EFFECTS OF PUBLIC PRICE TRANSPARENCY TOOLS ON SHOPPING FOR HEALTH CARE

AUSTIN KNIES

Abstract. Do public price transparency tools actually encourage health care patients to shop around more for care? As health care costs in the United States continue to soar, price transparency initiatives at the state and federal level have continued to gain traction among policymakers. While advocates hypothesize that more information on pricing will catalyze competitive forces in health care, it remains unclear to what extent reform will be effective in lowering expenses. Exploiting a unique state policy timetable in Arizona, I use state inpatient data to study how distance to care and total charges change as a response to the implementation and obsolescence of public price transparency tools. Estimation results indicate that patients are slightly shopping more for care when price transparency tools are implemented, but this effect does not appear to be driven by patients with the highest propensity to shop. Contrary to the existing literature, I also find that total charges increase, suggesting that health care outcomes are getting worse instead of better and ultimately building the case that public price transparency initiatives of the popular form alone may not be enough to curtail growing health expenditures.

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Please address correspondence to: Austin Knies, Department of Economics, Indiana University Bloomington, ausknies@iu.edu.

1. Introduction

Health expenditures in the United States have increased at an alarming pace over the last several decades. According to health care spending data from the Centers for Medicare and Medicaid Services, total national health expenditures in 1960 were $27 billion; by 2019, that number had risen to just under $3.8 trillion.[1] Adjusting for inflation, per-capita health care spending has increased almost twelve-fold within the last 70 years.

This significant rise in health care spending is perhaps more clear viewed when contextualized as a share of national gross domestic product (GDP). In the United States, total national health expenditures as a share of GDP were 5%. By 1984, that share had doubled; by 2003, that share had tripled. By 2019, total national health expenditures were just under 18% of GDP. Even more concerning is how large this share is in comparison to the rest of the world. Figure 1 displays how this share of GDP compares over time with other countries that belong to the Organization for Economic Cooperation and Development (OECD) over the last fifty years. It is clear to see that 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, that this contrast between spending in the United States and other countries has only grown more severe over time.

Coupled with this problem of rising costs, a complicating characteristic inherent to health care markets is the abundance of information asymmetry. Patients seek out health care providers who have specialized knowledge about medical conditions and receive treatment based on this unbalanced level of expertise. This lopsided patient-provider dynamic can be further dichotomized into two types of informational differences—one resulting from a patient's lack of knowledge about quality of care and another due to a lack of knowledge about the costs of care. While it may be natural for individuals seeking care to be

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

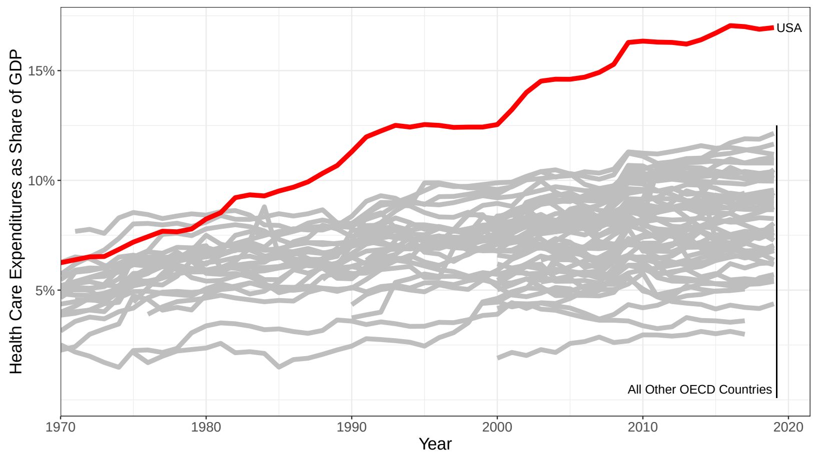

FIGURE 1. Health Care Expenditures as Share of GDP across OECD Countries, 1970-2019.

uninformed about the true state of their health status and future outcomes, they are also often uninformed about the cost of treatment until after services have been performed (Frost and Newman (2016), Lieber (2017), Buttorff et al. (2021)).

As health care costs have continued to skyrocket in the United States, policymakers at both state and federal levels in recent decades have been under pressure to find ways to curb costs. Given the information asymmetries in health care, one particular type of reform that has gained a significant degree of traction over the last two decades is price transparency, which typically requires health care providers to make available or publish prices charged for services. The main idea behind price transparency initiatives is that by increasing available pricing information, patients seeking health care services should be more equipped to search for cost-effective care. With higher competition for lower cost care, market forces should drive down prices for health services, which would help to combat the rise in health expenditures.

In recent years, price transparency reforms have been passed and initiated both at state and federal levels at unprecedented rates. Sinaiko and Rosenthal (2011) found that legislation in over 30 different states and three federal bills directly related to increasing price transparency were introduced by 2011. Kullgren et al. (2013) found that half of existing state health care price transparency websites in 2012 had launched at some point within the last six years. Similarly, Christensen et al. (2020) found that by 2013, 34 states had published a price transparency website.

Along with increases in state activity, perhaps the most notable contribution to price transparency reform in recent years came from the previous Trump administration. In 2019, former President Trump issued an executive order enacting and adding to a rule originally set forth by the Affordable Care Act that required hospitals to make public their charges in a machine-readable format. Former US Human and Health Services Secretary Alex Azar was quoted as viewing this action to be "a more significant change to American healthcare markets than any other single thing we've done."[2] Even after facing a challenge in court from the American Hospital Association (AHA), this controversial "final rule" ultimately went into effect on January 1, 2021.

Despite the frenzy of state and federal price transparency efforts over the last twenty years, it remains unclear whether public price transparency initiatives are as effective at lowering health expenses as legislators and policymakers make it out to be. The existing literature on price transparency has 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)). Most of the existing literature regarding price transparency has focused on employer-sponsored initiatives, which involve a patient's insurance company offering a price transparency tool tailored to a specific insurance plan. Secondly, the existing literature usually focuses on services that are more likely to be homogeneous across patients. Using these studies to make inferences about the potential efficacy of public price transparency reforms, which are intended to be accessible to any person regardless of insurance status or type of procedure, is challenging, if not altogether problematic.

[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)).

Subsequently, newer studies have focused more on public-facing price transparency initiatives. For instance, Brown (2019b) finds that access to a state-of-the-art New Hampshire price transparency website decreased the out-of-pocket costs of medical imaging procedures for patients by 5% and that this reduction effect increased as time went on. Christensen et al. (2020) looks at the effect of various state-level price transparency websites and finds a 5% reduction in provider charges, although finding no effect on patient prices. While these papers do look at publicly-available tools, they also focus on a handful of services that are typically similar across patients. Additionally, only Christensen et al. (2020) looks at inpatient procedures, and even this selection is limited. For this reason, there is still much to be learned about how public price transparency impacts prices beyond a small subset of procedures.

Outside of the empirical work on price transparency, there is a whole class of literature on the theory behind search costs and price information, building off of 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)). There is much evidence in existing literature that 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)).

However, 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)). Therefore, from a theoretical perspective, it is unclear whether we should expect prices to increase or decrease following a given price transparency initiative.

In this paper, I aim to contribute to the existing literature in the following ways. First, I focus on a type of public-facing price transparency effort that is much more common and less personalized than the reforms studied in most existing work. More specifically, I exploit a unique price transparency reform timetable in the state of Arizona, where two separate initiatives were implemented within the same time period: a publicly accessible website to compare total charge prices across state hospitals and state legislation requiring hospitals to post charges of common procedures. To understand the efficacy of these reforms, I use state inpatient data from hospitals before and after implementation of both transparency initiatives, as well as data after the hospital charge comparison website becomes obsolete due to a lack of updates.

Second, because the direction of changes in prices due to price transparency is theoretically ambiguous, I attempt to isolate the demand-side effects of price transparency in order to discover whether patients with more information on costs of care are actually shopping more for care. Typically, the main mechanism expected to bring down prices post-reform is the increased likelihood of shopping for cost-effective care on the part of the patient. Rather than attempting to identify complex changes to prices that are beyond patient behavior, I instead focus on whether price transparency reform simply causes more patients to shop for care. If patients are not shopping more for care after price transparency tools are implemented, then we have already learned enough, since this is the channel intended to lower prices. While I also study the effects on costs for completeness, my empirical emphasis is on changes in willingness to shop.

To do this, I build off of Whaley (2015), Brown (2019b), Brown (2019a), and White and Whaley (2019) by looking primarily at distance to care as a proxy for willingness to shop. The intuition follows that without information on how prices are dispersed across available hospitals, patients are more likely to visit a provider near them, as traveling further for care is costly to a patient. As price information becomes known, patients who shop for care are more likely to travel further distances to receive treatment at a lower cost provider. Thus, if distance to care is increasing with the implementation of price transparency reform, we have evidence that patients may be shopping more for care.

I find that, on average, patients are traveling 3.4 miles more for care after both the charge price website and the state legislation are implemented in Arizona. I also find that patients travel slightly less, about 2.9 miles, after the website becomes obsolete, providing modest evidence that patients' willingness to shop for care increases after price transparency reforms are implemented and that effect diminishes as a part of the reform becomes obsolete.

However, when partitioning the data by demographic characteristics, I find that the increased in distance to care is not being driven by patients with a higher propensity to shop, suggesting that information frictions may differ across groups and play a key role in the efficacy of public price transparency initiatives. Finally, in comparing changes in distance to care with changes in total charges, I find that total charges are increasing across years and across all patient groups, except for inpatient stays associated with emergency department visits. This counterintuitive result contradicts the existing findings regarding inpatient procedures in Christensen et al. (2020), which found that a variety of statewide price transparency efforts across the United States led to a decrease in inpatient charges. Ultimately, as distance to care and costs increase, patients are actually worse off in terms of health outcomes after reforms are implemented, suggesting that more than just public price transparency initiatives may be necessary to help solve the challenging problems that exist in health care markets.

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 and results, are given in Appendix A.

2. Model and Empirical Motivation

Following a similar discrete choice framework as the existing literature (Whaley (2015), Brown (2019a), Brown (2019b), Whaley et al. (2019)), we set up a model for choice of care. 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 which provider.

To reflect the decision-making process for the patient, we 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, we wish to motivate the empirical strategy of examining changes in distance to care as a proxy for changes in willingness to shop. In doing so, we want to characterize the relationship between changes in expected price and patient sensitivity to distance traveled to care within this framework.

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

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

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. Note that if $\gamma_1 > 0$ and $\gamma_2 < 0$, which is consistent with estimates from the existing literature, 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 increases in distance to care responds to a change in beliefs about the expected price. To explore this, we 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. We find that

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

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

Proposition 1. *If* $\gamma_1 > 0$ *and* $\gamma_2 < 0$*, 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.

This result provides 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 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.

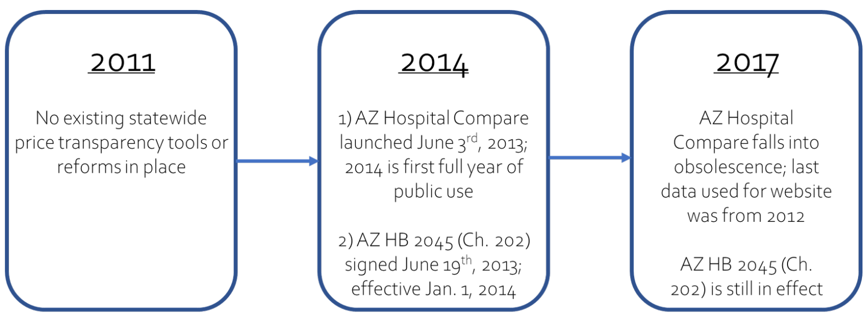

Figure 2. Policy timetable.

Prior to 2013, there were no statewide price transparency efforts ongoing or in place in Arizona. Then, in 2013, 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).[3]

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

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

Arizona's price transparency website is 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 (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, both Arizona's hospital charge comparison website and Arizona's state legislation 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. While there is currently little empirical evidence regarding how effective the new Trump-era regulations will be at lowering costs in the health care industry, its efficacy will be difficult to measure, given the various price transparency regulations at state levels that have been in place over the last two decades. Thus, studying the impact of legislation at the Arizona 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 State Inpatient Databases (SID), 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 hospitals.

For the purpose of studying the efficacy of the price transparency reforms implemented, as well as studying if there is any change when the website became outdated due to a lack of new data, we look at data from the years 2011, 2014, and 2017. As mentioned previously in Section 3.1 and summarized in Figure 2, no price transparency initiatives were in place at a state level in 2011. Both public price transparency reforms were initiated in 2013 and took effect at the beginning of 2014, such that 2014 would have been the first full year of effective policy implementation, where the tools would have been available for any patient to use. However, by 2017, the state legislation remained in effect, but the website was outdated with old hospital charge data. Thus, all three years of data can give insight into how willingness to shop evolved across policy implementation and obsolescence.[4]

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).

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

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 strategy and section 4.2 discuss the results.

4.1. **Estimation Strategy.** To look at the efficacy of public price transparency initiatives on our outcome variables, we estimate the following linear model using OLS regression:

$$y_{ijkmt} = \alpha + \beta_1 YEAR_{2014} + \beta_2 YEAR_{2017} + \mathbf{X}_i' \beta_3 + \omega_j + \varepsilon_{ijkmt} \tag{6}$$

As in Section 2, patient i with insurance status k chooses provider $j \in J$ for procedure m in year t. Here, y_{ijkmt} is the outcome variable we are interested in observing, which is primarily distance to care. For the sake of robustness, and for a clearer picture of efficacy, we also look at total charges, adjusted for inflation and log-transformed.

Additionally, $YEAR_{2014}$ and $YEAR_{2017}$ are time dummy variables such that β_1 and β_2 capture the marginal changes to distance to care and total charges from 2011, respectively. $\mathbf{X}_i$ are individual patient characteristics, including demographic factors like age, race, and median household income quartile, as well as record-specific characteristics like length of stay or the presence of emergency room charges on the bill.[5] We control for unobserved provider characteristics across years by using ω_j for provider fixed effects, and ε_{ijkmt} is our error term.

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

4.2. **Results.** We begin by exploring the results when we estimate our model in equation (6) on our data with distance to care as the dependent variable y_{ijkmt}. The results of this estimation are displayed in Table 1.

[5]A full list of the covariates used in the regression strategy can be found in Appendix A.2.

Table 1. Estimated Changes in Expected Distance to Care

	Dependent variable:			
	Distance to Care (mi)			
	(1)	(2)	(3)	(4)
YEAR_{2014}	-1.354^{***}	1.946^{***}	4.543^{***}	3.439^{***}
	(0.331)	(0.193)	(0.318)	(0.190)
YEAR_{2017}	-0.991^{***}	2.886^{***}	2.070^{***}	2.977^{***}
	(0.335)	(0.194)	(0.323)	(0.193)
Constant	45.836^{***}	59.861^{***}	$1,307.945^{***}$	212.766^{***}
	(0.230)	(17.583)	(29.666)	(17.753)
Individual Covariates	*N*	*Y*	*Y*	*Y*
Control for Outside AZ	*N*	*Y*	*N*	*Y*
Unobserved Provider FE	*N*	*N*	*Y*	*Y*
Observations	2,254,912	2,158,529	2,158,529	2,158,529
R^2	0.00001	0.681	0.156	0.698

*p<0.1; **p<0.05; ***p<0.01

Estimating a simplified regression with no individual covariates or provider fixed effects (i.e., dropping $\mathbf{X}_i'\beta_3$ and ω_j in equation (6)), we see that, on average, the distance between patient and provider actually *decreased* between 2011 and 2014 and that this was still the case, albeit slightly less so, in 2017. However, when we include patient characteristics, record-specific factors, and unobserved provider attributes, we find a different story: distance to care increased by 3.4 miles from 2011 to 2014. Interestingly, we also observe that this measured effect is lower but still positive and significant when comparing 2011 to 2017.

The results in Table 1 show slight evidence that the public price transparency reforms implemented in 2014 may have induced patients to shop more for care relative to no intervention. Additionally, we find that this effect diminished a bit in 2017, during the time frame when the website reform would have been obsolete. This modestly suggests that the combination of both reforms in 2014 led to a stronger change in patient shopping behavior than compared to when the website was outdated in 2017, although, overall, distance to care experienced a persistent increase beyond 2011.

In the estimations performed in Table 1, we also include an indicator variable when the patient on record has a billing ZIP code outside of Arizona, and the last two columns on the right compare the results with and without this control. One might imagine that patients traveling from outside Arizona for care 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 residents.[6] However, any patient seeking care at Arizona-based hospitals would have had access to the public price transparency tools implemented by 2014, so it is possible that patients outside Arizona incorporated the reforms into their search process for health care treatment. For these reasons, it is important to control for the non-Arizona-based residents in our data. I find that not controlling for patients traveling from outside Arizona overestimates the increase in distance to care in 2014 and overestimates the diminishing of that effect in 2017. This highlights the significance of controlling for non-Arizona patients while ultimately solidifying our main findings.

Given that we find a small but positive change in distance to care following the price transparency policy timeline in Arizona, we may also be interested in how prices are changing across years, even with the knowledge that the direction of movement can be ambiguous. Because our inpatient data originates at the hospital level, the only prices we observe are the total charges for the inpatient record. Of course, these charges are not typically charged fully to the patient if the patient is insured; however, out-of-pocket costs to patients are not observed in this data. That said, both public price transparency initiatives used

[6] I do find that the Arizona resident/non-resident makeup in my data remains constant across years, in any case. Further data visualization is available in Appendix A.2.

information on total charges rather than out-of-pocket costs, so it remains of interest to observe how these charges changed after the price transparency reforms were implemented. Table 2 displays these results.

Table 2. Estimated Changes in Expected Total Charges

	Dependent variable:			
	ln(Total Charges) ($)			
	(1)	(2)	(3)	(4)
$YEAR_{2014}$	0.112***	0.120***	0.113***	0.113***
	(0.002)	(0.001)	(0.001)	(0.001)
$YEAR_{2017}$	0.301***	0.280***	0.301***	0.301***
	(0.002)	(0.001)	(0.001)	(0.001)
Constant	10.031***	8.127***	7.415***	7.415***
	(0.001)	(0.094)	(0.090)	(0.090)
Individual Covariates	*N*	*Y*	*Y*	*Y*
Control for Outside AZ	*N*	*Y*	*N*	*Y*
Unobserved Provider FE	*N*	*N*	*Y*	*Y*
Observations	2,254,564	2,158,209	2,158,209	2,158,209
R^2	0.012	0.697	0.744	0.744

*p<0.1; **p<0.05; ***p<0.01

Alarmingly, we find that across specifications, inflation-adjusted total charges increased by approximately 11% from 2011 to 2014 and approximately 30% from 2011 to 2017.[7] This result is relatively stable whether we vary our specification by dropping individual covariates, provider effects, or both. Additionally, we note that our results in the last two columns, where we only change the control for patients traveling from outside Arizona, are identical, suggesting that Arizonians and non-Arizonians are facing the same increase in total charges.

[7]2011 and 2014 total charges were adjusted to be in 2017 dollars. This was done using the CPI-U U.S. city average series for all items, not seasonally adjusted, provided by the U.S. Bureau of Labor Statistics.

Given the previous discussion about theoretical predictions on price, it may not surprise us to find total charges are rising across time, especially since this is consistent with notion that health care expenditures continue to rise in the United States more generally. What is perplexing about this result is that the results are true even when controlling for observed patient and inpatient record details as well as unobserved provider attributes.

Here, we note that this finding is in stark contrast with the existing literature. Christensen et al. (2020) finds that total charges are *decreasing* across states with price transparency websites using a national sample of inpatient data from HCUP, known as the Nationwide Inpatient Sample (NIS).[8] However, exploiting additional data on insurance claims, they find that the out-of-pocket costs patients actually pay do not decrease. From this, they conclude that providers may be motivated to lower charges for reasons related to reputation and public relations, since these charges are what is publicly available. However, in the case of Arizona, which was not included in the set of states studied by Christensen et al. (2020), I do not find a similar result, and so I cannot arrive at this same conclusion. This contrast with the existing literature highlights the ambiguous direction of price changes after price transparency reforms have been implemented and the need to focus directly on the market mechanisms affected by policy if we are to understand efficacy more clearly.

All in all, continued increases in health care charges are the opposite of what policymakers promise when passing price transparency reforms. While we see a modest increase in distance to care, suggesting patients may be more willing to shop as a result of the publicly available price transparency tools, this does not appear to translate to a decrease in charges. Most importantly, if patients are driving more for care, and if we assume that increases in charges are translating to similar spikes in out-of-pocket costs, then inpatient treatment outcomes are getting worse over time for health care consumers in Arizona.

[8]Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality.

4.3. **Additional Specifications.** To further understand the impacts of the public price transparency initiatives in Arizona, we partition the data by different groups in order to identify any particular drivers of the estimated effects. For instance, we may suppose that a particular subgroup of patients have a higher propensity to shop for care than others, and so it is worthwhile to investigate whether we see if any one type of patient mainly drives the results we see. Further details about the partitions used and the estimated results from our regression approach can be found in Appendix A.3.

From this approach, we do have some findings to back up the take-away from the main estimation. I find that the increased distance to care is not primarily coming from patients who are traveling from out-side Arizona or from patients living in rural areas. In both cases, I find that the effect across years is either not significant or that distance to care is decreasing over time. This suggests that we are not attributing efficacy of price transparency reform incorrectly to factors that would be caused by increased travel either by rural or non-Arizona-based patients. Instead, these behavioral changes are happening across broad proportions of the patients in our data.

However, I also find counter-intuitive results from estimating equation (6) on partitioned data. I find that distance to care is increasing more for inpatient procedures that are not considered to be shoppable than otherwise; I find weak but similar evidence for rural patients whose inpatient record indicates an ER visit took place in association with their stay.[9] In both cases, we would expect that these groups of patient records would be least likely of all to shop for care prior to receiving treatment, one by construction and the other by urgency. Yet, I find distance to care is increasing across time for both groups and even more so than their counterparts.

Another counter-intuitive result discovered is that I observe similar effects for both insured and uninsured patients in the data. While I expect distance to care to increase more for uninsured patients due to

[9]For classification of shoppable vs. non-shoppable procedure, I follow the categorization by DRG code detailed in White and Eguchi (2014).

the reform, I did not expect to find that the efficacy for insured patients is similar to the estimates in the main specification. I also find that the effect for uninsured patients does not quite match the structure of what we saw previously, in that the increase in distance to care is greater for the uninsured patients in 2017 (a 12-mile increase) than 2014 (an 8-mile increase), relative to 2011. Additionally, in case insured patients are more likely to shop for care using the price transparency tools when their deductible has likely not been met, I run the estimation for the first and last quarters of each year. I find little difference in measured effects between the two, which resemble the results in the main specification.

With regard to total charges, I find an extremely similar story across essentially every partition of the data: total charges are increasing by about 11% from 2011 to 2014 and about 30% from 2011 to 2017, identical to the main specification. There is little deviation from this, and in fact, the only case where I find that charges are decreasing are, again, in an extremely unexpected case: for rural patients who have an ER charge associated with their inpatient stay. In this case, I find charges decrease by about 6% from 2011 to 2014 and by about 10% from 2011 to 2017.

Ultimately, I find that partitioning the data across groups exposes potential differences in information frictions. For instance, I find patients from ZIP codes with a median household income in the lower half of the national distribution are traveling further for care than patients from ZIP codes falling in the upper half of the distribution. This could reflect the fact that patients from poorer households have a lower opportunity cost of time and spend more time shopping for care. However, just like in the main specification, if total charges are increasing similarly across all patients, then poorer patients may be experiencing worse health outcomes than wealthier patients. This leaves room for future work in this area to further explain what makes some patients more willing to shop than others after price information is made public and, finally, whether reforms like the ones studied here can ever lead to a meaningful impact on health care costs.

5. Conclusion

In this paper, I exploit the implementation and obsolescence of price transparency policies 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 during the relevant years of this policy timeline, I find modest evidence supporting the notion that patients are shopping more for care, driving almost 3.5 miles more for care after the policy is implemented and still driving almost 3 miles more for care even after the hospital charge comparison website grows obsolete. Further examination of the partitioned data suggests that while there are some differences in willingness to shop across subgroups, total charges are consistently rising over time. This finding contradicts the existing literature and suggesting other mechanisms could be at play.

In attempting to isolate demand effects of public price transparency initiatives, I have not spoken to whether there are any supply-side effects independent of reforms that would contribute to increases in distance to care and total charges. One potential cause of this could be the effect of rural hospital closures, which are a well-documented problem across the United States and in the state of Arizona. While rural hospital closures are certainly a cause for concern, I either did not find a significant effect or found a strong negative effect on distance to care for rural patients, suggesting these patients are actually driving less for inpatient care over time in the observed data. As previously mentioned, the only evidence to the contrary is that distance to care is increasing for rural patients with an ER charge, but in these cases, we also observed total charges were decreasing over time. If rural hospital closures were driving the results found in this paper, we might expect the opposite findings.

Along with independent changes to the health care landscape in the same time frame, future work should consider more about how price transparency reform at the state and federal level impacts negotiated rates between hospitals and insurance providers. For now, I only look at the demand-side effects of public price transparency initiatives. Research to follow should continue to consider other supply-side mechanisms that may influence changes in distance to care, total charges, and patient health outcomes more generally.

For now, my estimation strategy remains simple: with only one state's data, I can only estimate changes across time. Thus, I cannot control for secular trends in outcomes that overlap with the timeline of price transparency reforms in the state of Arizona. Future work could involve obtaining additional inpatient data from another state to better tie causality to price transparency initiatives by using a difference-in-differences approach.

In finding that effects of price transparency reform differ across patient subgroups, there is much more to be said about the existence of heterogeneous information frictions in the context of choice of care. Not all price transparency initiatives are created equal, and the framework of rational inattention can help to explain why some price transparency reforms differ in efficacy from others. In future work, I hope to develop a structural framework that incorporates costly information acquisition within the decision-making process to model when patients will decide to update beliefs about expected prices, use price transparency tools available, and shop for care. With this addition, I hope to better identify effective steps that lead to patient shopping and lower health expenditures.

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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 each Arizona price transparency initiative studied in this paper. There were two 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.

A.1.1. *AZ Hospital Compare.*

On June 3rd, 2013, the Arizona Department of Health Services launched the AZ Hospital Compare website.[10] 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 3 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.[11][12]

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.

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[10] https://directorsblog.health.azdhs.gov/az-hospital-compare/

[11] https://pub.azdhs.gov/hospital-discharge-stats/2011/index.html

[12] https://pub.azdhs.gov/hospital-discharge-stats/2012/index.html

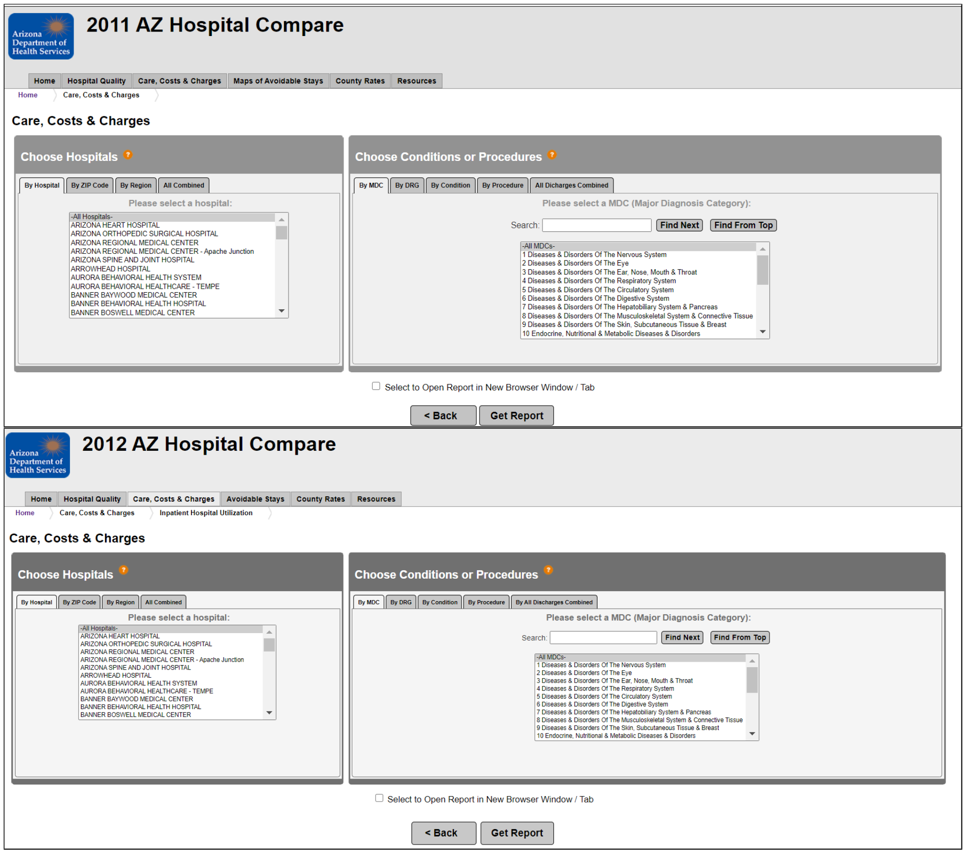

FIGURE 3. AZ Hospital Compare website.

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.[13] 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.[14]

A.1.2. *AZ HB 2045.* In 2013, Arizona's 51st state legislature passed House Bill 2045 (Chapter 202) in the First Regular Session.[15] 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:

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

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

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

> "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, 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)."[16]

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

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.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 state inpatient data used in this paper.

A.2.1. *Hospital Spending as a Share of Health Expenditures.* In Section 1, we 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 4 displays hospital spending as a share of total health expenditures alongside trends in the share of other types of health care spending.

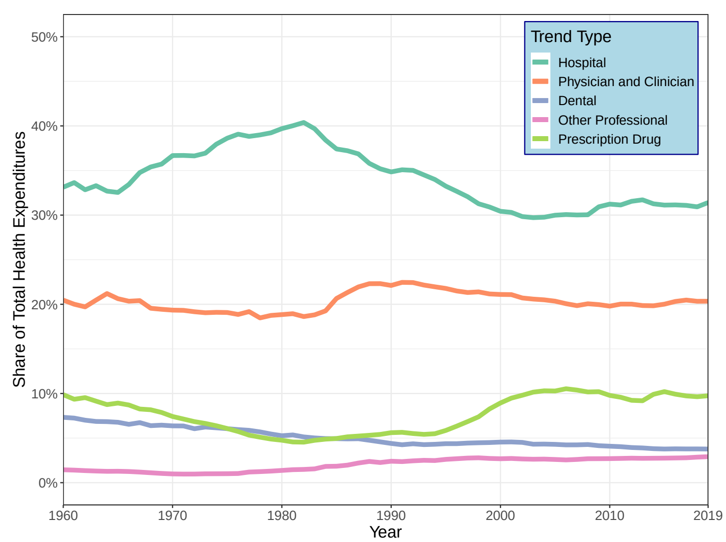

FIGURE 4. Hospital Spending as Share of Total Health Expenditures, 1960-2019. Source: NHE

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. *Arizona 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 State Inpatient Databases (SID), 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. Across 2011, 2014, and 2017, I have 2,254,912 total observations at the record level.

While I do not possess panel data to track individual patients and health outcomes over time, I do have a variety of patient-specific and record-specific information to capture how distance to care and total charges vary differently for any of these factors. On the other hand, I am able to track individual providers over years of data using an anonymized facility identifier.

Figure 5 displays a set of pie charts illustrating the makeup of the discharge data for each year across various subgroups. The first set shows the makeup of patients whose county of residence falls in an urban or rural area, with a "1" if the patient's county of residence is in a large metropolitan area with at least 1 million residents, "2" if the patient's county of residence is a small metro (< 1 million), "3" if a micropolitan area, and "4" if neither (thus, a rural area). Roughly 90% of the observations in the discharge data concern patients from large or small metropolitan areas, and a much smaller sample of the population is either from a micropolitan or rural area.

The second set in Figure 5 shows the percentage of patients who fall in each national quartile of median household income by ZIP code, with "1" indicating the poorest quartile and "4" indicating the wealthiest quartile. Almost two-thirds of the patients in the discharge data are from ZIP codes with lower median household incomes. The range of incomes that classify each quartile changes with each year. In 2011, the median household from a ZIP code in the lowest quartile was at or below below $38,999, but by 2017, it would have been at or below $43,999. Similarly, the median household from a ZIP code in the highest quartile was at or above $64,000 in 2011 and $74,000 by 2017.[17] It is also worth noting that the Arizona patients in this data are not representative of the entire country, in that, if it were, the percentage of patients would be equal at 25%.

The third set in Figure 5 shows the proportion of patients who live in Arizona versus those with a ZIP code outside Arizona. For this data, because I calculate distance to care using ZIP codes of patients and providers, I drop observations where patients are from outside the country or have a missing value for ZIP code. We note that the end proportion of patients who are from Arizona relative to patients from outside Arizona is essentially the same across years.

The final set of pie charts in Figure 5 denote the mix of inpatient procedures in our discharge data which are considered to be "shoppable" versus the mix of inpatient procedures that are not. For this categorization, I follow White and Eguchi (2014) by using the same set of diagnosis-related group (DRG) codes they use. I find a proportion of shoppable vs. non-shoppable inpatient procedures in my discharge data across all years that aligns with the proportion in the data used by White and Eguchi (2014). Ultimately, roughly one-third of the observations in my data are classified as shoppable following this convention.

[17]More information on this categorization can be found here: https://www.hcup-us.ahrq.gov/db/vars/zipinc_qrtl/nisnote.jsp

Finally, Table 3 lists and summarizes the individual covariates included to control for patient variation in distance to care (DIST2CARE_MI) and inflation-adjusted total charges (TOTCHG_INF).

Table 3. Individual-Specific Covariates Used in Estimation Strategy

Statistic	Description	N	Mean	St. Dev.	Min	Median	Max
DIST2CARE_MI	Distance to care (mi)	2,254,912	45.076	205.325	0.000	7.125	8,544.827
TOTCHG_INF	Total charges (infl.-adj.)	2,254,564	46,617.530	75,270.900	105.000	27,495.260	9,183,789.000
AMONTH	Admission month	2,254,912	6.430	3.478	1	6	12
YEAR	Calendar year	2,254,912	2013.887	2.453	2011	2014	2017
AGE	Age in years at adm.	2,254,783	47.245	27.605	0.000	52.000	114.000
FEMALE	Indicator of sex	2,254,392	0.562	0.496	0.000	1.000	1.000
ZIPINC_QRTL	Med. HINQ (ZIP Code)	2,183,569	2.177	1.066	1.000	2.000	4.000
RACE	Race	2,231,778	1.707	1.122	1.000	1.000	6.000
LOS	Length of stay	2,254,900	4.535	6.498	0.000	3.000	356.000
HCUP_ED	HCUP ED service ind.	2,254,912	1.009	1.018	0	2	4
OUTSIDE_AZ	Non-AZ resident	2,254,912	0.032	0.175	0	0	1
PAY1	Primary expected payer	2,254,807	2.115	1.166	1.000	2.000	6.000
PL_CBSA	PL: CBSA	2,254,851	1.928	0.301	0.000	2.000	2.000
PL_UR_CAT4	PL: Urban-Rural (1-4)	2,254,851	1.422	0.674	1.000	1.000	4.000
TRAN_IN	Transfer in indicator	2,252,856	0.108	0.349	0.000	0.000	2.000
NPR	Number of procedures	2,254,912	1.509	2.098	0	1	12
INSURED	Indicator if PAY1 is ins.	2,173,553	0.958	0.199	0.000	1.000	1.000
SHOPPABLE	Indicator by DRG code	2,254,912	0.357	0.479	0	0	1

Arizona State Inpatient Databases (SID), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality (AHRQ).

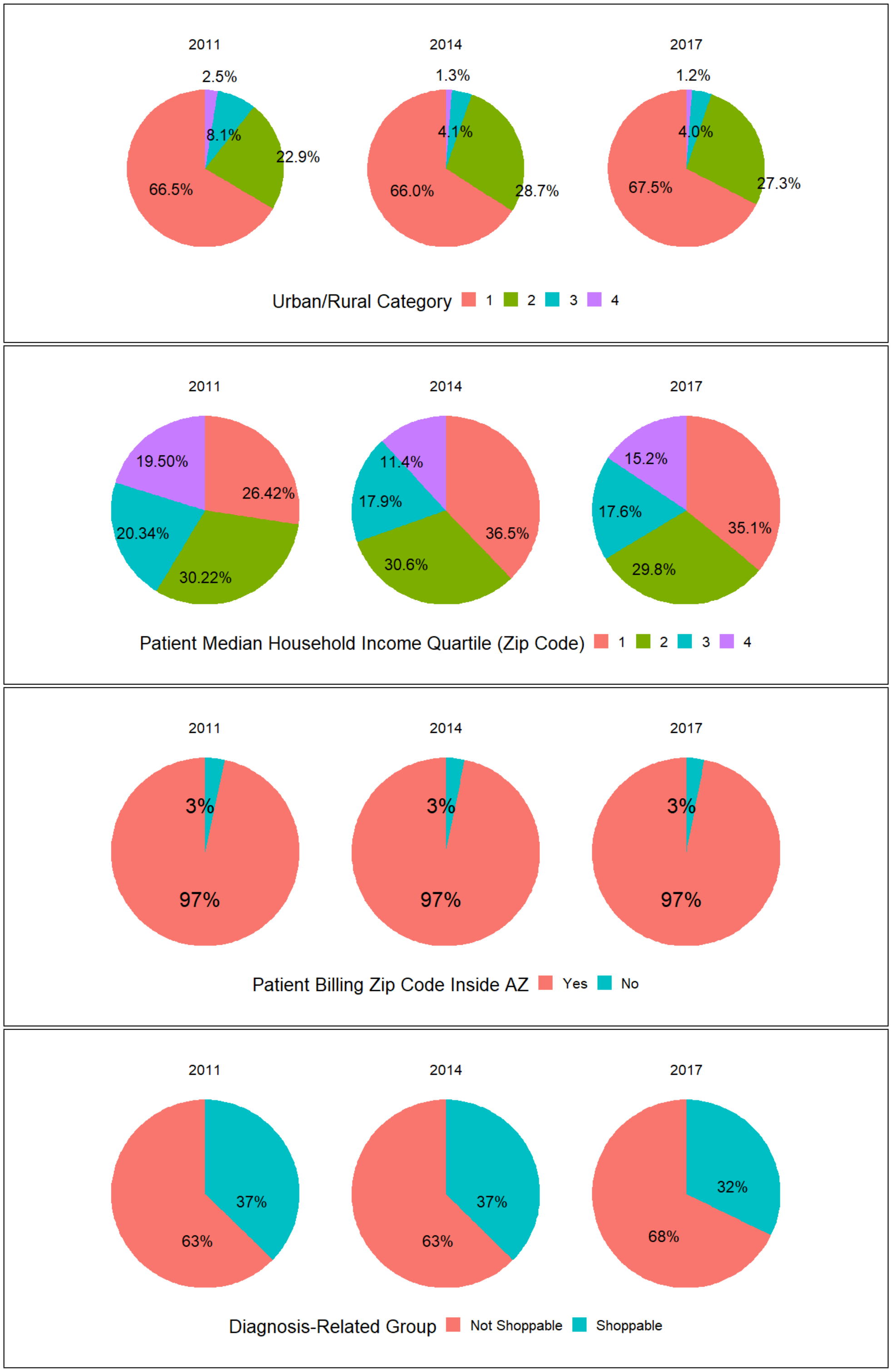

FIGURE 5. Makeup of Arizona State Inpatient Databases (SID), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality (AHRQ).

A.3. **Results from Additional Specifications.** In this section of the appendix, I provide regression results for the estimations performed on the partitioned data and discussed in Section 4.3.

For the final table in this set, Table 10, I add an interaction term between $YEAR_t$ and an indicator that takes a value if $HCUP\_ED$ has any value greater than one, which means that an emergency department service was detected in association with the inpatient stay. Then the model to be estimated becomes

$$\begin{aligned} y_{ijkmt} &= \alpha + \beta_1 YEAR_{2014} + \beta_2 YEAR_{2017} \\ &\quad + \beta_3 ER_1 + \beta_4 \Big(YEAR_{2014} \times ER_1 \Big) + \beta_5 \Big(YEAR_{2017} \times ER_1 \Big) \\ &\quad + \mathbf{X}_i' \beta_3 + \omega_j + \varepsilon_{ijkmt} \end{aligned} \tag{7}$$

All other individual covariates and provider fixed effects were included in the estimations on partitioned data.

TABLE 4. Estimated Changes across Shoppable/Non-Shoppable DRGs

	Shoppable DRGs		*Non-Shoppable DRGs*	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
$YEAR_{2014}$	3.009***	0.112***	3.707***	0.116***
	(0.289)	(0.001)	(0.268)	(0.001)
$YEAR_{2017}$	2.680***	0.334***	3.206***	0.293***
	(0.290)	(0.002)	(0.260)	(0.001)
Constant	−170.137***	6.390***	206.138***	7.930***
	(8.396)	(0.110)	(27.131)	(0.216)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	772,339	772,269	1,386,190	1,385,940
R^2	0.674	0.840	0.706	0.679

Note: robust SEs in parentheses *p<0.1; **p<0.05; ***p<0.01

TABLE 5. Estimated Changes across Rural/Urban Patients

	Rural†		*Urban*	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
YEAR_{2014}	-8.199	0.079^{***}	1.481^{***}	0.117^{***}
	(5.271)	(0.010)	(0.185)	(0.001)
YEAR_{2017}	-10.761^{**}	0.215^{***}	1.785^{***}	0.306^{***}
	(5.211)	(0.011)	(0.189)	(0.001)
Constant	219.720	6.532	296.471^{***}	7.476^{***}
	(4514.890)	(4.594)	(17.551)	(0.090)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	29,330	29,323	2,129,199	2,128,886
R^2	0.738	0.742	0.682	0.743

†Note: robust SEs in parentheses *p<0.1; **p<0.05; ***p<0.01

TABLE 6. Estimated Changes across Insured/Uninsured Patients

	Uninsured†		*Medicare/Medicaid/Private*	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
YEAR_{2014}	8.128^{***}	0.079^{***}	3.057^{***}	0.115^{***}
	(1.425)	(0.004)	(0.192)	(0.001)
YEAR_{2017}	12.673^{***}	0.255^{***}	2.689^{***}	0.309^{***}
	(1.852)	(0.005)	(0.194)	(0.001)
Constant	127.972^{***}	6.644^{***}	328.829^{***}	8.377^{***}
	(35.675)	(0.304)	(18.735)	(0.097)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	85,253	85,228	1,998,370	1,998,106
R^2	0.713	0.778	0.701	0.744

†Note: robust SEs in parentheses *p<0.1; **p<0.05; ***p<0.01

Table 7. Estimated Changes across AZ/Non-AZ Patients

	Billing Zip in AZ		*Billing Zip Outside AZ*†	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
$YEAR_{2014}$	1.158^{***}	0.113^{***}	-3.123	0.097^{***}
	(0.034)	(0.001)	(5.310)	(0.005)
$YEAR_{2017}$	1.294^{***}	0.302^{***}	-1.534	0.278^{***}
	(0.035)	(0.001)	(5.541)	(0.005)
Constant	111.124^{***}	7.424^{***}	1,429.424	8.539
	(3.635)	(0.104)	(1994.831)	(120.058)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	2,091,521	2,091,225	67,008	66,984
R^2	0.428	0.744	0.230	0.720

†Note: robust SEs in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8. Estimated Changes across Median Household Income Quartile of Patient Zip Code

	Higher Quartile		*Lower Quartile*	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
$YEAR_{2014}$	0.815^{**}	0.109^{***}	1.884^{***}	0.115^{***}
	(0.388)	(0.002)	(0.209)	(0.001)
$YEAR_{2017}$	1.178^{***}	0.302^{***}	1.721^{***}	0.301^{***}
	(0.378)	(0.002)	(0.209)	(0.001)
Constant	233.526^{***}	7.472^{***}	337.176^{**}	7.408^{***}
	(49.263)	(0.582)	(46.158)	(0.134)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	760,617	760,485	1,397,912	1,397,724
R^2	0.745	0.742	0.661	0.746

Note: robust SEs in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

TABLE 9. Estimated Changes across Earlier/Latter Parts of Year

	January - April		*September - December*	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
YEAR_{2014}	3.613^{***}	0.116^{***}	3.697^{***}	0.113^{***}
	(0.373)	(0.002)	(0.329)	(0.002)
YEAR_{2017}	3.286^{***}	0.289^{***}	2.854^{***}	0.314^{***}
	(0.371)	(0.002)	(0.320)	(0.002)
Constant	174.613^{***}	7.317^{***}	208.011^{***}	7.352^{***}
	(43.761)	(0.226)	(48.018)	(0.256)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	742,646	742,553	708,416	708,314
R^2	0.750	0.744	0.665	0.747

Note: robust SEs in parentheses *p<0.1; **p<0.05; ***p<0.01

TABLE 10. Estimated Changes across Rural/Urban Patients × Emergency Room Charges

	Rural†		*Urban*	
	(mi)	ln($)	(mi)	ln($)
	(1)	(2)	(3)	(4)
YEAR_{2014}	-9.719	0.109^{***}	2.040^{***}	0.123^{***}
	(5.987)	(0.013)	(0.262)	(0.001)
YEAR_{2017}	-21.332^{***}	0.263^{***}	2.373^{***}	0.329^{***}
	(5.845)	(0.015)	(0.268)	(0.001)
ER_1	28.216^{***}	0.145^{***}	-0.499^{*}	0.124^{***}
	(4.496)	(0.012)	(0.293)	(0.002)
$\text{YEAR}_{2014} \times \text{ER}_1$	3.151	-0.068^{***}	-1.098^{***}	-0.011^{***}
	(8.039)	(0.016)	(0.365)	(0.002)
$\text{YEAR}_{2017} \times \text{ER}_1$	24.178^{***}	-0.109^{***}	-1.147^{***}	-0.045^{***}
	(7.977)	(0.018)	(0.372)	(0.002)
Constant	217.182	6.528	296.530^{***}	7.478^{***}
	(7487.611)	(9.266)	(17.551)	(0.090)
Controls/FE	*Y*	*Y*	*Y*	*Y*
Observations	29,330	29,323	2,129,199	2,128,886
R^2	0.739	0.742	0.682	0.743

†Note: robust SEs in parentheses *p<0.1; **p<0.05; ***p<0.01