EFFECTS OF PUBLIC PRICE TRANSPARENCY TOOLS ON SHOPPING FOR HEALTH CARE

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Abstract. Public-facing price transparency tools have become increasingly common, but whether patients actually shop more with access to these tools is unclear. In this paper, I exploit a unique statewide price transparency roll-out to study changes in patient shopping through distance traveled to care. Using a difference-in-differences methodology with Arizona and Iowa inpatient records, I find that price transparency tools have little to no impact on distance to care, while billed charges decrease upon implementation and increase after obsolescence of price transparency reform. I observe this disconnect between distance and charge movement for relatively homogeneous inpatient procedures as well. Medicaid expansion and insurance status, facility closures and openings, and time of year can explain changes in distance to care but not charges. Results suggest that additional steps should be taken to target consumer behavior if curbing health expenditures is the primary goal of price transparency reform.

Keywords: price transparency reform, health care, distance to care, inpatient care, willingness to shop. *JEL classification: I11, I18, H75, D83*

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1. Introduction

Health expenditures in the United States have increased at an alarming pace over the last several decades, from $27 billion in 1960 to $4.1 trillion in 2020.[1] Adjusting for inflation, per-capita health care spending has increased almost twelve-fold within the last 70 years. Figure 1 displays how growth in health expenditures as a share of gross domestic product (GDP) exceeds other countries that belong to the Organization for Economic Cooperation and Development (OECD). By 2019, US national health expenditures were just under 18% of GDP, and by 2020, as the COVID-19 pandemic spread, health expenditures rose to 19.7% of GDP. For the majority of the last half-century, the United States has been an outlier in terms of how much it spends on health care, and, alarmingly, this contrast between spending in the United States and other countries has only grown more severe over time.

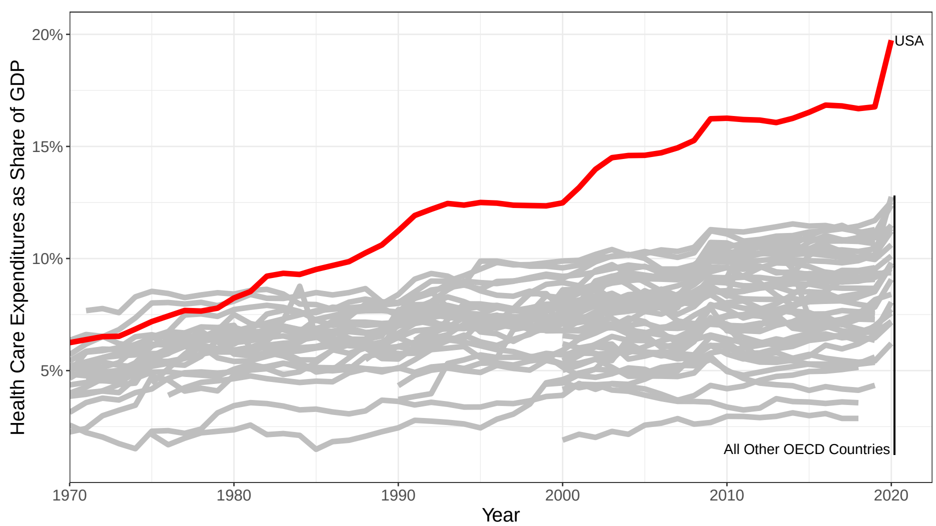


Figure 1. Health Care Expenditures as Share of GDP across OECD Countries, 1970-2020.

In the United States, price transparency regulation has gained traction at various levels of public policy as a proposed method of curbing skyrocketing health care costs, with a majority of states either enacting legislation or launching websites for health care price transparency within the last two decades alone (Sinaiko and Rosenthal (2011), Kullgren et al. (2013), Christensen et al. (2020)). At the federal level, former President Trump issued an executive

[1]National Health Expenditure Data, Centers for Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group.

order in 2019 enacting and adding to an Affordable Care Act rule requiring hospitals to make public a set of rates in a machine-readable format.[2] Despite legal challenges, this controversial "final rule" ultimately went into effect on January 1, 2021, with implementation and enforcement being continued by the current Biden administration.[3] At all levels of reform, advocates of price transparency argue that because patients are often uninformed about the cost of treatment until after services have been performed (Frost and Newman (2016), Lieber (2017), Buttorff et al. (2021)), patients seeking health care services should be more equipped to search for cost-effective care by increasing available pricing information. With higher competition for such care, market forces should drive down prices for health services, which would help to combat the rise in health expenditures.

I evaluate this claim by analyzing how patient shopping behavior responds to a more common and yet less understood form of statewide price transparency effort. Using inpatient discharge data from hospitals in Arizona and Iowa, I exploit a unique timeline of price transparency implementation and obsolescence to study whether changes in willingness to shop evolve from interventions on available price information. To capture this behavior, I study changes in distance traveled to care as a proxy for changes in willingness to shop. Ultimately, I find that while changes in price expectations should induce changes in distance sensitivity, there is little to no effect on observed distance traveled to care. I also demonstrate that actual changes in distance to care and billed charges do not move in conjunction with one another.

The existing literature on price transparency in health care has mostly focused on cases where pricing information can be tailored to individuals or insurance plans, and in these cases, there is mixed or little measured efficacy. Studies looking at impacts of employer-sponsored price transparency tools on homogeneous health care services have found evidence of lower prices in some cases (Whaley et al. (2014), Lieber (2017)) but not others (Desai et al. (2016), Whaley et al. (2019)). More recent studies on public-facing price transparency initiatives either focus on cream-of-the-crop price transparency tools like New Hampshire's price comparison website (Brown (2019b)) or instead focus on a small subset of services

[2]https://www.cms.gov/newsroom/press-releases/trump-administration-announces-historic-price-transparency-requirements-increase-competition-and (Centers for Medicare and Medicaid Services (2019)).

[3]https://www.cms.gov/newsroom/press-releases/biden-harris-administration-improves-transparency-and-oversight-prescription-drug-and-medical-costs (Centers for Medicare and Medicaid Services (2021)).

(Christensen et al. (2020)). Instead, I examine the case of the typical non-personalized state-level price transparency tools, which host aggregated charge prices irrespective of payer for hospital comparison. In doing so, I analyze the set of all inpatient discharges as well as a subset of joint replacement discharges to observe efficacy for both the entire scope of services that are affected and for homogeneous services where shopping behavior may be more likely.

Additionally, the existing literature has focused on observing whether prices decrease as a result of price transparency reform. This empirical research on price transparency is founded on the theoretical literature behind search costs and price information such as Stigler (1961) and Diamond (1971). Indeed, there is plenty of evidence of price dispersion within health care markets, even for services that are extremely similar across patients (Philipson et al. (2010), Newhouse and Garber (2013), White (2017), Cooper et al. (2018), White and Whaley (2019)). However, this literature has also shown that there may be ambiguity in price changes following reform in price transparency. While increasing price advertising in markets where prices are dispersed can lead to increased competition and, thus, lower prices (Luksetich and Lofgreen (1976), Glazer (1981), Kwoka (1984), Milyo and Waldfogel (1999)), there is also evidence both outside (Albæk et al. (1997)) and within the context of health care markets (Tu and Lauer (2009), Cutler and Dafny (2011)) that improving the dissemination of pricing information in more concentrated market structures can actually lead to provider collusion and, thus, higher prices. Additionally, patients may interpret high prices as weak signals of high quality and seek more expensive care (Mehrotra et al. (2012)). To combat this, I isolate the demand-side effects of price transparency to first discover whether patients with access to more information on costs of care are actually shopping more for care, using changes in distance traveled to care as a proxy for changes in willingness to shop. Then, I pair demand effects with changes in billed charges to evaluate the efficacy of price transparency reform.

In my empirical analysis, I find that while charge prices of inpatient procedures do decrease by approximately 6% upon implementation of the Arizona price transparency tools and increase 3% above pre-intervention levels after obsolescence, I observe a null overall effect on distance traveled to care and only an estimated 2-mile increase in distance within Hospital Referral Region (HRR) upon implementation. I break down these results further by partitioning across primary payer and quarter of admission, as well as introducing measures to account for hospital openings and closures. These help to explain movements in distance to care but do not appear to drive changes in billed charges. In conducting a similar analysis with a limited data set consisting of joint replacement discharges, I find a stronger effect on shopping behavior: patients drive between 4 to 7 miles more for care upon implementation of price transparency tools and continue to drive from 2 to 3.5 miles more even after the tools grow obsolete. However, the charge price movement is even more extreme and disconnected from patterns of change in shopping behavior.

The findings in this paper suggest that the most common kinds of public-facing price transparency initiatives, often advertised as addressing and curtailing growing health expenses, may fall short of meeting these policy goals. This echoes the existing literature on limited use or efficacy in even the most ideal forms of price transparency interventions (Mehrotra et al. (2014), Desai et al. (2017), Desai et al. (2021)). Additional policies or changes in health care markets may be necessary to encourage patient shopping, such as reference pricing through insurers (White and Eguchi (2014), Whaley et al. (2019)) or more personalized price comparison tools that offer more information beyond charge prices (Zhang et al. (2020)). While we might view increased price transparency as a key step in improving the health care system, its limitations as a unilateral measure taken to combat growing costs should be acknowledged (Emanuel and Diana (2021)).

The remaining portion of the paper takes the following structure: Section 2 details a model to motivate the empirical approach, Section 3 provides a policy and data overview, Section 4 discusses the strategy and estimation results, and Section 5 concludes with a discussion on future work. Additional policy and data descriptions, along with additional empirical strategy specifications, results, and robustness checks, are given in Appendix A.

2. Model and Empirical Motivation

I use a standard discrete choice model where choice of care is constrained by price and distance to care (Whaley (2015), Brown (2019a), Brown (2019b), Whaley et al. (2019)). In this model, patient i with insurance status k chooses provider $j \in J$ for procedure m in year t that maximizes the random utility

$$u_{ijkmt} = -\gamma_1\, p_{ijkmt} - \gamma_2\, distance_{ijkmt} + \delta_{ijkmt} + \epsilon_{ijkmt} \tag{1}$$

where p_{ijkmt} is the price of treatment and $distance_{ijkmt}$ is the distance to care. In this model, δ_{ijkmt} is a term that can include any range of patient, provider, insurance, or procedure characteristics from our data, and ϵ_{ijkmt} is an independently and identically distributed error term that is known to the patient when making the choice on provider.

To reflect the decision-making process for the patient, I assume that $distance_{ijkmt}$ is fully observed to the patient but p_{ijkmt} is not. Thus, we have

$$p_{ijkmt} = \mathbb{E}_{B_i}[\rho_{ijkmt}] \tag{2}$$

where ρ_{ijkmt} is the ex-post actual cost and p_{ijkmt} is the expected cost of procedure m through provider j according to beliefs $B_i \in \Omega_J$, such that Ω_J is the set of all probability distributions pertaining to the set of provider choices J. Thus, we can anticipate how a change in patient i's beliefs B_i about the cost of care might affect the utility-maximizing choice of care. If patient i's beliefs B_i are updated such that p_{ijkmt} is lower, then patient i expects to receive a higher utility from provider j, with insurance status, procedure, and year held constant.

Using this model, I wish to motivate the empirical strategy of examining changes in distance traveled to care as a proxy for changes in willingness to shop. In doing so, I want to characterize the relationship between changes in expected price and patient sensitivity to distance traveled to care within this framework.

To this end, I assume the error terms follow a Gumbel distribution. I simplify the notation by fixing the patient, insurance status, procedure, and year so that the subscripts can be suppressed. Following McFadden (1974) and Train (2009), the probability that a patient chooses provider $j \in J$ for a given procedure can be written as

$$\mathbb{P}_j = \frac{e^{v_j}}{\sum_{j' \in J} e^{v_{j'}}} > 0 \qquad \forall j \in J \tag{3}$$

where $v_j = -\gamma_1 p_j - \gamma_2 distance_j + \delta_j$.

A few remarks are in order regarding equation (3). This equation gives us the probability that a patient will choose an arbitrary provider $j \in J$ as a function of the expected price and distance to care for that provider. If we assume that $\gamma_1, \gamma_2 > 0$, formalizing that price and distance to care decrease utility of health care, then $\mathbb{P}_j$ is decreasing in p_j and $distance_j$. In other words, the likelihood that a patient chooses a provider j for a given procedure decreases as either the expected price or the distance to care increases.

For the purposes of our empirical strategy, we want to determine how patient choice sensitivity to distance to care responds to a change in beliefs about the expected price. To explore this, I derive the patient's elasticity of $\mathbb{P}_j$ with respect to $distance_j$:

$$
\begin{aligned}
\xi_{j,distance_j} &= \frac{\partial \mathbb{P}_j}{\partial distance_j} \cdot \frac{distance_j}{\mathbb{P}_j} \\
&= \frac{\partial v_j}{\partial distance_j} \cdot \frac{\mathbb{P}_j(1-\mathbb{P}_j)}{\mathbb{P}_j} \cdot distance_j \\
\implies \xi_{j,distance_j} &= -\gamma_2 \cdot (1-\mathbb{P}_j) \cdot distance_j
\end{aligned}
\tag{4}
$$

Note that if $\gamma_2 > 0$, then $\xi_{j,distance_j} < 0$. This reflects the idea stated previously that as distance to care increases, the likelihood of choosing provider j for care decreases. Likewise, as distance to care decreases, the likelihood of choosing provider j increases.

Furthermore, we want to know how $\xi_{j,distance_j}$ changes with respect to a change in p_j, the expected price of care received through provider j. I find that

$$
\begin{aligned}
\frac{\partial \xi_{j,distance_j}}{\partial p_j} &= \frac{\partial}{\partial p_j}\Big(-\gamma_2 \cdot (1-\mathbb{P}_j) \cdot distance_j \Big) \\
&= \gamma_2 \cdot distance_j \cdot \frac{\partial \mathbb{P}_j}{\partial p_j} \\
&= \gamma_2 \cdot distance_j \cdot \Big(-\gamma_1 \cdot \mathbb{P}_j \cdot (1-\mathbb{P}_j) \Big) \\
\implies \frac{\partial \xi_{j,distance_j}}{\partial p_j} &= -\gamma_1 \cdot \gamma_2 \cdot distance_j \cdot \mathbb{P}_j \cdot (1-\mathbb{P}_j)
\end{aligned}
\tag{5}
$$

From equation (5), we have a result telling us how choice sensitivity to distance responds to a change in expected price.

Proposition 1. *Assume* $\gamma_1, \gamma_2 > 0$. *Then* $\xi_{j,distance_j} < 0$ *and*

$$\frac{\partial \xi_{j,distance_j}}{\partial p_j} < 0.$$

Proof. Immediately follows from equation (5). □

Proposition 1 gives us a useful result for the empirical strategy to follow. When the elasticity of the choice probability with respect to distance to care is negative for each $j \in J$, a decrease in elasticity means the choice probability is more elastic with respect to distance to care. Similarly, an increase in elasticity means the choice probability is less elastic with respect to distance to care.

Thus, as the expected price of a procedure through a particular provider decreases, the choice probability grows more inelastic with respect to distance to care. In other words, when expected prices fall, the likelihood of choosing a particular provider decreases less for a given increase in distance to care. Put simply, patients are less sensitive to traveling further distances to care when expected prices drop and more sensitive to further distances to care when expected prices increase.

We may also find it useful to anticipate changes in sensitivity to distance to care if there is a change in the expected price of another health care provider $k \in J$. In a similar fashion, I derive and show how the patient sensitivity to distance will respond to a change in another provider's prices.

Proposition 2. *Assume* $\gamma_1, \gamma_2 > 0$. *Then* $\xi_{j,distance_j} < 0$ *and*

$$\frac{\partial \xi_{j,distance_j}}{\partial p_k} > 0.$$

Proof. If $\gamma_1, \gamma_2 > 0$, then

$$\begin{aligned} \frac{\partial \xi_{j,distance_j}}{\partial p_k} &= \frac{\partial}{\partial p_k}\Big(- \gamma_2 \cdot (1 - \mathbb{P}_j) \cdot distance_j \Big) \\ &= \gamma_2 \cdot distance_j \cdot \frac{\partial \mathbb{P}_j}{\partial p_k} \\ &= \gamma_2 \cdot distance_j \cdot \Big(- \gamma_1 \cdot \mathbb{P}_j \cdot (-\mathbb{P}_k) \Big) \\ \implies \quad \frac{\partial \xi_{j,distance_j}}{\partial p_k} &= \gamma_1 \cdot \gamma_2 \cdot distance_j \cdot \mathbb{P}_j \cdot \mathbb{P}_k > 0. \end{aligned}$$

□

As one might expect, Proposition 2 tells us that the sensitivity of distance to care for one provider and the expected price of a competing provider move in the same direction. When the expected price of a procedure through provider k decreases, the patient's choice probability of selecting provider j for that procedure grows more elastic with respect to distance to care. Alternatively, if the expected price through provider k increases, the patient grows more inelastic in their choice of provider j with respect to distance to care.

To summarize the results of both propositions, a decrease in the expected price of a procedure through a given health care provider should make patients less sensitive to the distance traveled to receive care from that provider and more sensitive to the distance to care for all other providers.

These results provide the foundation necessary to focus on how price transparency reform affects distance to care. As pricing information is made available through public tools, and as cost-effective providers are discovered, patients can update their beliefs on expected prices. For decreases in expected price as a result of information obtained through price transparency tools, patients tolerate traveling further distances for care in order to maximize utility. Understanding this relationship between expected prices and distance to care, we have the foundation necessary to motivate the empirical approach to follow.

3. Policy and Data Overview

In this section, I provide a detailed description of the price transparency policy timetable exploited in the estimation strategy used in Section 4. Additionally, I provide a summary of the data used to study the effects of these public price transparency initiatives.

3.1. **Policy Overview.** For the empirical strategy and estimation performed in this paper, I exploit a unique price transparency policy timetable within the state of Arizona, depicted in Figure 2.

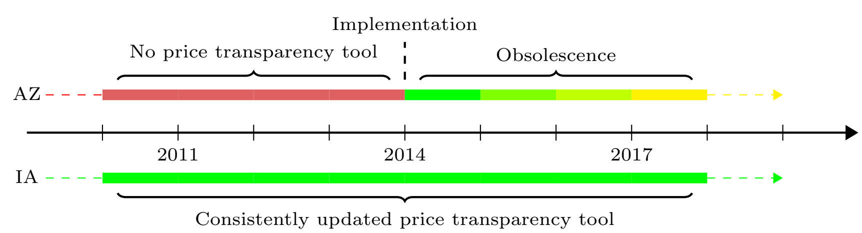


Figure 2. Policy timetable.

Prior to 2014, there were no statewide price transparency efforts ongoing or in place in Arizona. Then, in 2014, two different types of public price transparency initiatives were implemented, one being a statewide hospital charge price comparison website (AZ Hospital Compare) and another being a statewide bill requiring hospitals to make available common charge prices for patient inquiry (AZ HB 2045).[4] While the bill remained in effect for the years following, the website became outdated as the charge price information used for comparison was not updated after implementation. Thus, the implementation and obsolescence

[4]Each of the price transparency initiatives studied in this paper are described with more detail in Appendix A.1.

of price transparency reform in Arizona provides a natural experiment to exploit for the purpose of understanding the influence on patient behavior.

During this time period, a public-facing price transparency website in Iowa allowing patients to compare charges across hospitals had been consistently accessible and maintained with up-to-date charge information (Iowa Hospital Charges). Iowa had initially enabled patients to compare hospital charges as early as 2009 (Christensen et al. (2020)) using a PricePoint website derived from Wisconsin's own hospital charge comparison website. Prior to 2011, Iowa ultimately moved to hosting and maintaining a unique price transparency website through the Iowa Hospital Association. Throughout the timeline of changes in price transparency in Arizona, Iowa provided consistent access to hospital charge prices, which allows comparison of patient experience across Iowa and Arizona to understand the impact of changes in state-level price transparency.

Arizona and Iowa's price transparency websites are very similar to the great majority of price transparency websites that have been created at state levels across the United States in the last twenty years. Unlike the rare cases where a state charge comparison website actually provides an estimate of out-of-pocket costs based on insurance plan, like New Hampshire's website (Tu and Lauer (2009), Mehrotra et al. (2014), Brown (2019a), Brown (2019b)), most state hospital comparison websites merely report average and median charges for a procedure at a given hospital, as well as minimum and maximum charges. While total charges for a procedure are arguably less informative than a personalized estimate for out-of-pocket costs, this information structure has nevertheless historically dominated the landscape of state price transparency websites created for public use (Kullgren et al. (2013), Christensen et al. (2020)). Additionally, Arizona's price transparency website came after the price transparency websites previously implemented and studied in other states. Therefore, understanding how this reform changed the health care landscape in Arizona is a novel contribution to the existing literature.

Similarly, the state-level hospital charge comparison websites and legislation in focus for this analysis preceded similar price transparency initiatives that continued to follow in the future, both at the state and federal level. Most notably, Arizona's state legislation requiring hospitals to make available the charge prices of common procedures is reminiscent of the language from the recent CMS "final rule" under the previous Trump administration and now being implemented by the current Biden administration. While the current attention towards efficacy of the new federal changes center around compliance (PatientRightsAdvocate.org (2021)), studying the impact of legislation at the state level that share similarities with the newer CMS "final rule" offers a potential path for predicting the impact of the more recent federal pushes for price transparency.

3.2. **Data Overview.** For the empirical strategy employed in Section 4, I use discharge data from Arizona and Iowa State Inpatient Databases (SIDs), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality (AHRQ). These discharge data are structured as longitudinal all-payer claims data sets, are de-identified at the patient and hospital level, and are originally sourced from Arizona and Iowa hospitals. I use data from 2011, 2014, and 2017, which capture the periods of no reform as well as implementation and obsolescence, as discussed in Section 3.1 and shown in Figure 2.[5]

From our motivation in Section 2, I focus on changes in willingness to shop by using distance to care as a proxy. To estimate this measure, I follow Brown (2019a) and Brown (2019b) and construct distance to care as the distance between patient billing ZIP code and hospital location ZIP code. While patient billing ZIP code is included in the inpatient data described previously, supplementary de-identified provider ZIP codes were provided by the Arizona Department of Health Services (AZDHS) and the Iowa Hospital Association (IHA). I use the 2017 ZIP Code Tabulation Areas Gazetteer file from the US Census Bureau to obtain latitude and longitude coordinates for each ZIP code, which are then used to estimate the distance between two ZIP codes.[6]

Finally, I also incorporate data on Hospital Service Area (HSA) and Hospital Referral Region (HRR) available as a ZIP code crosswalk through the Dartmouth Atlas of Health Care. These measures provide a way to aggregate ZIP codes into geographic groups based on service by a given hospital or a set of hospitals. I incorporate these data in both primary and alternative specifications to more completely capture changes in patient shopping behavior through my analysis.

[5]Additional descriptions and visualization of the data are in Appendix A.2.

[6]For robustness, I also use coordinates obtained through GeoNames, an open-source geographical database, as an alternative specification. Results using these coordinates can be found in Appendix A.3.

4. Estimation Strategy and Results

With an understanding of the policy and data to be used in our empirical approach, we now move to a discussion regarding the estimation strategy and the main findings. Section 4.1 details the baseline empirical strategy conducted. Section 4.2 discusses the main results with a full analysis of all inpatient data across states. In Section 4.3, I show results when the analysis is limited to major joint replacement discharges with no complications or comorbidities (DRG 470).

4.1. **Estimation Strategy.** To analyze the efficacy of public price transparency initiatives, I use a standard difference-in-differences methodology and estimate the following linear model by OLS regression:

$$
\begin{aligned}
y_{ijkmt} =& \beta_1 \mathrm{AZ}_j \times \mathrm{Y2014}_t + \beta_2 \mathrm{AZ}_j \times \mathrm{Y2017}_t + \beta_3 \mathrm{AZ}_j \\
&+ \beta_4 \mathrm{Y2014}_t + \beta_5 \mathrm{Y2017}_t + \mathbf{X}'_{im}\beta_6 + HRR_j + \varepsilon_{ijkmt}
\end{aligned} \tag{6}
$$

As in Section 2, patient i with insurance status k chooses provider $j \in J$ for procedure m in year t. Here, y_{ijkmt} represents outcome variables where I expect the efficacy of the initiatives to manifest. As explored in Section 2, I expect that efficacy will show up primarily in changes in distance traveled to care. For completeness, I also look at total charges, adjusted for inflation and log-transformed.

As AZ_j and $\mathrm{Y2014}_t$ and $\mathrm{Y2017}_t$ are state and time dummy variables, respectively, β_1 and β_2 capture the marginal treatment effect of the Arizona public price transparency initiatives upon implementation and then after obsolescence, respectively, while Iowa discharges are treated as the control group. $\mathbf{X}_{im}$ are individual patient characteristics, including demographic factors like age, race, and median household income quartile, as well as record-specific characteristics like point of origin or the presence of emergency room charges on the bill.[7] To focus on the impact of treatment effects within each Hospital Referral Region (HRR), I also test specifications with HRR fixed effects HRR_j, and, finally, ε_{ijkmt} is the error term.

With this baseline strategy, I estimate the effects of the price transparency tools on distance to care and total charges in section 4.2.

[7] Summary statistics of the variables used in the regression strategy can be found in Appendix A.2.

4.2. **Main Results.** I begin by estimating the model in equation (6) on the data with distance to care as the dependent variable y_{ijkmt}. The results of this estimation are displayed in Table 1.

TABLE 1. Estimated Changes in Distance to Care, All Inpatient Procedures

	Dependent variable:				
	Distance to Care (mi)				
	(1)	(2)	(3)	(4)	(5)
AZ	45.721***	82.288***	78.160***	156.745**	128.079***
	(0.000)	(28.440)	(6.495)	(73.622)	(5.901)
Y2014	21.465***	−1.301	1.370	−1.939	0.035
	(0.000)	(0.895)	(1.977)	(1.248)	(1.069)
Y2017	23.633***	3.457	1.564***	2.982	0.345
	(0.000)	(2.468)	(0.303)	(2.253)	(0.441)
AZ × Y2014	−22.923***	3.438	0.524	4.085	2.054***
	(0.000)	(3.358)	(1.092)	(3.429)	(0.465)
AZ × Y2017	−25.041***	−3.263***	−0.207	−2.382***	0.836
	(0.000)	(0.599)	(1.554)	(0.657)	(2.147)
$\mathbf{X}_{im}$	*N*	*Y*	*Y*	*Y*	*Y*
$\mathbf{1}_{OutsideState}$	*N*	*N*	*Y*	*N*	*Y*
HRR_j	*N*	*N*	*N*	*Y*	*Y*
Observations	3,043,074	-	-	-	-
R^2	0.048	0.086	0.453	0.096	0.471

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

Estimating the simplest specification with only the state and year dummies included, (i.e., dropping $\mathbf{X}_{im}'\beta_6$ and HRR_j in equation (6)), the distance between patient and provider in Arizona appears to continuously decrease as the Arizona price transparency interventions become available in 2014 and grow outdated by 2017. However, when I include patient and procedure characteristics, as well as a dummy variable for whether the patient resides in the same state as the provider, I find a different story, shown in column 3 of Table 1. Here, I find no statistically significant effect of the Arizona price transparency policies on distance traveled to care for inpatient procedures. Both in 2014 and 2017, the estimated coefficients of the implemented treatment and obsolete treatment are not significantly different from zero.

Because patients may not be likely to shop between HRRs but within them, I isolate the treatment effect within HRRs by including HRR_j, with the results of the full specification in equation (6) shown in column 5 of Table 1. Here, I find a subtle but more optimistic result: the fully implemented Arizona public price transparency initiatives appear to have increased distance traveled to care within a given HRR by just over 2 miles, suggesting patients are possibly shopping and switching hospitals as a result of the price transparency implementation. However, upon obsolescence in 2017, the effects of the treatment cannot be statistically distinguished from zero.

In the estimations performed in Table 1, I also allow inclusion of an indicator variable when the patient on record has a billing ZIP code outside of the state in which they received care. One might imagine that patients traveling from outside Arizona or Iowa for care in those states could greatly impact the estimated effect on distance, especially if either 2014 or 2017 saw an unexpected change in care given to non-Arizona-based or non-Iowa-based residents, respectively.[8] However, any patient seeking care at Arizona- or Iowa-based hospitals would have had access to the public price transparency tools available, so it is possible that patients outside Arizona and Iowa incorporated the tools into their search process for health care treatment. For these reasons, it is important to control for the non-residents in our data, and this importance can be seen in the difference in fit when this control is included in the specification versus without it.

While the results in Table 1 from the full specification suggest a null effect, there is modest evidence that patients obtaining inpatient procedures may have shopped more for care by traveling further distances within a given HRR upon implementation of the Arizona price

[8] I do find that the Arizona and Iowa resident/non-resident makeup in my data remains constant across years, in any case. Further information on this is available in Appendix A.2, Table 8.

transparency initiatives in 2014. By 2017, however, it seems that any changes in distance traveled to care had disappeared. While changes in this channel of distance to care suggests optimism regarding induced shopping behavior, the remaining analyses will help to clarify the drivers of the effects we see.[9]

Given these results with respect to distance traveled to care, we now turn to analyzing how charge prices are changing across years. However, there are multiple caveats to analyzing charge prices as a means of understanding effects of price transparency in Arizona. As mentioned previously, price movement can be ambiguous when price transparency is implemented in a given market. Additionally, because our inpatient data originates at the hospital level, the only prices I observe are the total charges for the inpatient record, which represent the billed amount for services from the hospital. Of course, these charges are not typically charged fully to the patient if the patient is insured, yet out-of-pocket costs to patients are not observed in this data set. While it would be ideal to study the effects of public-facing price transparency initiatives on data that include richer detail on prices paid directly by patients, these data are not always available when considering an all-payer state-level inpatient discharge data set, which encapsulates a primary trade-off for studying the more commonplace versions of price transparency interventions at the public level.

That said, a key reason for looking at charge prices at the discharge level is that public-facing price transparency initiatives use information on total charges rather than out-of-pocket costs. In other words, the very signal patients often have on the expense of care is the distribution of charge prices available to study through these data. Patients update their beliefs on expected prices based on charge prices made available through price transparency tools. Thus, it remains of interest to observe how these charges changed after the price transparency reforms were implemented and then grew obsolete. Table 2 displays these results.

I find that in the fully specified model without HRR fixed effects (column 3 of Table 2), charge prices in Arizona decrease in 2014 upon implementation of the price transparency initiatives, indicating patients are being charged an estimated 5.7% less across inpatient

[9] In addition, robustness checks using alternative measures of distance to care are performed and discussed in Appendix A.3.

Table 2. Estimated Changes in Total Charges, All Inpatient Procedures

	Dependent variable:				
	log(Total Charges) ($)				
	(1)	(2)	(3)	(4)	(5)
AZ	10.024***	0.358***	0.358***	0.739***	0.736***
	(0.000)	(0.008)	(0.007)	(0.033)	(0.030)
Y2014	9.730***	0.200***	0.200***	0.200***	0.201***
	(0.000)	(0.004)	(0.004)	(0.003)	(0.003)
Y2017	9.804***	0.277***	0.276***	0.281***	0.281***
	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
AZ × Y2014	−9.610***	−0.059***	−0.059***	−0.066***	−0.066***
	(0.000)	(0.004)	(0.004)	(0.001)	(0.001)
AZ × Y2017	−9.499***	0.035***	0.035***	0.028***	0.028***
	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
$\mathbf{X}_{im}$	*N*	*Y*	*Y*	*Y*	*Y*
$\mathbf{1}_{OutsideState}$	*N*	*N*	*Y*	*N*	*Y*
HRR_j	*N*	*N*	*N*	*Y*	*Y*
Observations	3,043,074	-	-	-	-
R2	0.902	0.996	0.996	0.996	0.996

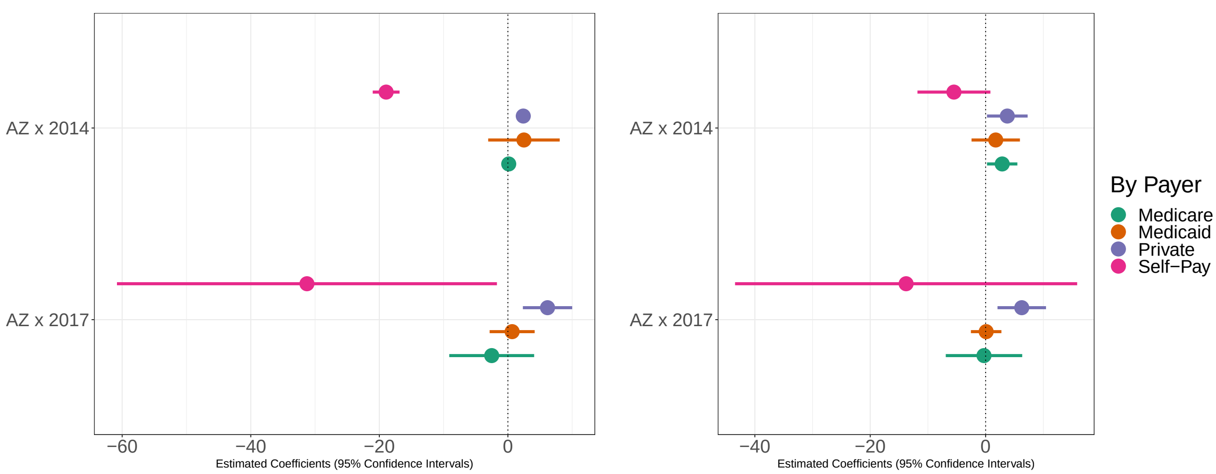
Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

procedures. However, in 2017, once the Arizona price transparency website has grown obsolete, patients are being charged 3.6% more than 2011 pre-intervention levels. Estimates for within HRR are also very similar, estimating a 6.4% decrease in charge prices in 2014 and a 2.8% increase from pre-intervention levels in 2017.

While these results trace the timeline of the price transparency implementation and obsolescence in Arizona, the reduction and subsequent increase in charge prices do not appear to be driven by changes in shopping behavior. If this were the case, we would expect to find a more substantial effect from the price transparency initiatives on distance traveled to care in Arizona from the results in Table 1 alongside these estimates. Instead, the subtle effects I do observe do not appear to fully account for the movement in prices shown in Table 2.

Other than price transparency initiatives, the potential impacts of any other changes to the health care landscape in Arizona could be driving certain results in key channels. To identify and isolate other potential drivers, I discuss results when I partition data by insurance status and admission month in Section 4.2.1 and when I account for hospital openings and closures across years in Section 4.2.2.

4.2.1. *Additional Specifications.* For a more detailed picture of the effects on patient behavior and charge prices following the timeline of price transparency intervention, I separate patients first by payer type. For this exercise, I only include patients whose primary payer is coded as Medicare, Medicaid, private insurance, or self-pay.[10]



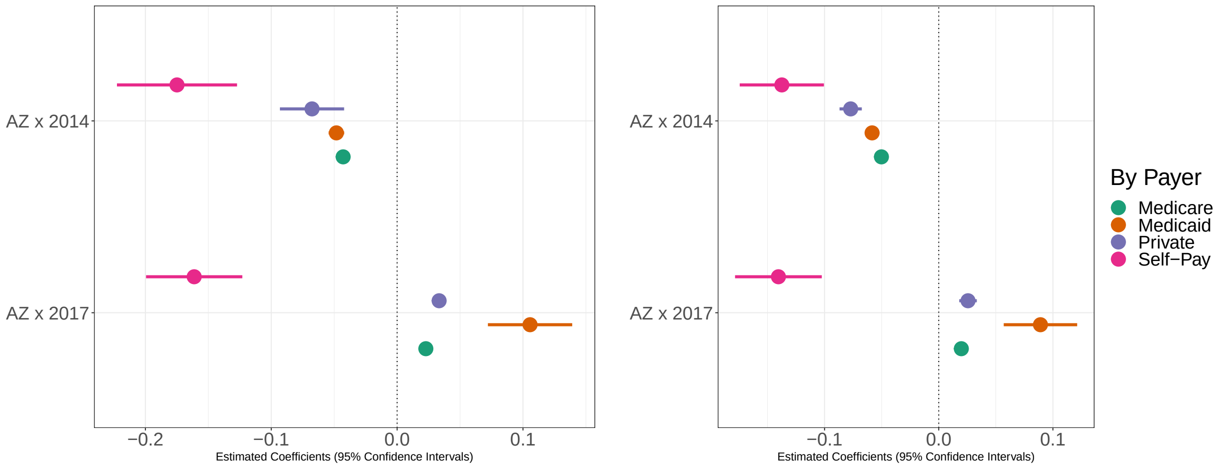
(A) Full Specification

(B) Within HRR

Figure 3. Estimated Changes in Distance to Care, All Inpatient Procedures, By Payer

Figure 3 shows that very little change in distance traveled to care occurs in either 2014 or 2017 for insured groups, reflecting the main results. Interestingly, for non-insured patients, we might expect a higher likelihood of using public price transparency tools, yet I see, if

[10]Further detail on the distribution of patients by primary payer across states and years is available in Appendix A.2, Table 8.



(A) Full Specification

(B) Within HRR

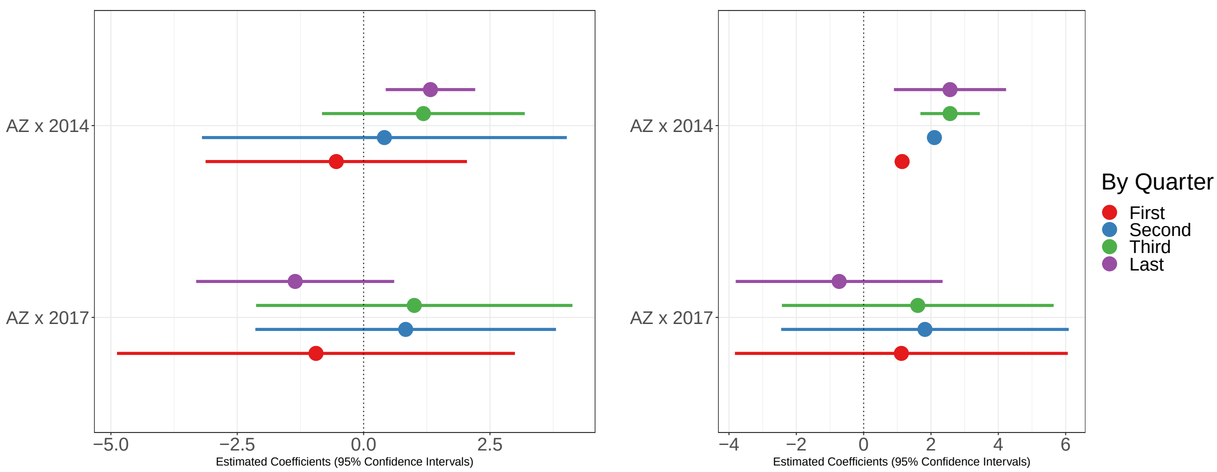
FIGURE 4. Estimated Changes in Total Charges, All Inpatient Procedures, By Payer

anything, a decline in distance traveled to care. Additionally, Figure 4 shows that each payer group experiences a decline in charges billed for inpatient services in 2014, while all insured groups experience an increase in 2017. Again, uninsured patients are different from other groups, with persistent drops in charges billed for inpatient services from pre-intervention.

There are a few considerations to make regarding conclusions that can be drawn from Figures 3 and 4. First, it is important to keep in mind that as Medicaid expansion occurred in both Iowa and Arizona in 2014, the sorting of patients into these groups may certainly affect the differences we can see, specifically previously uninsured patients transitioning to receiving coverage through Medicaid. The patients who remain uninsured post-Medicaid expansion in each state might behave differently than the uninsured pre-expansion; for example, these groups may also be more likely to remain uninformed about the price transparency initiatives taking place. Unfortunately, without panel data to tracking uninsured patients before and after Medicaid expansion, I cannot provide an answer to this specific possibility.

However, it is important to remember that while distance to care is a channel reflecting changes in willingness to shop, it is such because travel is a cost incurred when receiving health care. For uninsured patients, both distance traveled to care and charge prices decreasing across time could signify that access to care is improving in the state of Arizona alongside the price transparency timetable. I will pick up the question of whether access to care is changing when looking at hospital openings and closures in Section 4.2.2.

We may not expect insured patients to have the same incentives to use public price transparency tools if they are not the primary payer. However, the subtle shifts I see in distance to care from these patients could come from insurers or payers with an incentive for patients covered to access cost-effective care. It is possible that insurer communication of price transparency tools or even in-network referrals may have been impacted by price transparency initiatives, which could lead to a shift in behavior in insured groups.



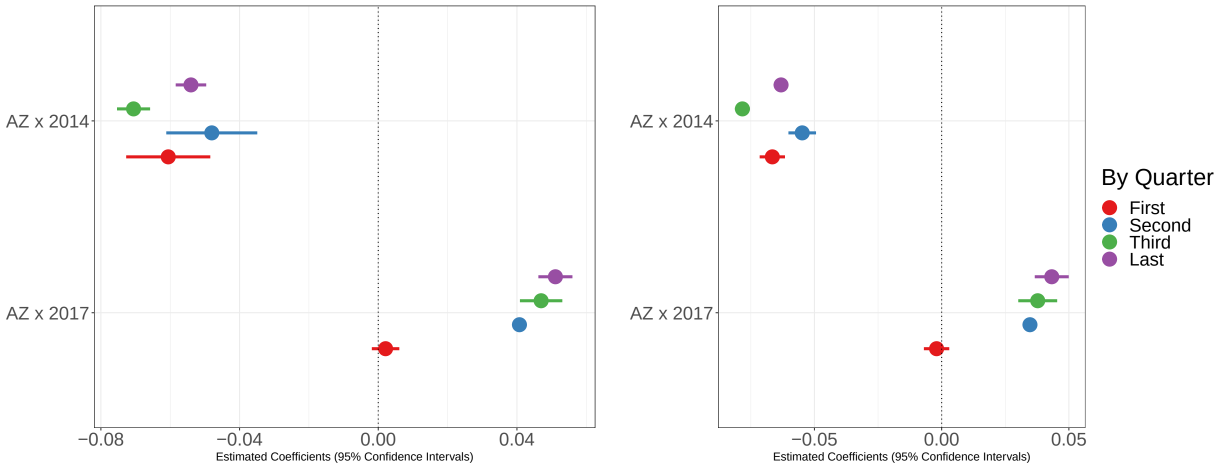
(A) Full Specification

(B) Within HRR

FIGURE 5. Estimated Changes in Distance to Care, All Inpatient Procedures, By Quarter

Similarly, we may also expect that patients may shop more depending on the time of year, since their deductible may be reached by the end of the year. Figures 5 and 6 show estimates for patient groups broken down by the quarter of year that the admission month of inpatient care occurs.

In Figure 5, I do observe a pattern in these estimates that reflects patients may indeed be motivated by their deductible. However, this weak pattern seems to suggest patients are driving further once their deductible is more likely to have been reached, which goes against the idea that patients would be more incentivized to shop for care before reaching their deductible. Perhaps patients are using price information as a signal on quality (Mehrotra et al. (2012)) and, once reaching their deductible, look for high quality care. However, this



(A) Full Specification (B) Within HRR

FIGURE 6. Estimated Changes in Total Charges, All Inpatient Procedures, By Quarter

behavior does not seem so clearly distinguishable in 2017. These conclusions also remain true when looking at the effects estimated within HRR.

Figure 6 bolsters the story that movements in charge prices are independent of changes in shopping behavior. Across quarters in 2014, charge prices are roughly 6% lower, and in 2017, while the first quarter looks similar to pre-intervention, the remaining quarters depict a 3-to-4% increase in charge prices. This does not appear to follow any pattern observed with changes in distance to care observed in these quarters.

In the next section, I attempt to incorporate one of the potential factors that may drive the disconnected results between distance traveled and charges billed.

4.2.2. *Hospital Openings and Closures.* A key assumption made in this analysis is that the health care landscape is not changing drastically as a result of something besides the price transparency implementation and obsolescence in Arizona that I am not already accounting for. However, one major factor that I have not yet taken into account is the possibility that hospital openings and closures drive the differences in distance traveled to care and changes in charges billed that we observe. If some facilities close and others open, then the location of providers does not remain constant, meaning that distance traveled to care may not reflect a change in willingness to shop. Additionally, the opening and closing of hospitals may reflect supply-side changes to the market, including changing market concentration. If hospital markets are becoming more consolidated, for instance, we can expect that charge prices might be going up simply as a result of these closures and openings. In other words, this factor potentially affects both channels I have analyzed so far.

To account for hospital closures and openings, I develop a set of ZIP-code-level indexes that take the form

$$\text{ClosureShare}_{ZIP,t} = \sum_{j=1}^{J_{closed}} \mathbf{1}_{\{\text{First Year } j \text{ is Not Observed}\}} \times \frac{\text{\# of Records from ZIP Code in Last Year Observed}}{\text{Total \# of Records at Facility from Last Year Observed}} \tag{7}$$

and

$$\text{OpeningShare}_{ZIP,t} = \sum_{j=1}^{J_{open}} \mathbf{1}_{\{\text{First Year } j \text{ is Observed}\}} \times \frac{\text{\# of Records from ZIP Code in First Year Observed}}{\text{Total \# of Records at Hospital from First Year Observed}} \tag{8}$$

where J_{closed} (J_{open}) is the set of closed (newly opened) hospitals with a record of at least one patient from a given ZIP code in the last (first) year observed.

These measures provide a self-contained data-driven approach to dealing with hospital openings and closures by observing which hospitals leave and enter the data set.[11] In simple terms, I use the share of records with a given ZIP code out of all discharges at a particular hospital to weight the incidence of experiencing a hospital closing or opening in a given patient ZIP code. Then, I sum across all incidences of openings or closures, respectively. These indexes are then added into the original specification of equation (6) and are allowed to take their value only on or after the year for which they are calculated.

Tables 3 and 4 compare the main results from the full and within specification in Tables 1 and 2 with inclusion of hospital opening and closures in the estimation.

Controlling for the effects of hospitals opening and closing does not appear to overturn conclusions drawn from the main results. For distance traveled, I continue to estimate a null effect, although the coefficients are larger, with larger estimated standard errors. However, this inclusion does remove the positive and significant effect estimated within HRRs upon implementation of the price transparency initiatives, suggesting that increases in distance

[11] More details about the hospital closures and openings observed in the data can be found in Appendix A.2.

Table 3. Estimated Changes in Distance to Care, All Inpatient Procedures, with Closure and Opening Share

	Dependent variable:			
	Distance to Care (mi)			
	(Full)		(Within)	
AZ	78.160***	79.816***	128.079***	128.571***
	(6.495)	(5.172)	(5.901)	(4.947)
Y2014	1.370	1.525	0.035	0.261
	(1.977)	(1.788)	(1.069)	(0.884)
Y2017	1.564***	1.560***	0.345	0.398
	(0.303)	(0.147)	(0.441)	(0.573)
AZ × Y2014	0.524	4.674	2.054***	6.122
	(1.092)	(6.721)	(0.465)	(4.727)
AZ × Y2017	−0.207	12.882	0.836	11.915
	(1.554)	(12.198)	(2.147)	(10.791)
Opening/Closure Shares	*N*	*Y*	*N*	*Y*
HRR_j	*N*	*N*	*Y*	*Y*
Observations	3,043,074	-	-	-
R2	0.453	0.455	0.471	0.472

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

traveled may not have arisen from increased willingness to shop. Additionally, inclusion of closures and opening shares do not appear to fully account for the changes in charges billed to patients.

All in all, it appears that while the price transparency initiatives may have had a subtle effect on changes in consumer behavior detectable through distance traveled to care, changes

Table 4. Estimated Changes in Total Charges, All Inpatient Procedures, with Closure and Opening Share

	Dependent variable:			
	log(Total Charges) ($)			
	(Full)		(Within)	
AZ	0.358***	0.357***	0.736***	0.734***
	(0.007)	(0.008)	(0.030)	(0.032)
Y2014	0.200***	0.200***	0.201***	0.200***
	(0.004)	(0.004)	(0.003)	(0.003)
Y2017	0.276***	0.276***	0.281***	0.281***
	(0.002)	(0.002)	(0.001)	(0.001)
AZ × Y2014	−0.059***	−0.059***	−0.066***	−0.069***
	(0.004)	(0.004)	(0.001)	(0.000)
AZ × Y2017	0.035***	0.031***	0.028***	0.024***
	(0.002)	(0.005)	(0.003)	(0.006)
Opening/Closure Shares	*N*	*Y*	*N*	*Y*
HRR_j	*N*	*N*	*Y*	*Y*
Observations	3,043,074	-	-	-
R2	0.996	0.996	0.996	0.996

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

in charges billed to patients appear disconnected from price transparency initiatives or other observable factors like hospital closures and openings. Thus far, I have focused my analysis on the entire set of discharges spanning all inpatient procedures in Iowa and Arizona. While public-facing price transparency initiatives did not restrict patients from learning about certain kinds of procedures, characteristics of inpatient care can vary substantially across hospitals for similar treatment (Philipson et al. (2010), Newhouse and Garber (2013), Cooper et al. (2018)). In the next section, I limit my analysis to discharges for a set of relatively homogeneous joint replacement inpatient procedures.

4.3. **DRG 470 Results.** In this section, I focus my estimation strategy on a subset of inpatient procedures where patients may be more likely to use available price transparency tools and shop for care before obtaining it. To do this, I restrict my inpatient data across Iowa and Arizona to just discharges coded with Diagnosis Related Group (DRG) 470, which is assigned when patients are obtaining hip or knee replacement without major complications or comorbidities. Out of the various situations under which a patient might receive inpatient care, previous literature has studied joint replacement as a relatively homogeneous type of care where effects of price transparency initiatives may be most represented (White and Eguchi (2014), Christensen et al. (2020)). Because the effects of public-facing price transparency reform on all inpatient discharges appear to have a small, subtle effect on patient willingness to shop, I analyze major joint replacements separately in this section to pair with the main results and provide a clearer picture of extent of efficacy.[12]

Table 5 displays estimation results from the full specification as well as with HRR fixed effects for both distance to care and log-transformed total charges as outcome variables for DRG 470 discharges. Here, I see a stronger initial effect of change in distance traveled upon implementation of the price transparency tools (a 4.31-mile increase), as well as potential evidence of persistent shopping behavior after the Arizona website becomes obsolete in 2017 (a 1.98-mile increase from pre-intervention). Within HRR, these effects are even higher, with an almost 7-mile increase in distance driven to care in 2014 and a diminished 3.5-mile increase over 2011 remaining in 2017.

However, while it appears that patients are more willing to shop in the case of DRG 470, charges billed decrease less in the year of implementation than in the main results (by 5.2%) and increase more once the website has become obsolete (by 6.6%). Within HRR, this difference is even more stark. While I again see a pattern of change in charges that follows the Arizona timeline, the movement appears to be even more disconnected from changes in behavior manifested through increased distance traveled to care than in the main results.

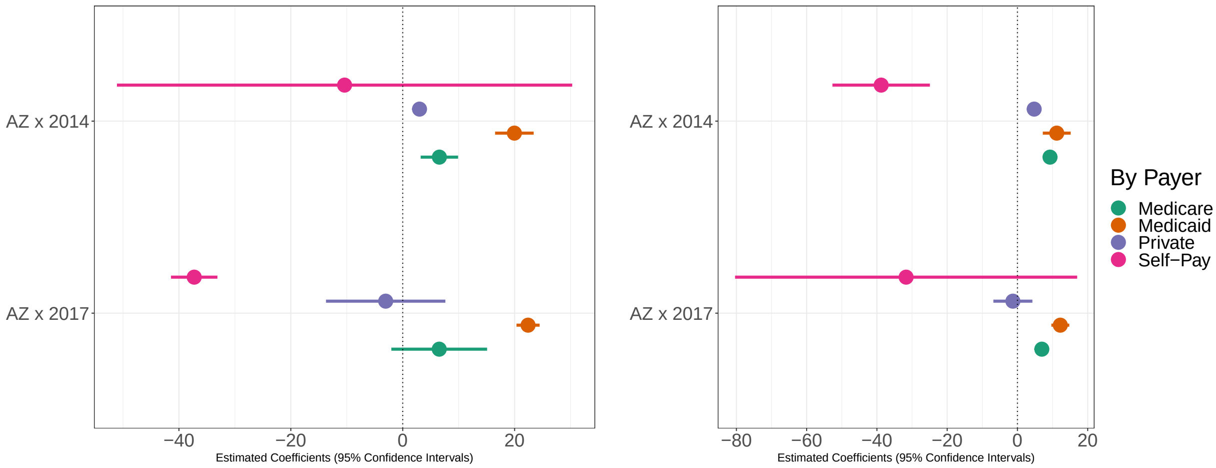
[12]Further description of this subset of data can be found in Appendix A.2.2.

Table 5. Estimated Changes in Distance to Care and Total Charges, DRG 470

	Dependent variable:			
	Distance to Care (mi)		log(Total Charges) ($)	
	(Full)	(Within)	(Full)	(Within)
AZ	89.901***	169.235***	0.311***	0.636***
	(7.823)	(14.763)	(0.002)	(0.005)
Y2014	2.938	1.904	0.100***	0.088***
	(2.146)	(2.901)	(0.004)	(0.002)
Y2017	3.459	1.915	0.130***	0.117***
	(2.642)	(3.108)	(0.004)	(0.004)
AZ × Y2014	4.314***	6.787***	−0.053***	−0.043***
	(0.172)	(1.163)	(0.006)	(0.003)
AZ × Y2017	1.976***	3.520**	0.064***	0.074***
	(0.693)	(1.462)	(0.005)	(0.004)
HRR_j	*N*	*Y*	*N*	*Y*
Observations	108,393	-	-	-
R2	0.373	0.405	0.999	0.999

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

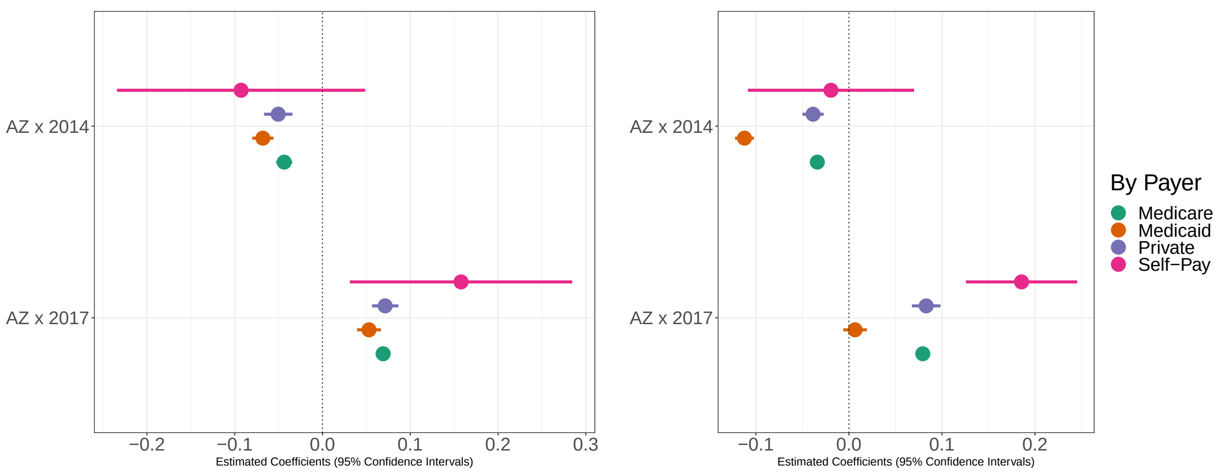
Figures 7 and 8 break down estimated effects on distance to care and total charges by primary payer. One key difference between the main results across all inpatient discharges in Figures 3 and 4 and here is that Medicaid patients appear to experience more substantial, persistent increases in distance to care. This observation perhaps suggests that Medicaid expansion and either a difference in Medicaid expansion characteristics present in Arizona and not Iowa or group consistency post-expansion may play a role in estimation results for DRG 470 discharges.



(A) Full Specification

(B) Within HRR

FIGURE 7. Estimated Changes in Distance to Care, DRG 470, By Payer

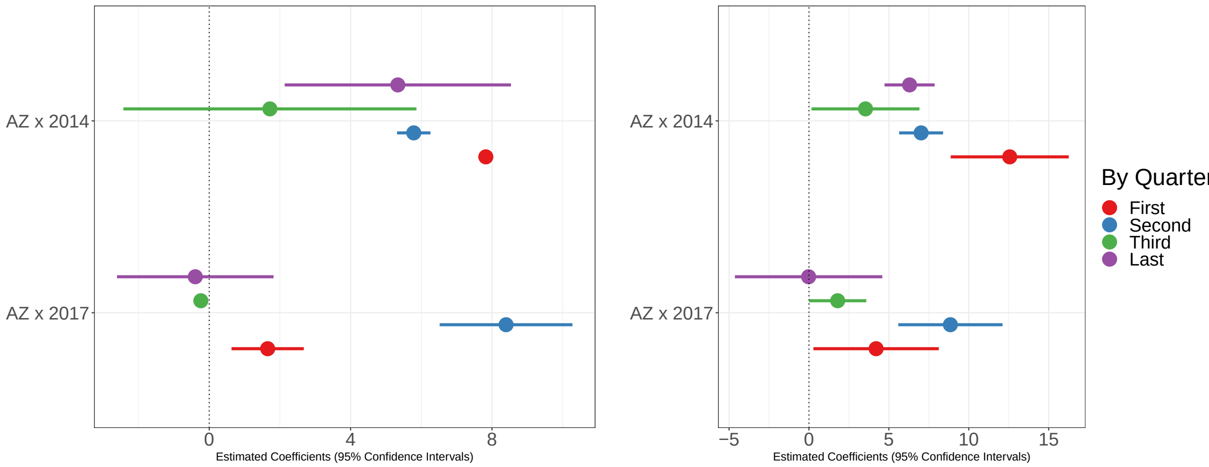


(A) Full Specification

(B) Within HRR

FIGURE 8. Estimated Changes in Total Charges, DRG 470, By Payer

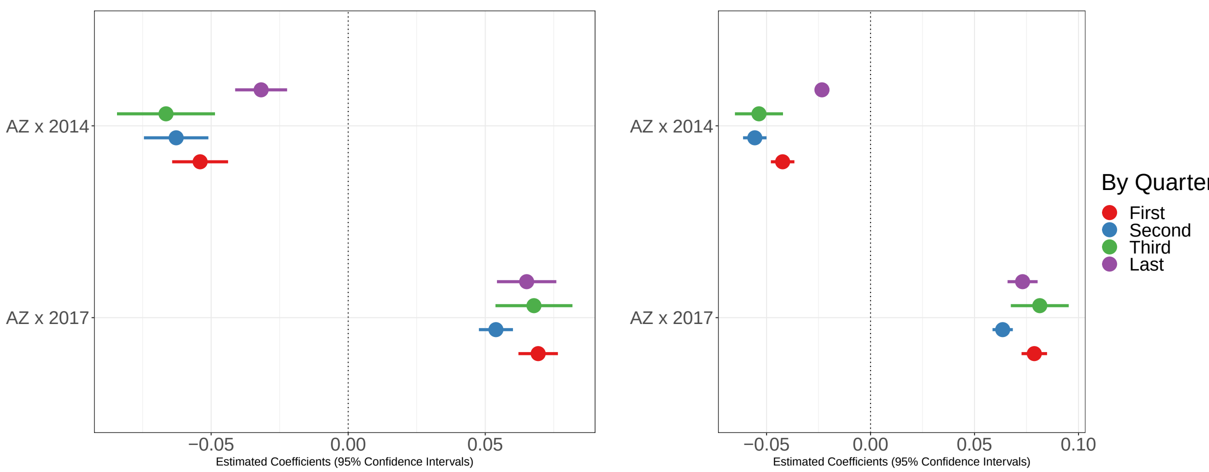
On the other hand, Figures 9 and 10 indicate that patients may be paying attention to their deductible in a slight reversal of the main results. Contrary to Figure 5, we see for DRG 470 discharges that patients appear to travel further for care in earlier quarters of



(A) Full Specification

(B) Within HRR

FIGURE 9. Estimated Changes in Distance to Care, DRG 470, By Quarter



(A) Full Specification

(B) Within HRR

FIGURE 10. Estimated Changes in Total Charges, DRG 470, By Quarter

the year when any deductible had is less likely to be met. Only the last quarter deviates from this pattern, and one line of reasoning previously discussed is that this could signify the shopping on a quality dimension that occurs once a patient's deductible has been met. However, there is little difference with what I see here on billed charges and the main results from Figure 6.

To summarize, while it appears that that there is stronger evidence of increased and persistent willingness to shop for inpatient joint replacement care after price transparency tools are implemented and then grow outdated, I still see a disconnect between movements in charge prices and changes to consumer behavior. While patients seem to follow expected behavior with respect to the likelihood of meeting deductibles later in the year, there also appears to be a strong response from Medicaid groups in this category of care that would not be explained by price transparency tool implementation and obsolescence.

5. Conclusion

In this paper, I exploit the implementation and obsolescence of price transparency tools in the state of Arizona to study how reforms change patients' willingness to shop for care. By examining changes in distance to care and total charges using inpatient data from Iowa and Arizona during the relevant years of this policy timeline, I find little evidence supporting the notion that patients are shopping more for inpatient care, while billed charges appear to decrease 6% in 2014 and rise above pre-intervention levels by 3% in 2017. Attempting to account for Medicaid expansion and hospital openings and closures, as well as differences in patient insurance status and admission month, can elucidate changes in distance to care but little of the movement in charge prices. When limiting the discharge data to joint replacement procedures, I find that these results are amplified: a predictably stronger response in distance to care with a stark movement in charge prices that does not match up with consumer behavior changes.

It is important to note that because billed charges may not translate in a direct way to the prices that patients pay out-of-pocket, increases or decreases in charge prices do not necessarily reflect a certain change in patient expenses for care. However, even if there was a direct relationship between movements in charge prices and patient expenses, this analysis suggests that Arizona's public price transparency reforms did not induce the charge price movement I see. By isolating changes in patient willingness to shop through the channel of distance to care, I see that patient behavior and charge prices appear to move in disconnected ways from each other during this timeline.

While I expect that patients will reveal their willingness to shop for care through traveling further distances to receive care, it is also possible that patients use price transparency tools in ways this paper does not address. For instance, it is possible that patients use the price transparency tools post-treatment to hold hospitals accountable for billed charges, rather than using tools preemptively to shop for the most cost-effective provider. Additionally, recent literature suggests patients may even be using price transparency tools to simply anticipate medical costs but not necessarily to shop for care (Gourevitch et al. (2021)). Further work and data is necessary to look at the intensive and extensive margin effects of pricing information campaigns and interventions in health care markets.

Future research must continue to address the ever-changing nature of price transparency in health care markets, along with other dimensions of transparency, such as quality of and access to care. With recent and new pushes for price transparency coming into effect at the federal level, it will be important to understand and anticipate the effects of these policies in order to inform consumers of possible gains from use as well as hold policymakers accountable for benefits promised.

Ultimately, it seems that the most common kinds of public-facing price transparency tools similar to those analyzed in this paper are not enough on their own to induce lower health care expenses once implemented. Along with being maintained to prevent obsolescence in the future, price transparency initiatives should find ways to encourage learning about, shopping for, and accessing cost-effective care more directly. Targeting changes in consumer behavior to induce shopping is a prerequisite to creating competition in health care, and if competition is the mechanism by which health care costs will be driven down, policymakers must take additional steps to make the most common price transparency tools effective at their intended purpose.

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Appendix A. Additional Details and Data Descriptions

A.1. **Policy Details.** In this section of the appendix, I provide a detailed look at the price transparency initiatives studied in this paper in Arizona and Iowa. There were two Arizona reforms initiated within the same time frame: one was a public-facing hospital charge comparison website created by the Arizona Department of Health Services (AZDHS), and the other was a charge publishing requirement for hospitals set forth by the Arizona state legislature. Meanwhile, Iowa maintained a consistently accessible charge price comparison website for patients to compare charges across hospitals. In the following subsections, I discuss the details of each initiative.

A.1.1. *AZ Hospital Compare.* On June 3rd, 2013, the Arizona Department of Health Services launched the AZ Hospital Compare website.[13] From the outset, the justification and explanation of the website's existence was to assist patients with being able to assess the nature of the healthcare landscape in Arizona, and AZDHS advocated that this website could contribute methods for working toward transparency in health care.

Figure 11 displays the interface that the public has access to when visiting AZ Hospital Compare. Patients can search charges across hospitals by name, location, or all combined. Patients can look at how charges compare across conditions, procedures, or all combined. These versions of the website are still accessible to the public.[14][15]

Upon the initial implementation, AZ Hospital Compare was equipped with 2011 data from all hospitals in the state, but by the beginning of 2014, an additional website was added with 2012 data. This is the last year of data that AZ Hospital Compare was updated with. Thus, patients who used AZ Hospital Compare upon its implementation looked at information from less than two years prior and, in any case, were most likely to find relevant information to the present health care system at that time.

[13]https://directorsblog.health.azdhs.gov/az-hospital-compare/
[14]https://pub.azdhs.gov/hospital-discharge-stats/2011/index.html
[15]https://pub.azdhs.gov/hospital-discharge-stats/2012/index.html

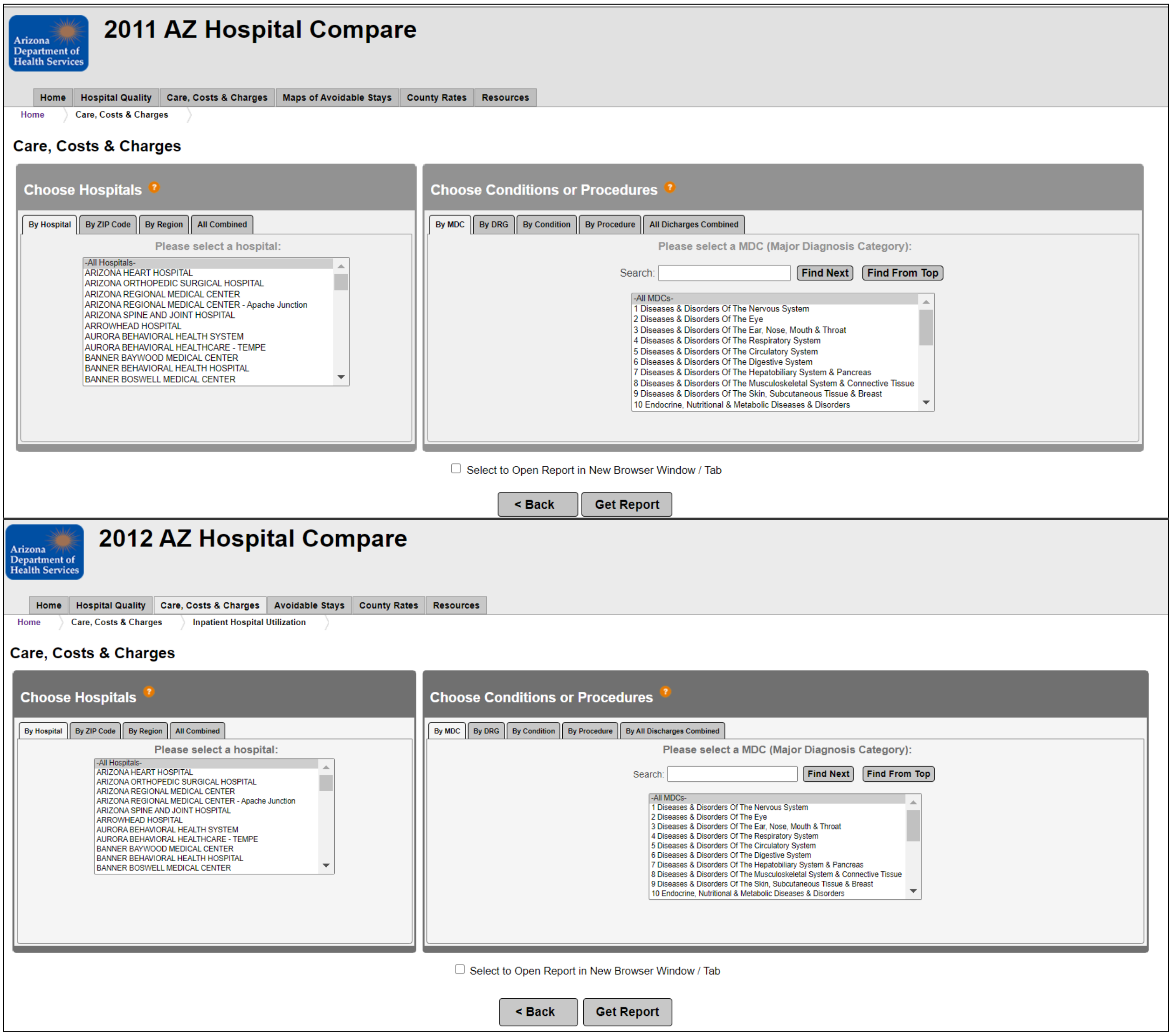

Figure 11. AZ Hospital Compare website.

However, in just a few short years, this version of the AZ Hospital Compare website became outdated, since it was never updated beyond 2012 data. For instance, by 2017, the data used to shop for care would have been at least 5 years old. New hospitals that did not exist in 2011 or 2012 would not be included on the website, and hospitals that were around in 2011 and 2012 may have closed in 2017. While patients could have used the website to shop for care in 2017, the information contained on the website was outdated, thus making AZ Hospital Compare obsolete.

It is worth mentioning that in November 2020, the Arizona Department of Health Services launched a newer version of AZ Hospital Compare, which is updated with data as recent as

2019, contains historical data and trends on hospital charges, and has a sharper interface with a clickable map for patients.[16] While this launch occurred after the time frame studied in this paper, future work should continue to study the impacts of improvements (and any lack thereof) to public-facing price transparency tools across all health care systems.[17]

A.1.2. *AZ HB 2045.* In 2013, Arizona's 51st state legislature passed House Bill 2045 (Chapter 202) in the First Regular Session.[18] Prior to the bill passing the legislature, the Barto Floor Amendment was adopted and placed in the bill. The amendment revised section 32-3216 of the Arizona Revised Statutes to include the following requirement:

> "A HEALTH CARE PROVIDER MUST MAKE AVAILABLE ON REQUEST OR ONLINE THE DIRECT PAY PRICE FOR AT LEAST THE TWENTY-FIVE MOST COMMON SERVICES, IF APPLICABLE, FOR THE HEALTH CARE PROVIDER. THE SERVICES MAY BE IDENTIFIED BY A COMMON PROCEDURAL TERMINOLOGY CODE OR BY A PLAIN-ENGLISH DESCRIPTION. THE DOCUMENT OR ONLINE POSTING MUST BE UPDATED AT LEAST ANNUALLY. THE DIRECT PAY PRICE MUST BE FOR THE STANDARD DIAGNOSIS FOR THE SERVICE AND MAY INCLUDE ANY COMPLICATIONS OR EXCEPTIONAL TREATMENT. HEALTH CARE PROVIDERS WHO ARE OWNERS OR EMPLOYEES OF A LEGAL ENTITY WITH FEWER THAN THREE LICENSED HEALTH CARE PROVIDERS ARE EXEMPT FROM THE REQUIREMENTS OF THIS SUBSECTION. "

The Barto Floor Amendment also revised section 36-437 of the Arizona Revised Statutes to include the following requirement:

> "A HEALTH CARE FACILITY MUST MAKE AVAILABLE ON REQUEST OR ONLINE THE DIRECT PAY PRICE FOR AT LEAST THE FIFTY MOST USED DIAGNOSIS-RELATED GROUP CODES, IF APPLICABLE,

[16] https://gis.azdhs.gov/hospitalcompare/comparehospitals.html

[17] I am grateful toward Joseph Spadafino and David Olson at AZDHS for the questions answered and information provided on AZ Hospital Compare.

[18] https://apps.azleg.gov/BillStatus/BillOverview/31557?Sessionid=110

> FOR THE FACILITY AND AT LEAST THE FIFTY MOST USED OUTPATIENT SERVICE CODES, IF APPLICABLE, FOR THE FACILITY. THE SERVICES MAY BE IDENTIFIED BY A COMMON PROCEDURAL TERMINOLOGY CODE OR BY A PLAIN-ENGLISH DESCRIPTION. THE HEALTH CARE FACILITY MUST UPDATE THE DOCUMENT OR ONLINE POSTING AT LEAST ANNUALLY. THE DIRECT PAY PRICE MUST BE FOR THE STANDARD DIAGNOSIS FOR THE SERVICE AND MAY INCLUDE ANY COMPLICATIONS OR EXCEPTIONAL TREATMENT. "

House Bill 2045, with the adopted Barto Floor Amendment, passed the state legislature and was signed into law by the governor on June 19th, 2013, just over two weeks after the AZ Hospital Compare website launch. The bill states that these requirements on hospitals were to take effect after December 31st, 2013.

It is important to compare the Trump administration's 2019 executive order related to price transparency with its predecessors, including the Arizona state law just described. According to the CMS website,

> "The final rule implements Section 2718(e) of the Public Health Service Act and improves upon prior agency guidance that required hospitals to make public their standard charges (defined as the hospital's chargemaster charges) upon request starting in 2015 (79 FR 50146) and subsequently online in a machine-readable format starting in 2019 (83 FR 41144)."[19]

While the remainder of this action redefined "standard charges" to include even more than the chargemaster prices by January 1st, 2021, the initial ruling immediately required hospitals to post or make available the "standard charges" as they were already defined. This requirement is strikingly similar to the language and definitions used in the Barto Floor Amendment for AZ HB 2045, where "direct pay prices" were to be made available online or by request.

A.1.3. *Iowa Hospital Charges.* The earliest available date of public price transparency tools in Iowa appears to be by January 2009 (Christensen et al. (2020)). At this time, Iowa used a PricePoint tool made available from the Wisconsin Hospital Association. At some point

[19]https://www.cms.gov/newsroom/fact-sheets/cy-2020-hospital-outpatient-prospective-payment-system-opps-policy-changes-hospital-price

FIGURE 12. Iowa Hospital Charges website.

prior to 2011, Iowa moved away from WI PricePoint and the Iowa Hospital Association created Iowa Hospital Charges with no gap in access. Between 2011 and 2017, Iowa Hospital Association maintained Iowa Hospital Charges and updated information quarterly.[20]

Figure 12 shows the home page of Iowa Hospital Charges as it would have appeared in July 2017.[21] Once patients select the type of care, a prompt allows for you to select a provider either by city or by county search. There is an option that allows for patients to compare information upon hospitals in search or just view the information for one provider at a time.

Once patients have made it to selection of provider, they choose the type of service and service category, as well as the specific reason for admission, and then the website displays statistics for the selected providers on the care chosen for comparison. The website displays the number of discharges, average length of stay, average and median charges, and median age broken down by severity for the services and hospitals chosen. The website also allows for comparison to all Iowa hospitals for each of the categories listed. Patients are also given the option to download a spreadsheet or file reporting all MSDRGs by hospitals.

[20]I am thankful to Kathy Tritten and Kara Staiert from the Iowa Hospital Association for providing information on the history of the Iowa Hospital Charges website.

[21]While minor updates have occurred throughout the years, the main interface of the website has largely appeared to remain the same.

A.2. **Data Summary and Visualization.** In this section of the appendix, I provide a more detailed description of the health expenditure data and the Arizona and Iowa state inpatient data used in this paper.

A.2.1. *Hospital Spending as a Share of Health Expenditures.* In Section 1, I discussed how total health expenditures have increased dramatically over the last several decades, even when adjusting for inflation. A natural follow-up question is how much of this spending is due to the typical targets of price transparency reform, which usually center around hospital spending. Figure 13 displays hospital spending as a share of total health expenditures alongside trends in the share of other types of health care spending.

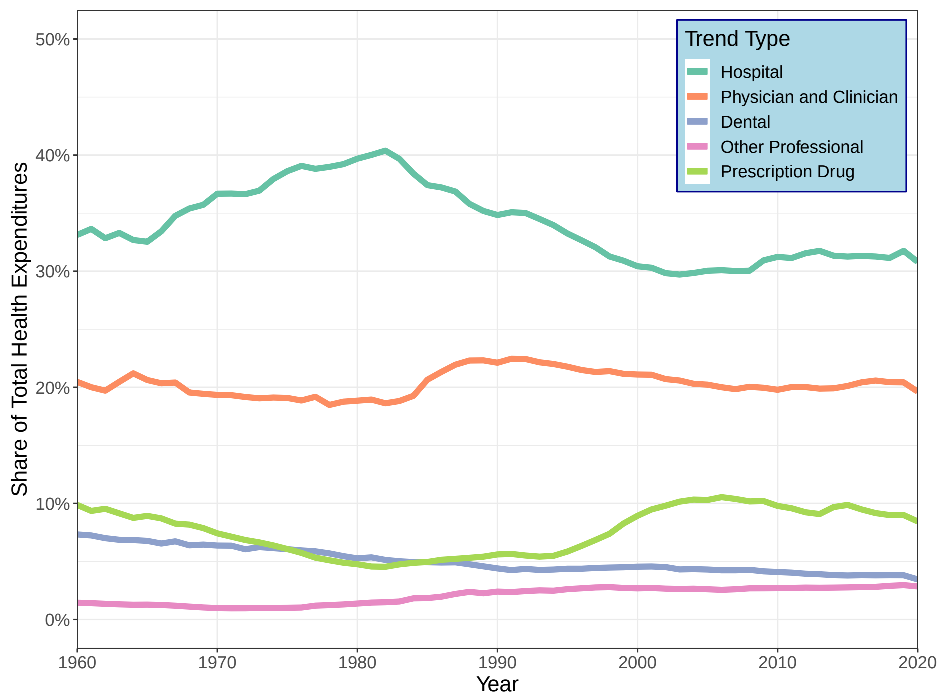

FIGURE 13. Hospital Spending as Share of Total Health Expenditures, 1960-2020. Source: NHE

While the share has fluctuated between 30% to 40% across the last 60 years, hospital spending has remained a consistently large proportion of total health expenditures in the United States relative to other types of health care spending. As total health expenditures continue to increase, the fact that hospital spending remains large signifies that the focus on pricing for hospital spending in the context of price transparency reform is certainly justifiable.

A.2.2. *State Inpatient Data.* Here, I wish to provide a more detailed description of the data introduced in Section 3.2 and used for the estimation strategy in this paper. As mentioned, I use discharge data from Arizona and Iowa State Inpatient Databases (SIDs), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality (AHRQ). These discharge data are structured as longitudinal all-payer claims data sets, are de-identified at the patient and hospital level, and are originally sourced from the hospitals.

Table 6 shows the main summary statistics for patient and procedure-specific variables included in the estimation procedure. Table 7 compares the distribution across states and years of distance to care (in miles) and total charges (inflation-adjusted, in US dollars).[22] Table 8 shows primary payer and status of in-state/out-of-state residence frequency with respect to provider of care by state and year.[23]

Tables 9, 10, and 11 repeat the same summary and descriptive statistics for the Arizona and Iowa data when limited to discharges coded with DRG 470.

A.2.3. *Hospital Openings and Closures.* Table 12 displays summary statistics of number of closures and openings as well as for opening and closure shares calculated and used for the analysis in Section 4.2.2. These statistics are at the patient ZIP code level (i.e., the average number of hospital closures a patient in a given ZIP code experienced in a given year, etc.).

A.3. **Robustness Results.** In this section, I provide robustness checks for the results in this paper, including when alternative measures of distance to care are used as well as a discussion of the parallel trends assumption.

A.3.1. *Alternative Calculations of Distance to Care.* I calculate distance to care using latitude-longitude coordinates with respect to the patient and provider ZIP codes in my data set. For the main analysis in the paper, I use the 2017 ZIP Code Tabulation Areas Gazetteer file from the US Census Bureau to obtain latitude and longitude coordinates for each ZIP code. As an alternative specification, I use ZIP code latitude and longitude coordinates obtained through GeoNames, an open-source geographical database.[24]

[22]Inflation is adjusted to 2017 US dollars using the BLS series CUUR0000SA0: Items in US City Average, All Urban Consumers, Not Seasonally Adjusted.

[23]In adherence to the data use agreement with HCUP, any tables shown are subject to removal of rows for any categorical variables where cell size representing individual discharges is less than 10.

[24]http://www.geonames.org/

Tables 13 and 14 display estimation results for the empirical strategy outlined in Section 4 when GeoNames coordinates are used. These results can be compared with Tables 1 and 5, respectively, and it is clear in doing so that the main results only deviate slightly as a result of any differences in main and alternative specifications of coordinates.

A.3.2. *Alternative Specification Using Net Distance Traveled to Care.* While the main analysis in the paper uses an unadjusted measure of distance between patient and provider to calculate distance to care, I employ an alternative specification where net distance traveled to care is used as an additional robustness check. Here, net distance to care is measured as the distance between the patient ZIP code and provider ZIP code observed on the inpatient claim, minus the distance to the closest available provider to the patient with respect to ZIP code and year.

Table 15 displays the results for all inpatient procedures, while Table 16 considers only inpatient claims with DRG 470. While the main results yield an effect that is not statistically significant for the full effect and only a 2 mile increase within HRR in 2014, the results in Table 15 suggest the observed distances patients travel to receive care are closer to their nearest provider by half a mile in 2014 and over two miles in 2017. There is also a statistically insignificant effect measured within HRR for all inpatient procedures. For claims with DRG 470, Table 16 shows just over a one-mile increase in 2014 and a slight increase above that in 2017 for the full effect, and within HRR, patients are traveling over 2 miles in 2014 and 2017 relative to their nearest provider.

Behavior in line with increased willingness to shop as motivated in Section 2 would be expected to result in further net distances traveled, such that patients using tools to shop for additional providers to obtain care. In the overall case, there does not seem to be evidence that this occurs in estimates for net distance to care; for DRG 470 claims, there is a small effect upon implementation that diminishes in 2017. In both cases, I find that estimates reinforce the conclusions in Sections 4.2 and 4.3.

A.3.3. *Parallel Trends.* My analysis of Iowa and Arizona inpatient data is constrained to discharge data from years 2011, 2014, and 2017. As a result, it is difficult within the data set used in my analysis to provide internal evidence that the parallel trends assumption should hold. I am limited in how I can approach this with other aggregate data, since little on distance traveled to care can be found at the state level. However, I am able to get at this with health expenditure data at the state level, which is available through the Centers for Medicare and Medicaid Services (CMS) Office of the Actuary.

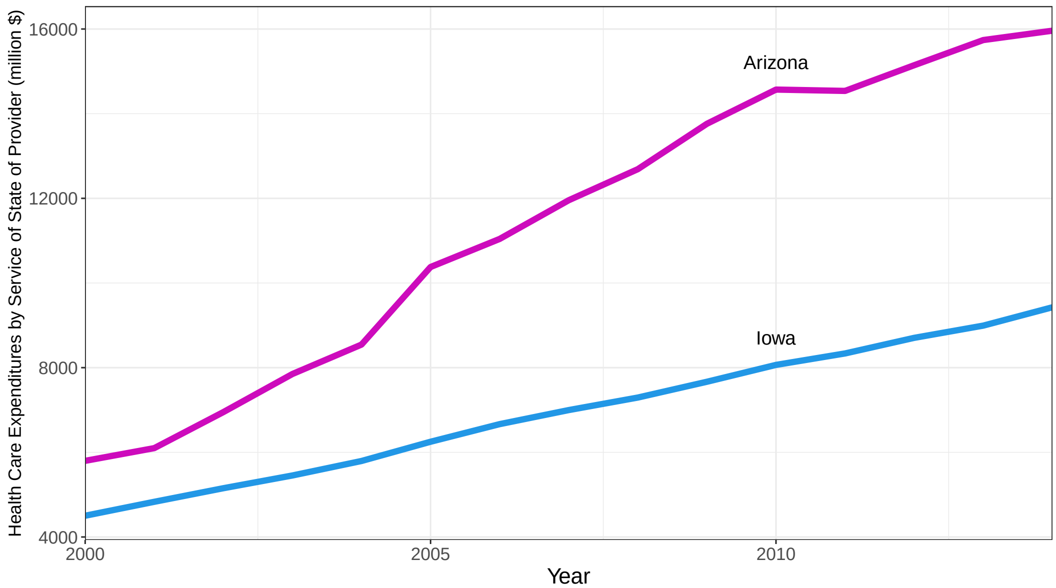

Figure 14. Health Care Expenditures by Service of State of Provider, Arizona and Iowa, 2000-2014.

To provide some insight into spending patterns prior to the timeline of Arizona price transparency implementation and obsolescence, I have plotted health care expenditures by service of the state of provider for Arizona and Iowa from 2000 to 2014, the year of full price transparency implementation in Arizona. Figure 14 shows these trends, reported in units of millions of US dollars.

While it is clear that there is movement in Arizona expenditures that is not observed equally in Iowa in the mid-to-late 2000s, a similar increasing trend in health care expenditures can be observed just prior to the first year of analysis conducted in this paper. While observing trends in health expenditures only provides so much scope into the validity of the parallel trends assumption for the analysis conducted, growth in expenditures appears to be increasing and similar in magnitude on average leading up to the relevant years of treatment for the conducted analysis.

Table 6. Summary Statistics, All Discharges

	AZ (N=2133323)	IA (N=909751)	Overall (N=3043074)
Year			
2011	734684 (34.4%)	292083 (32.1%)	1026767 (33.7%)
2014	710265 (33.3%)	293521 (32.3%)	1003786 (33.0%)
2017	688374 (32.3%)	324147 (35.6%)	1012521 (33.3%)
Age			
Mean (SD)	47.2 (27.6)	51.5 (28.4)	48.5 (27.9)
Median [Min, Max]	52.0 [0, 114]	58.0 [0, 113]	54.0 [0, 114]
No. of Procedures			
Mean (SD)	1.51 (2.10)	1.44 (2.06)	1.49 (2.09)
Median [Min, Max]	1.00 [0, 12.0]	1.00 [0, 50.0]	1.00 [0, 50.0]
No. of Repeat Admissions at Facility			
Mean (SD)	1.65 (1.41)	1.82 (1.54)	1.70 (1.45)
Median [Min, Max]	1.00 [1.00, 26.0]	1.00 [1.00, 25.0]	1.00 [1.00, 26.0]
Sex			
Male	932245 (43.7%)	383761 (42.2%)	1316006 (43.2%)
Female	1201078 (56.3%)	525990 (57.8%)	1727068 (56.8%)
Median Household Income for Patient ZIP Code			
Lowest	718758 (33.7%)	114119 (12.5%)	832877 (27.4%)
Second	669263 (31.4%)	409114 (45.0%)	1078377 (35.4%)
Third	408265 (19.1%)	297402 (32.7%)	705667 (23.2%)
Highest	337037 (15.8%)	89116 (9.8%)	426153 (14.0%)
Race			
White	1441988 (67.6%)	822914 (90.5%)	2264902 (74.4%)
Black	109528 (5.1%)	38268 (4.2%)	147796 (4.9%)
Hispanic	461105 (21.6%)	28403 (3.1%)	489508 (16.1%)
Asian/Pacific Islander	47125 (2.2%)	10144 (1.1%)	57269 (1.9%)
Native American	70723 (3.3%)	5080 (0.6%)	75803 (2.5%)
Other	2854 (0.1%)	4942 (0.5%)	7796 (0.3%)
Emergency Department Indicator			
0	1060981 (49.7%)	523435 (57.5%)	1584416 (52.1%)
1	1072342 (50.3%)	386316 (42.5%)	1458658 (47.9%)
Patient CBSA			
Non-CBSA	21297 (1.0%)	225773 (24.8%)	247070 (8.1%)
Micro	91762 (4.3%)	179453 (19.7%)	271215 (8.9%)
Metro	2020264 (94.7%)	504525 (55.5%)	2524789 (83.0%)
Patient Urban Rural			
Large Metro	1458166 (68.4%)	3367 (0.4%)	1461533 (48.0%)
Small Metro	538024 (25.2%)	501143 (55.1%)	1039167 (34.1%)
Micro	107912 (5.1%)	170674 (18.8%)	278586 (9.2%)
Rural	29221 (1.4%)	234567 (25.8%)	263788 (8.7%)
Transfer Status			
No Transfer/Newborn	1934774 (90.7%)	823483 (90.5%)	2758257 (90.6%)
From Acute Care	172770 (8.1%)	63454 (7.0%)	236224 (7.8%)
Other Facility Type	25779 (1.2%)	22814 (2.5%)	48593 (1.6%)
Point of Origin			
Non-Health Care Facility	1472022 (69.0%)	646358 (71.0%)	2118380 (69.6%)
Clinic/Physician's Office	208974 (9.8%)	72659 (8.0%)	281633 (9.3%)
Hospital	172770 (8.1%)	63454 (7.0%)	236224 (7.8%)
Nursing Facility	236924 (11.1%)	96648 (10.6%)	333572 (11.0%)
Health Care Facility	14963 (0.7%)	6455 (0.7%)	21418 (0.7%)
Law Enforcement	15439 (0.7%)	1592 (0.2%)	17031 (0.6%)
Distinct Unit Within Hospital	11466 (0.5%)	22248 (2.4%)	33714 (1.1%)
Ambulatory Surgery Center	521 (0.0%)	152 (0.0%)	673 (0.0%)
Hospice	202 (0.0%)	185 (0.0%)	387 (0.0%)

Table 7. Summary of Distance to Care and Total Charges, All Inpatient Discharges

	AZ	IA	Overall
2011	(N=734684)	(N=292083)	(N=1026767)
Distance to Care (mi)			
Mean (SD)	45.7 (207)	21.0 (65.2)	38.7 (179)
Median [Min, Max]	7.34 [0, 3080]	8.35 [0, 4050]	7.51 [0, 4050]
Total Charges ($)			
Mean (SD)	40500 (66200)	25700 (42500)	36300 (60800)
Median [Min, Max]	24100 [113, 4910000]	14500 [152, 3480000]	21100 [113, 4910000]
2014	(N=710265)	(N=293521)	(N=1003786)
Distance to Care (mi)			
Mean (SD)	44.3 (201)	21.5 (70.3)	37.6 (173)
Median [Min, Max]	7.75 [0, 3160]	8.59 [0, 3900]	7.85 [0, 3900]
Total Charges ($)			
Mean (SD)	45400 (72000)	29200 (48700)	40600 (66500)
Median [Min, Max]	27200 [105, 4850000]	16500 [119, 4040000]	23800 [105, 4850000]
2017	(N=688374)	(N=324147)	(N=1012521)
Distance to Care (mi)			
Mean (SD)	44.3 (200)	23.6 (70.2)	37.7 (170)
Median [Min, Max]	8.05 [0, 3060]	8.95 [0, 4060]	8.32 [0, 4060]
Total Charges ($)			
Mean (SD)	54300 (85900)	31100 (50300)	46900 (77100)
Median [Min, Max]	32300 [105, 9180000]	17800 [133, 3920000]	27000 [105, 9180000]

Table 8. Summary of Primary Payer, Outside State, and Admission Month, All Inpatient Discharges

	AZ	IA	Overall
2011	(N=734684)	(N=292083)	(N=1026767)
Patient Resides Outside State Where Care is Received			
No	711004 (96.8%)	274528 (94.0%)	985532 (96.0%)
Yes	23680 (3.2%)	17555 (6.0%)	41235 (4.0%)
Primary Payer			
Medicare	269963 (36.7%)	129599 (44.4%)	399562 (38.9%)
Medicaid	192040 (26.1%)	48269 (16.5%)	240309 (23.4%)
Private Ins.	207974 (28.3%)	102068 (34.9%)	310042 (30.2%)
Self-Pay	33004 (4.5%)	7731 (2.6%)	40735 (4.0%)
2014	(N=710265)	(N=293521)	(N=1003786)
Patient Resides Outside State Where Care is Received			
No	687960 (96.9%)	276986 (94.4%)	964946 (96.1%)
Yes	22305 (3.1%)	16535 (5.6%)	38840 (3.9%)
Primary Payer			
Medicare	264627 (37.3%)	135617 (46.2%)	400244 (39.9%)
Medicaid	195253 (27.5%)	50858 (17.3%)	246111 (24.5%)
Private Ins.	198847 (28.0%)	97076 (33.1%)	295923 (29.5%)
Self-Pay	28209 (4.0%)	6698 (2.3%)	34907 (3.5%)
2017	(N=688374)	(N=324147)	(N=1012521)
Patient Resides Outside State Where Care is Received			
No	667980 (97.0%)	304204 (93.8%)	972184 (96.0%)
Yes	20394 (3.0%)	19943 (6.2%)	40337 (4.0%)
Primary Payer			
Medicare	270351 (39.3%)	146942 (45.3%)	417293 (41.2%)
Medicaid	202921 (29.5%)	67048 (20.7%)	269969 (26.7%)
Private Ins.	172493 (25.1%)	101016 (31.2%)	273509 (27.0%)
Self-Pay	23328 (3.4%)	5757 (1.8%)	29085 (2.9%)

Table 9. Summary Statistics, DRG 470

	AZ	IA	Overall
	(N=66267)	(N=42126)	(N=108393)
Year			
2011	18361 (27.7%)	11847 (28.1%)	30208 (27.9%)
2014	23776 (35.9%)	13744 (32.6%)	37520 (34.6%)
2017	24130 (36.4%)	16535 (39.3%)	40665 (37.5%)
Age			
Mean (SD)	67.6 (10.8)	66.9 (11.0)	67.4 (10.9)
Median [Min, Max]	68.0 [11.0, 104]	67.0 [11.0, 108]	67.0 [11.0, 108]
No. of Procedures			
Mean (SD)	1.51 (0.766)	1.35 (0.724)	1.45 (0.754)
Median [Min, Max]	1.00 [1.00, 12.0]	1.00 [1.00, 10.0]	1.00 [1.00, 12.0]
No. of Repeat Admissions at Facility			
Mean (SD)	1.27 (0.617)	1.39 (0.761)	1.32 (0.679)
Median [Min, Max]	1.00 [1.00, 18.0]	1.00 [1.00, 17.0]	1.00 [1.00, 18.0]
Sex			
Male	26751 (40.4%)	16563 (39.3%)	43314 (40.0%)
Female	39516 (59.6%)	25563 (60.7%)	65079 (60.0%)
Median Household Income for Patient ZIP Code			
Lowest	16167 (24.4%)	3895 (9.2%)	20062 (18.5%)
Second	21635 (32.6%)	17958 (42.6%)	39593 (36.5%)
Third	14689 (22.2%)	15353 (36.4%)	30042 (27.7%)
Highest	13776 (20.8%)	4920 (11.7%)	18696 (17.2%)
Race			
White	56911 (85.9%)	41079 (97.5%)	97990 (90.4%)
Black	1686 (2.5%)	602 (1.4%)	2288 (2.1%)
Hispanic	5920 (8.9%)	286 (0.7%)	6206 (5.7%)
Asian/Pacific Islander	1018 (1.5%)	93 (0.2%)	1111 (1.0%)
Native American	649 (1.0%)	43 (0.1%)	692 (0.6%)
Other	83 (0.1%)	23 (0.1%)	106 (0.1%)
Emergency Department Indicator			
0	61088 (92.2%)	40191 (95.4%)	101279 (93.4%)
1	5179 (7.8%)	1935 (4.6%)	7114 (6.6%)
Patient CBSA			
Non-CBSA	855 (1.3%)	10796 (25.6%)	11651 (10.7%)
Micro	2875 (4.3%)	8725 (20.7%)	11600 (10.7%)
Metro	62537 (94.4%)	22605 (53.7%)	85142 (78.5%)
Patient Urban Rural			
Large Metro	42575 (64.2%)	51 (0.1%)	42626 (39.3%)
Small Metro	19135 (28.9%)	22554 (53.5%)	41689 (38.5%)
Micro	3480 (5.3%)	8203 (19.5%)	11683 (10.8%)
Rural	1077 (1.6%)	11318 (26.9%)	12395 (11.4%)
Transfer Status			
No Transfer/Newborn	65928 (99.5%)	41620 (98.8%)	107548 (99.2%)
From Acute Care	240 (0.4%)	379 (0.9%)	619 (0.6%)
Other Facility Type	99 (0.1%)	127 (0.3%)	226 (0.2%)
Point of Origin			
Non-Health Care Facility	40086 (60.5%)	36602 (86.9%)	76688 (70.8%)
Clinic/Physician's Office	25785 (38.9%)	4966 (11.8%)	30751 (28.4%)
Hospital	240 (0.4%)	379 (0.9%)	619 (0.6%)
Nursing Facility	35 (0.1%)	62 (0.1%)	97 (0.1%)
Health Care Facility	63 (0.1%)	42 (0.1%)	105 (0.1%)
Law Enforcement	21 (0.0%)	20 (0.0%)	41 (0.0%)

Table 10. Summary of Distance to Care and Total Charges, DRG 470

	AZ	IA	Overall
2011	(N=18361)	(N=11847)	(N=30208)
Distance to Care (mi)			
Mean (SD)	47.5 (203)	23.5 (49.4)	38.1 (162)
Median [Min, Max]	9.07 [0, 2810]	13.7 [0, 2780]	10.4 [0, 2810]
Total Charges ($)			
Mean (SD)	58400 (20100)	41400 (10100)	51700 (18800)
Median [Min, Max]	55100 [7700, 491000]	39700 [8510, 206000]	48300 [7700, 491000]
2014	(N=23776)	(N=13744)	(N=37520)
Distance to Care (mi)			
Mean (SD)	49.9 (210)	23.6 (65.9)	40.3 (173)
Median [Min, Max]	10.7 [0, 2910]	12.4 [0, 3010]	11.2 [0, 3010]
Total Charges ($)			
Mean (SD)	60300 (23200)	44900 (27900)	54700 (26200)
Median [Min, Max]	57500 [1880, 468000]	42900 [1320, 3040000]	50500 [1320, 3040000]
2017	(N=24130)	(N=16535)	(N=40665)
Distance to Care (mi)			
Mean (SD)	45.8 (200)	22.0 (47.7)	36.2 (158)
Median [Min, Max]	10.7 [0, 2850]	12.3 [0, 3160]	11.3 [0, 3160]
Total Charges ($)			
Mean (SD)	68100 (25300)	45600 (11900)	59000 (23700)
Median [Min, Max]	65000 [6840, 339000]	43200 [6110, 217000]	53700 [6110, 339000]

TABLE 11. Summary of Primary Payer, Outside State, and Admission Month, DRG 470

	AZ	IA	Overall
2011	(N=18361)	(N=11847)	(N=30208)
Patient Resides Outside State Where Care is Received			
No	17744 (96.6%)	11030 (93.1%)	28774 (95.3%)
Yes	617 (3.4%)	817 (6.9%)	1434 (4.7%)
Primary Payer			
Medicare	11054 (60.2%)	6713 (56.7%)	17767 (58.8%)
Medicaid	1074 (5.8%)	257 (2.2%)	1331 (4.4%)
Private Ins.	5497 (29.9%)	4733 (40.0%)	10230 (33.9%)
Self-Pay	102 (0.6%)	15 (0.1%)	117 (0.4%)
2014	(N=23776)	(N=13744)	(N=37520)
Patient Resides Outside State Where Care is Received			
No	23028 (96.9%)	12881 (93.7%)	35909 (95.7%)
Yes	748 (3.1%)	863 (6.3%)	1611 (4.3%)
Primary Payer			
Medicare	14371 (60.4%)	7801 (56.8%)	22172 (59.1%)
Medicaid	1339 (5.6%)	529 (3.8%)	1868 (5.0%)
Private Ins.	7018 (29.5%)	5195 (37.8%)	12213 (32.6%)
Self-Pay	273 (1.1%)	45 (0.3%)	318 (0.8%)
2017	(N=24130)	(N=16535)	(N=40665)
Patient Resides Outside State Where Care is Received			
No	23422 (97.1%)	15507 (93.8%)	38929 (95.7%)
Yes	708 (2.9%)	1028 (6.2%)	1736 (4.3%)
Primary Payer			
Medicare	15704 (65.1%)	9842 (59.5%)	25546 (62.8%)
Medicaid	1395 (5.8%)	650 (3.9%)	2045 (5.0%)
Private Ins.	6273 (26.0%)	5835 (35.3%)	12108 (29.8%)
Self-Pay	111 (0.5%)	27 (0.2%)	138 (0.3%)

Table 12. Hospital Openings and Closures, by Patient ZIP Code

	AZ	IA	Overall
	(N=2133323)	(N=909751)	(N=3043074)
No. of Hospital Closures between 2011 and 2014			
Mean (SD)	1.78 (1.12)	0.0385 (0.195)	1.26 (1.24)
Median [Min, Max]	2.00 [0, 5.00]	0 [0, 5.00]	1.00 [0, 5.00]
2014 Closure Share			
Mean (SD)	0.0395 (0.0824)	0.0000774 (0.00168)	0.0277 (0.0713)
Median [Min, Max]	0.00823 [0, 0.647]	0 [0, 0.647]	0.00203 [0, 0.647]
No. of Hospital Openings between 2011 and 2014			
Mean (SD)	2.62 (1.41)	0.0156 (0.131)	1.84 (1.68)
Median [Min, Max]	3.00 [0, 6.00]	0 [0, 6.00]	2.00 [0, 6.00]
2014 Opening Share			
Mean (SD)	0.0531 (0.0885)	0.0000270 (0.00184)	0.0373 (0.0780)
Median [Min, Max]	0.0279 [0, 0.696]	0 [0, 0.696]	0.0125 [0, 0.696]
No. of Hospital Closures between 2014 and 2017			
Mean (SD)	2.55 (1.29)	0.0765 (0.325)	1.81 (1.58)
Median [Min, Max]	3.00 [0, 6.00]	0 [0, 6.00]	2.00 [0, 6.00]
2017 Closure Share			
Mean (SD)	0.0250 (0.0610)	0.0000219 (0.00125)	0.0175 (0.0523)
Median [Min, Max]	0.0105 [0, 0.801]	0 [0, 0.801]	0.00285 [0, 0.801]
No. of Hospital Openings between 2014 and 2017			
Mean (SD)	2.45 (1.12)	0.0421 (0.204)	1.73 (1.45)
Median [Min, Max]	2.00 [0, 5.00]	0 [0, 5.00]	2.00 [0, 5.00]
2017 Opening Share			
Mean (SD)	0.0357 (0.0499)	0.0000421 (0.00130)	0.0250 (0.0448)
Median [Min, Max]	0.0253 [0, 0.564]	0 [0, 0.564]	0.0115 [0, 0.564]

Table 13. Estimated Changes in Distance to Care (Alternative Specification), All Inpatient Procedures

	Dependent variable:				
	Distance to Care (mi)				
	(1)	(2)	(3)	(4)	(5)
AZ	44.894***	81.438***	77.307***	155.200**	126.509***
	(0.000)	(28.393)	(6.431)	(73.673)	(5.872)
Y2014	20.969***	−1.245	1.427	−1.879	0.096
	(0.000)	(0.891)	(1.985)	(1.233)	(1.088)
Y2017	23.125***	3.485	1.591***	3.015	0.377
	(0.000)	(2.468)	(0.299)	(2.264)	(0.435)
AZ × Y2014	−22.481***	3.283	0.368	3.923	1.891***
	(0.000)	(3.335)	(1.121)	(3.406)	(0.438)
AZ × Y2017	−24.521***	−3.336***	−0.279	−2.464***	0.756
	(0.000)	(0.619)	(1.538)	(0.679)	(2.129)
$\mathbf{X}_{im}$	N	Y	Y	Y	Y
$\mathbf{1}_{OutsideState}$	N	N	Y	N	Y
HRR_j	N	N	N	Y	Y
Observations	3,043,074	-	-	-	-
R2	0.046	0.085	0.452	0.094	0.469

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

Table 14. Estimated Changes in Distance to Care (Alternative Specification), DRG 470

	Dependent variable:				
	Distance to Care (mi)				
	(1)	(2)	(3)	(4)	(5)
AZ	46.655***	96.764***	89.158***	194.264***	167.823***
	(0.000)	(28.312)	(7.780)	(67.113)	(14.736)
Y2014	23.103***	−0.498	2.949	−2.916	1.899
	(0.000)	(0.925)	(2.150)	(1.992)	(2.911)
Y2017	21.538***	0.499	3.460	−1.429*	1.914
	(0.000)	(1.312)	(2.645)	(0.831)	(3.110)
AZ × Y2014	−20.891***	6.149	4.118***	11.667**	6.571***
	(0.000)	(4.474)	(0.154)	(5.317)	(1.188)
AZ × Y2017	−23.334***	2.185	1.827***	5.886***	3.348**
	(0.000)	(1.610)	(0.709)	(1.668)	(1.483)
$\mathbf{X}_{im}$	*N*	*Y*	*Y*	*Y*	*Y*
$\mathbf{1}_{OutsideState}$	*N*	*N*	*Y*	*N*	*Y*
HRR_j	*N*	*N*	*N*	*Y*	*Y*
Observations	3,043,074	-	-	-	-
R2	0.052	0.093	0.372	0.109	0.404

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

Table 15. Estimated Changes in Net Distance to Care, All Inpatient Procedures

	Dependent variable:				
	Net Distance to Care (mi)				
	(1)	(2)	(3)	(4)	(5)
AZ	14.668***	19.709	19.075	11239.560	13324.018
	(0.000)	(6.764)	(3.392)	(74873.906)	(37135.412)
Y2014	12.589***	0.836	1.246	0.652	0.956*
	(0.000)	(0.145)	(0.297)	(0.190)	(0.135)
Y2017	14.701***	3.155	2.864	3.079	2.674***
	((0.000)	(0.845)	(0.512)	(1.068)	(0.037)
AZxY2014	−12.628***	−0.078	−0.526**	0.109	−0.204
	((0.000)	(0.720)	(0.035)	(0.669)	(0.342)
AZxY2017	−14.148***	−2.394*	−1.924**	−2.259	−1.764
	(0.000)	(0.194)	(0.138)	(0.654)	(0.761)
$\mathbf{X}_{im}$	*N*	*Y*	*Y*	*Y*	*Y*
$\mathbf{1}_{OutsideState}$	*N*	*N*	*Y*	*N*	*Y*
HRR_j	*N*	*N*	*N*	*Y*	*Y*
Observations	3,043,074	-	-	-	-
R^2	−0.012	0.128	0.366	−3.872	−0.365

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.

Table 16. Estimated Changes in Net Distance to Care, DRG 470

	Dependent variable:				
	Net Distance to Care (mi)				
	(1)	(2)	(3)	(4)	(5)
AZ	16.305***	21.239	20.153*	54.894	51.019**
	(0.000)	(5.020)	(1.966)	(11.495)	(3.626)
Y2014	15.367***	0.319	0.811	−0.510	0.195
	(0.000)	(0.304)	(0.191)	(0.276)	(0.477)
Y2017	14.742***	0.019	0.442	−0.718	−0.228
	(0.000)	(0.089)	(0.327)	(0.291)	(0.650)
AZxY2014	−13.996***	1.640	1.350*	3.021	2.275**
	(0.000)	(0.831)	(0.181)	(0.943)	(0.047)
AZxY2017	−14.412***	1.599**	1.548*	2.509**	2.138*
	(0.000)	(0.093)	(0.244)	(0.161)	(0.320)
$\mathbf{X}_{im}$	N	Y	Y	Y	Y
$\mathbf{1}_{OutsideState}$	N	N	Y	N	Y
HRR_j	N	N	N	Y	Y
Observations	3,043,074	-	-	-	-
R^2	−0.027	0.125	0.285	0.162	0.340

Note: SEs clustered at state level. *p<0.1; **p<0.05; ***p<0.01.