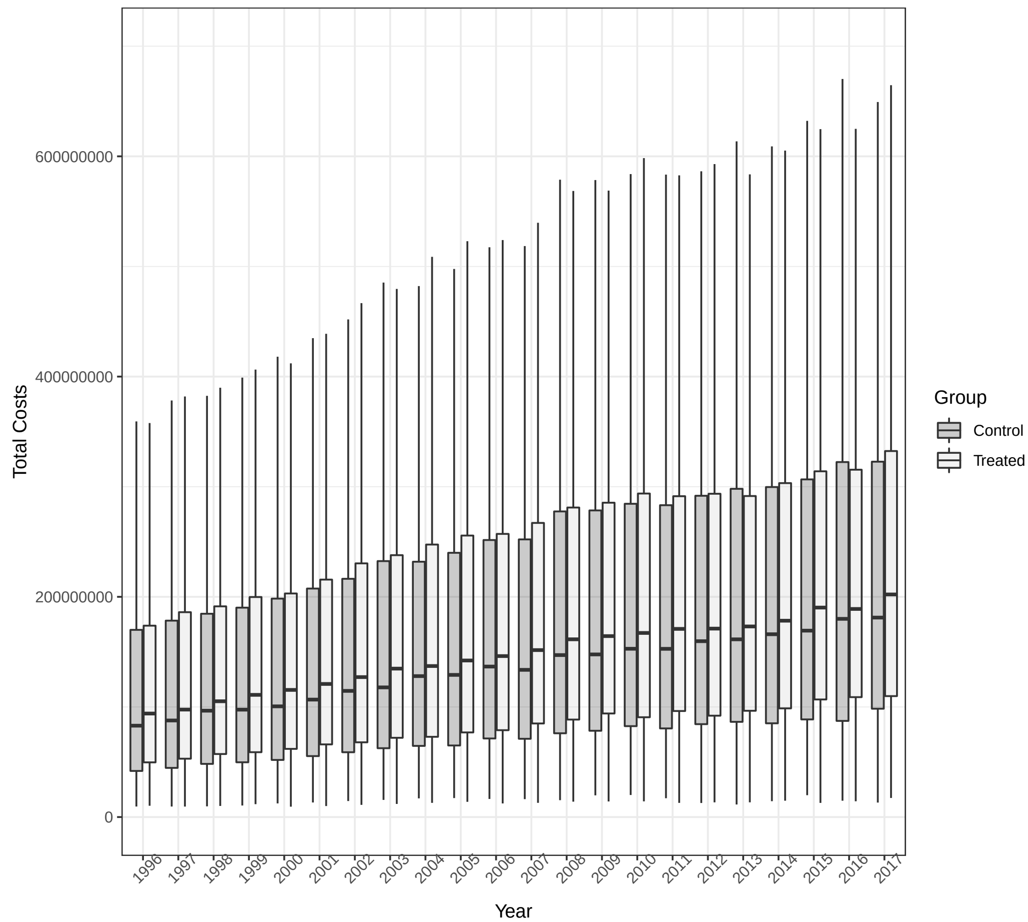
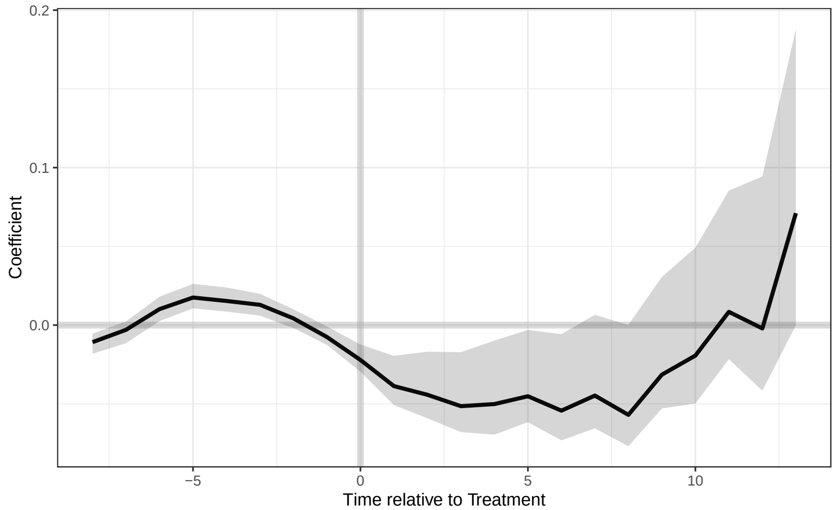
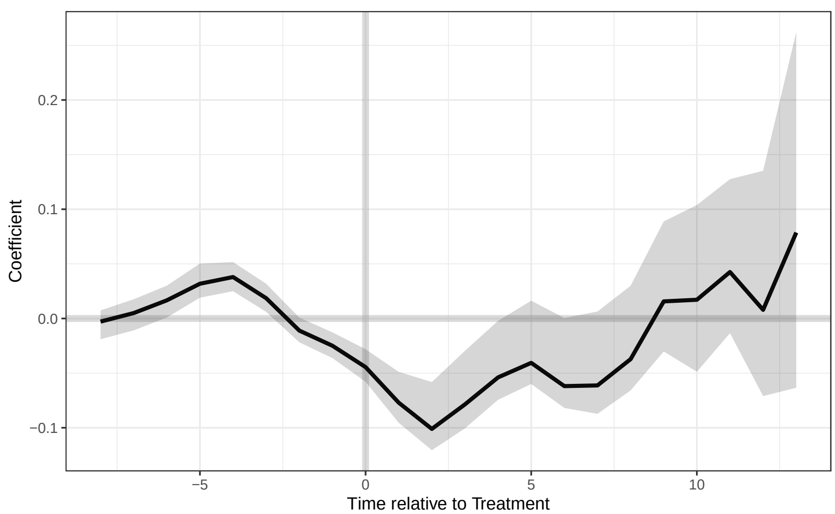


Figure 4: Box-Plot Time Trends of Total Hospital Costs

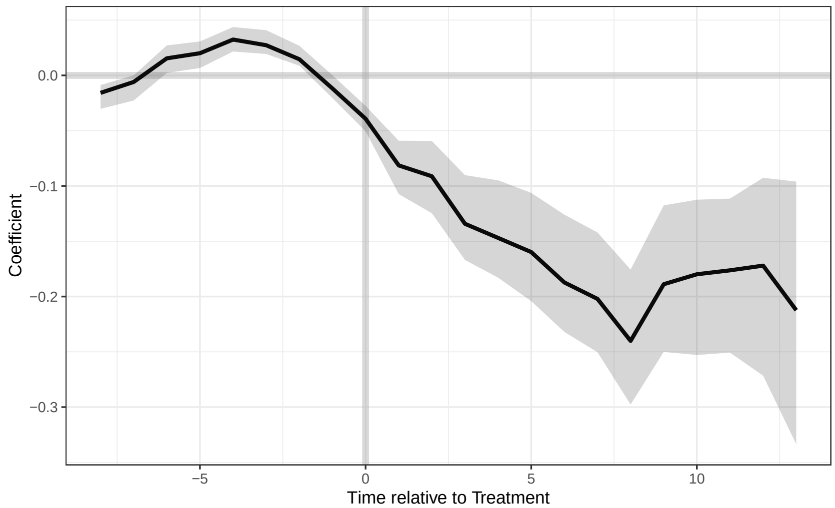


(a) ATT for ln(Charge Price).

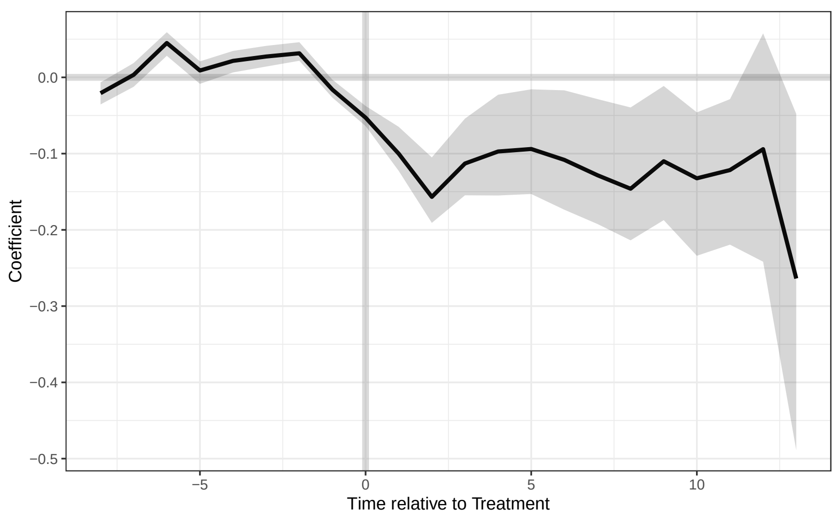


(b) ATT for ln(SD(Charge Price)).

Figure 5: These plots shows the difference between the treated and counterfactual averages for the log of the charge prices and the standard deviations of such prices at the HRR level across all hospitals and states. The solid black line denotes the estimated ATT, while the gray bounds designate the 95% confidence intervals (based on 1,000 bootstraps).



(a) ATT for ln(Negotiated Price).



(b) ATT for ln(SD(Negotiated Price)).

Figure 6: These plots shows the difference between the treated and counterfactual averages for the log of the negotiated prices and the standard deviations of such prices at the HRR level across all hospitals and states. The solid black line denotes the estimated ATT, while the gray bounds designate the 95% confidence intervals (based on 1,000 bootstraps).

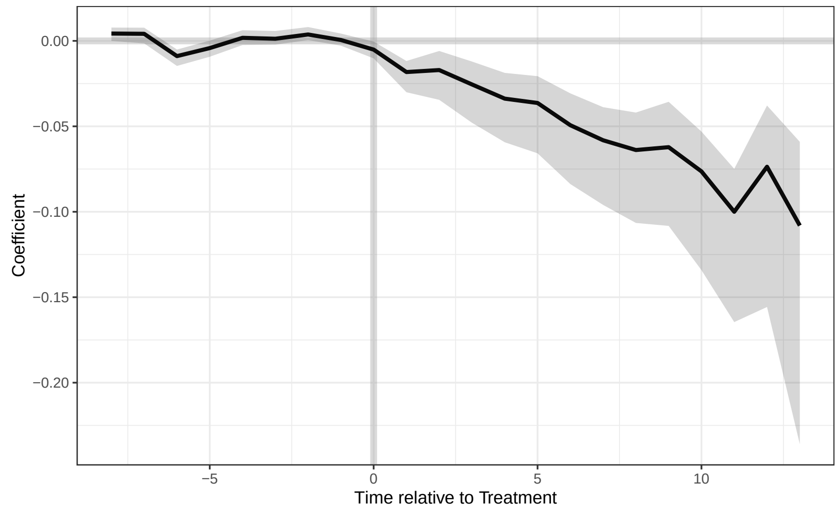


Figure 7: These plots shows the difference between the treated and counterfactual averages for the log of the total costs and the standard deviations of such prices at the HRR level across all hospitals and states. The solid black line denotes the estimated ATT, while the gray bounds designate the 95% confidence intervals (based on 1,000 bootstraps).

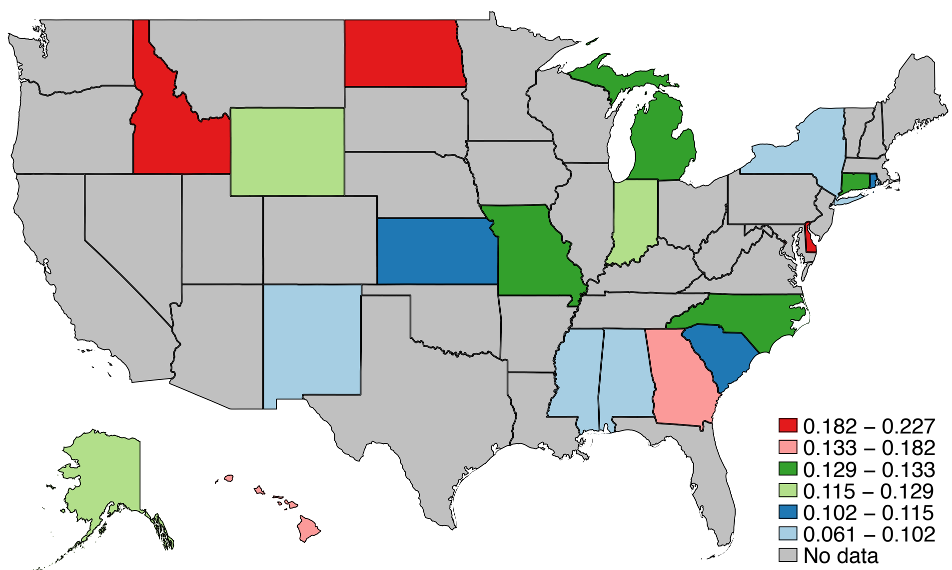


Figure 8: State Map: Predicted ln(CPs) for Untreated States in 2014

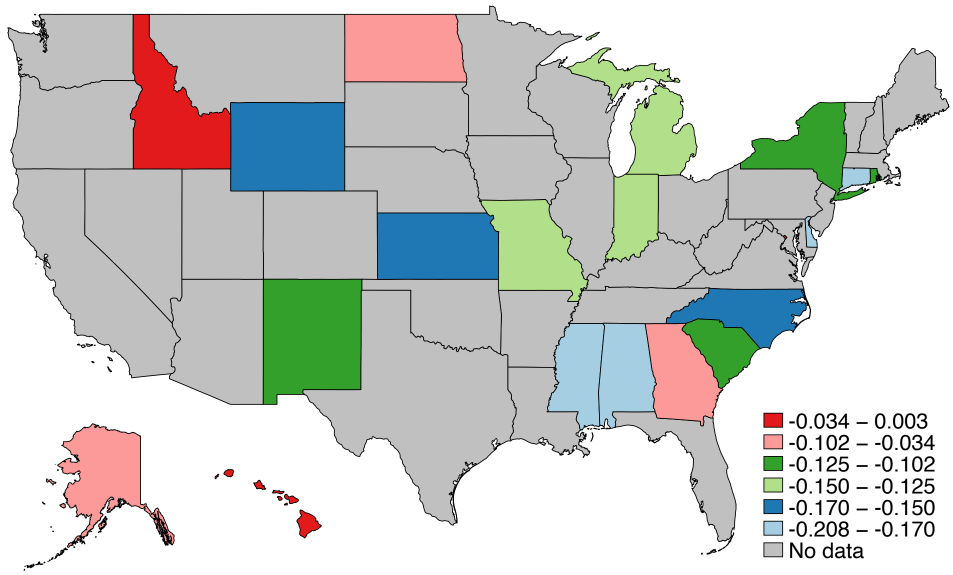


Figure 9: State Map: Predicted ln(NPs) for Untreated States in 2014

Tables

Variable	Mean	Std. Dev.	Observations
Outcome Variables			
Avg. Charge Price (Per Discharge)	28,127.82	19,340.89	51,391
SD Charge Price (Per Discharge) in HRR	10,822.31	6,823.72	50,996
Avg. Negotiated Price	9,207.67	4,892.3	51,391
SD Negotiated Price in HRR	3,843.56	1,772.58	50,996
Total Cost	218mil	265mil	51,391
Total Cost / Total Hospital Days	5,732.65	2,901.79	51,391
Hospital Characteristics			
For-Profit Ownership	0.2	0.4	51,391
Not-For-Profit Ownership	0.65	0.48	51,391
Government Ownership	0.15	0.36	51,391
Teaching Status	0.48	0.5	51,391
Case Mix Index	1.42	0.26	51,391
Capacity Used (%)	0.54	0.17	51391
Medicare (%)	0.47	0.14	51,391
Medicaid (%)	0.12	0.09	51,391
DSH (%)	0.26	0.16	51,391
Competition			
Beds	219.59	269.04	51,391
HHI (<20miles, Beds)	0.14	0.31	14,119
Quality Controls			
Hospital Patient Satisfaction Survey			
Rated High	68.38	7.47	16,620
Would Recommend to Friend	69.98	8.54	16,620
Mortality & Readmission Rates			
Heart Attack Readmission Rate	18.34	1.76	13,931
Heart Attack Mortality Rate	14.98	1.65	14,955
Heart Failure Readmission Rate	23.26	2.24	16,505
Heart Failure Mortality Rate	11.67	1.61	16,480
Pneumonia Readmission Rate	17.78	1.65	16,512
Pneumonia Mortality Rate	12.84	2.76	16,500

Table 1: Summary Statistics of Prices, Costs, Hospital, and Market Characteristics. HRR stands for Hospital Referral Region and defines local markets.

Average Treatment Effects on the Treated				
PANEL A: Charge Prices				
Outcome Measure: ln(Charge Price)				
Avg(ATT)	SE	CI-lower	CI-upper	P-value
-0.039	0.014	-0.051	0.002	0.076
Outcome Measure: ln(SD(Charge Price))				
Avg(ATT)	SE	CI-lower	CI-upper	P-value
-0.043	0.015	-0.059	0.002	0.076
PANEL B: Negotiated Prices				
Outcome Measure: ln(Negotiated Price)				
Avg(ATT)	SE	CI-lower	CI-upper	P-value
-0.159	0.019	-0.193	-0.118	0.000
Outcome Measure: ln(SD(Negotiated Price))				
Avg(ATT)	SE	CI-lower	CI-upper	P-value
-0.119	0.019	-0.148	-0.075	0.000
PANEL C: Hospital Costs				
Outcome Measure: ln(Total Costs)				
Avg(ATT)	SE	CI-lower	CI-upper	P-value
-0.047	0.010	-0.074	-0.037	0.000

Table 2: Average Treatment Effects on the Treated. The average is taken over all post treatment periods. Number of bootstraps = 1,000.

ATT From:	(1) ln(CP)	(2) ln(NP)	(3) ln(TC)
Charge Price Distribution Position in 2004			
Top CP Quantile (in 2004)	-0.143***	-0.128***	0.006
	(0.009)	(0.013)	(0.009)
Bottom CP Quantile (in 2004)	0.107***	0.088***	0.001
	(0.010)	(0.016)	(0.009)
Hospital Characteristics			
System Affiliated	0.009	0.015	-0.039***
	(0.009)	(0.015)	(0.009)
Government	-0.183***	-0.112***	0.030*
	(0.016)	(0.027)	(0.016)
Not-For-Profit	-0.188***	-0.077***	0.060***
	(0.010)	(0.016)	(0.010)
Urban	0.033***	-0.029	0.008
	(0.012)	(0.022)	(0.010)
Teaching	0.008	-0.014	0.058***
	(0.008)	(0.014)	(0.007)
Case Mix Index	0.386***	0.459***	-0.028
	(0.024)	(0.037)	(0.026)
Capacity	0.063*	0.018	-0.042
	(0.033)	(0.054)	(0.032)
Medicare (%)	-0.034	-0.231***	0.020
	(0.044)	(0.070)	(0.043)
Medicaid (%)	-0.040	-0.202**	0.117*
	(0.057)	(0.091)	(0.062)
DSH (%)	0.047	0.252***	-0.055
	(0.036)	(0.055)	(0.035)
Competition and Factor Price Controls			
Beds	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
HHI (<20mile, Beds)	0.051***	-0.006	0.018
	(0.016)	(0.031)	(0.015)
Cost-Of-Labor	-0.000***	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Cost-Of-Capital	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)
Quality Controls			
High Rating	-0.002***	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
AMI RR	0.006*	0.008	-0.000
	(0.003)	(0.005)	(0.003)
HF RR	-0.001	-0.004	0.002
	(0.002)	(0.004)	(0.002)
PN RR	0.001	-0.008*	0.001
	(0.003)	(0.004)	(0.003)
Observations	7,900	7,900	7,900
R-squared	0.197	0.118	0.080
Year FE	YES	YES	YES
State FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Decomposition of Average Treatment Effects. Each column represents a regression of the hospital-specific treatment effect (ATT_{it}) with respect to the variable under consideration (i.e. ln(CP), ln(NP), and ln(TC)).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Price Distr. Position:	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
ATT From:	ln(CP)	ln(CP)	ln(CP)	ln(NP)	ln(NP)	ln(NP)	ln(TC)	ln(TC)	ln(TC)
Charge Price Distribution Position in 2004									
Top CP Quantile (in 2004)	-0.143***			-0.128***			0.006		
	(0.009)			(0.013)			(0.009)		
Bottom CP Quantile (in 2004)	0.107***			0.088***			0.001		
	(0.010)			(0.016)			(0.009)		
Hospital Characteristics									
System Affiliated	0.009	0.036*	-0.017	0.015	0.044*	-0.035	-0.039***	-0.033	-0.062***
	(0.009)	(0.021)	(0.019)	(0.015)	(0.024)	(0.032)	(0.009)	(0.024)	(0.015)
Government	-0.183***	-0.152***	-0.270***	-0.112***	0.126***	-0.241***	0.030*	-0.019	0.007
	(0.016)	(0.036)	(0.045)	(0.027)	(0.048)	(0.079)	(0.016)	(0.047)	(0.030)
Not-For-Profit	-0.188***	-0.197***	-0.233***	-0.077***	-0.064**	-0.157***	0.060***	0.072***	-0.070***
	(0.010)	(0.018)	(0.029)	(0.016)	(0.027)	(0.048)	(0.010)	(0.023)	(0.025)
Urban	0.033***	0.107***	0.055**	-0.029	0.140***	-0.079*	0.008	0.108***	0.001
	(0.012)	(0.034)	(0.023)	(0.022)	(0.043)	(0.045)	(0.010)	(0.030)	(0.019)
Teaching	0.008	-0.064***	0.008	-0.014	-0.087***	0.023	0.058***	0.129***	0.048***
	(0.008)	(0.019)	(0.019)	(0.014)	(0.028)	(0.033)	(0.007)	(0.018)	(0.016)
Competition and Factor Price Controls									
Beds	0.000*	-0.000	0.000	0.000	-0.000***	0.000***	0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Case Mix Index	0.386***	0.546***	0.296***	0.459***	0.640***	0.423***	-0.028	-0.049	0.174***
	(0.024)	(0.042)	(0.070)	(0.037)	(0.063)	(0.123)	(0.026)	(0.042)	(0.062)
Capacity	0.063*	0.074	-0.142*	0.018	-0.177*	-0.387**	-0.042	-0.151**	0.019
	(0.033)	(0.066)	(0.083)	(0.054)	(0.100)	(0.159)	(0.032)	(0.071)	(0.061)
Medicare (%)	-0.034	0.098	-0.005	-0.231***	0.105	-0.274	0.020	0.002	-0.075
	(0.044)	(0.085)	(0.101)	(0.070)	(0.147)	(0.170)	(0.043)	(0.091)	(0.082)
Medicaid (%)	-0.040	0.162*	-0.116	-0.202**	-0.194	-0.594**	0.117*	0.295***	-0.123
	(0.057)	(0.090)	(0.141)	(0.091)	(0.127)	(0.251)	(0.062)	(0.095)	(0.125)
DSH (%)	0.047	-0.194***	0.177*	0.252***	0.238**	0.135	-0.055	-0.245***	-0.036
	(0.036)	(0.060)	(0.101)	(0.055)	(0.093)	(0.186)	(0.035)	(0.072)	(0.079)
HHI (<20miles, Beds)	0.051***	0.101***	0.088***	-0.006	0.043	-0.089	0.018	0.139***	0.051**
	(0.016)	(0.034)	(0.031)	(0.031)	(0.052)	(0.064)	(0.015)	(0.046)	(0.024)
Cost-Of-Labor	-0.000***	-0.000*	0.000*	0.000	0.000***	0.000	-0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cost-Of-Capital	0.000***	0.000***	-0.000	0.000***	-0.000	-0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quality Controls									
High Rating	-0.002***	-0.005***	-0.003**	-0.000	-0.002	0.002	-0.001	-0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
AMI RR	0.006*	0.005	-0.004	0.008	0.003	-0.030**	-0.000	-0.004	-0.017**
	(0.003)	(0.005)	(0.008)	(0.005)	(0.008)	(0.014)	(0.003)	(0.005)	(0.007)
HF RR	-0.001	-0.007	-0.005	-0.004	-0.007	0.001	0.002	0.003	-0.005
	(0.002)	(0.004)	(0.005)	(0.004)	(0.007)	(0.008)	(0.002)	(0.005)	(0.004)
PN RR	0.001	-0.001	0.016***	-0.008*	-0.010	0.016*	0.001	-0.002	0.000
	(0.003)	(0.005)	(0.005)	(0.004)	(0.008)	(0.009)	(0.003)	(0.006)	(0.004)
Observations	7,900	2,503	1,314	7,900	2,503	1,314	7,900	2,503	1,314
R-squared	0.197	0.310	0.269	0.118	0.219	0.180	0.080	0.107	0.195
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Decomposition of Average Treatment Effects. Each column represents a regression of the hospital-specific treatment effect (ATT_{it}) with respect to the variable under consideration (i.e. ln(CP), ln(NP), and ln(TC)).

Appendix

Appendix A: Additional Data Details

This appendix provides details on the data sources, variable definitions, and data cleaning criteria. The resulting sample consists of U.S. acute care hospitals that were paid by the CMS using a prospective payment system. The sample covers the years 1996 - 2017 and builds on two Medicare cost reports, the CMS-2552-1996 and the CMS-2552-2010. While the CMS-2552-1996 report covers the period 1996 - 2011, the CMS-2552-2010 report covers the period from 2010 onward. The years of 2010 and 2011 are covered by both reports. In order to use unique observations for those years, we use a crosswalk for data entries across the two reports, provided by the CMS.

Data Cleaning and Restrictions

- **Provider Type:**
  - Medicare cost reports contain several different types of hospitals. Each of these have different cost structures, payment systems/rates, and characteristics. As such, it is common to focus on particular types of hospitals to avoid heterogeneity and selection issues.
  - In this study, we focus on acute-care inpatient hospitals since they are the most common hospital type (they make up the majority of the full sample–ca. 87%).
- **Focus on Hospitals under PPS:**
  - We exclude critical access hospitals since these are granted exemption from the PPS.
  - We exclude U.S. Territories and Maryland. The latter is excluded since hospitals in Maryland are exempt from PPS (as such, these are commonly excluded from analyses of PPS hospitals), see Maryland Health Services (2019).
- **Dealing with Multiple Reports for a Provider:**
  - Providers are able to submit multiple cost reports within a year to update their data or to make corrections. In cases where multiple reports are submitted, we keep the last submission.
  - We only keep "complete" fiscal year reports (some reports are partial year submissions, so we check for the length of the fiscal year to ensure it is not shorter than a year).
- **Check for Outliers:**
  - We trim the top and bottom outliers (ca. 1% on the top and bottom of the distributions) of data after imputations.

Imputations

- **Sign errors:** In cases where a negative value of a variables was entered but a positive value was expected (by the reporting guidelines), we took the absolute values of these variables.
- **Logical data imputations:** These are dealt with using the following "rule of thumb" approaches.
  - **Missing value instead of zero entry:** Suppose there is a section X of the cost report. Hospital i has filled in entry a, but not entry b within this section, however, both of these entries are required. In these cases, a missing entry is commonly associated with a "zero" entry, hence we inserted a "0" in place of the missing entry.

* **Missing categorical variables:** In years where the hospital fails to supply information regarding its teaching status, urban vs. rural status, or DSH status, we impute this information based on the information supplied in previous years.

Inclusion Criteria

While the generalized synthetic control method allows for using unbalanced panel data, a sufficiently large number of observations for each unit (hospital) is required for proper performance. These requirements are a function of the model specification and, in our case, it required us to stipulate that each hospital was observed for at least 5 years in the pre-treatment period (and at least 10 years overall).

Appendix B: Additional Results

Factor Component Selection: Leave-One-Out-Cross-Validation Results

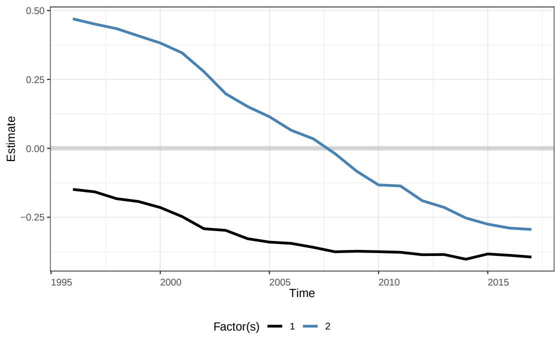
Cross Validation Results				
Outcome Variable: ln(Charge Price)				
Components	sigma2	IC	PC	MSPE
0	0.251	-1.379	0.251	0.229
1	0.095	-1.717	0.125	0.108
2	0.013	-3.033	0.022	0.014*
3	0.009	-2.763	0.018	0.017
Outcome Variable: ln(SD(Charge Price))				
Components	sigma2	IC	PC	MSPE
0	0.388	-0.946	0.388	0.331
1	0.214	-0.899	0.282	0.199
2	0.075	-1.307	0.123	0.106*
3	0.061	-0.862	0.121	0.182

Table 5: Leave-One-Out-Cross-Validation Results for Charge Prices.

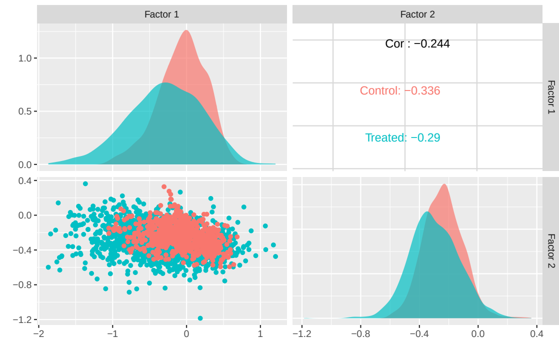
Cross Validation Results				
Outcome Variable: ln(Negotiated Price)				
Components	sigma2	IC	PC	MSPE
0	0.199	-1.609	0.199	0.187
1	0.059	-2.196	0.078	0.060
2	0.036	-2.053	0.059	0.043*
3	0.027	-1.691	0.054	0.125
Outcome Variable: ln(SD(Negotiated Price))				
Components	sigma2	IC	PC	MSPE
0	0.208	-1.567	0.208	0.222
1	0.127	-1.417	0.168	0.155
2	0.091	-1.109	0.149	0.147*
3	0.078	-0.618	0.154	0.179

Table 6: Leave-One-Out-Cross-Validation Results for Negotiated Prices.

Factors and Factor Loadings

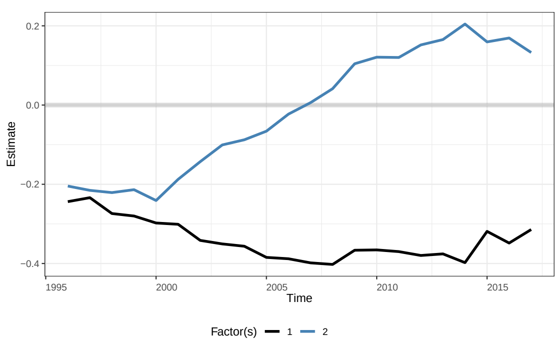


(a) Latent Factor Time Trend

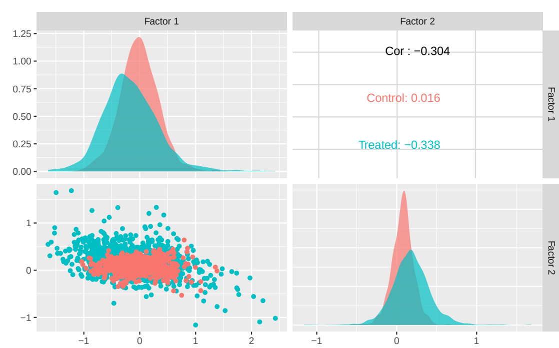


(b) Distribution of Factor Loadings Across Treated and Control Hospitals

Figure 10: This figure provides details on the factor and factor loadings for the charge price regression.



(a) Latent Factor Time Trend



(b) Distribution of Factor Loadings Across Treated and Control Hospitals

Figure 11: This figure provides details on the factor and factor loadings for the negotiated price regression.