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Provider responses to online price transparency☆

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ABSTRACT

Price transparency initiatives have recently emerged as a solution to the lack of health care price information available to consumers. This paper uses the staggered and nationwide diffusion of a leading internet-based price transparency platform to estimate the effects of price transparency on provider prices. I find a 1–4% reduction in provider prices for homogenous services, laboratory tests, but find no price response for differentiated services, office visits. Price responses are driven by active consumer use of price information. This paper demonstrates how reducing consumer search costs can spur limited firm price competition in health care markets.

1. Introduction

Starting with the work of Stigler (1961), economists have studied the relationship between consumer search costs and firm prices. Few sectors of the economy have search costs as high as those in the health care industry. While price dispersion exists in many markets, the magnitude of price dispersion in health care markets combined with the lack of available price information imposes substantial burdens on consumers (Anderson et al., 2003; Cooper et al., 2018).[1] Even motivated consumers face difficulty obtaining price estimates for health care providers (Rosenthal et al., 2013; Anthony, 2015). At the same time, if providers wanted to provide price quotes, they may not be able to readily assess the insurance characteristics that determine the costs of providing care to a given patient.[2] Moreover, because insurance benefits have traditionally insulated consumers from marginal costs, the institutional mechanisms to provide patients with price estimates have not been developed.

The lack of readily available price information, combined with increasing patient cost-sharing, has prompted a move towards increased transparency of health care prices. More than 30 states require or are in the process of requiring either insurers or providers to make prices available to consumers (Sinaiko and Rosenthal, 2011; Sinaiko et al., 2015). Some states, most notably New Hampshire, maintain searchable websites of provider prices but use of these sites remains minimal and they have not been linked to changes in consumer behavior (Mehrotra et al., 2014; Tu and Lauer, 2009). At the same time, several private sector solutions have recently emerged. Several technology companies deliver personalized price information to consumers through internet-based applications. These applications display out-of-pocket provider prices and take into account benefit designs, networks, and other features that influence how patients choose providers. Price transparency technologies have become increasingly common and at least half of the commercially insured population now has access to some form of online health care price transparency (Phillips and Labno, 2014).

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[1] The substantial variation in health care prices is well documented in the academic literature (Robinson, 2011; Baker et al., 2013; Hsia et al., 2014; Pasalic et al., 2015; Cooper et al., 2015). Recent media stories have focused on both the wide range and opacity of prices for the commercially insured population (Rosenthal, 2013; Brill, 2013). One recent example includes a BlueCross BlueShield report that finds variances of 267% for knee replacement surgeries in Dallas, TX and 313% for hip replacements in Boston, MA (BlueCross BlueShield. “A Study of Cost Variations for Knee and Hip Replacement Surgeries in the U.S.”. January 21, 2015. Available from http://www.bcbs.com/healthofamerica/BCBS_BHI_Report-Jan-_21_Final.pdf).

[2] Due to the negotiation process, a given provider's negotiated price may vary greatly between different insurance companies and health plans.

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0167-6296/

Yet, our understanding of the dynamic impacts of these technologies on one of the largest sectors of the U.S. economy remains limited. This paper examines if the growth of patient access to a leading online price transparency platform leads providers to change their prices. This paper builds on the work of Christensen et al. (2015), which examines provider responses to state price transparency laws. They find an approximately 6% decrease in hospital "chargemaster" prices but find no effect for the negotiated prices between providers and insurers. The lack of a price response to state policies is not surprising as nearly all state regulations require disclosure of hospital charges, rather than actual negotiated rates between hospitals and insurers.[3] More recent work has found that the state-run New Hampshire site has an impact on prices for imaging services (Brown, 2017a,b). This paper extends the existing literature by examining the effects of more actionable price transparency technologies on negotiated provider prices for common medical services. This is the first nationwide study to examine how health care providers respond to online price transparency tools.

To measure provider responses to price transparency information, I leverage micro-level data from several sources. Over the 2010–2014 period and for nearly all geographic markets in the United States, I measure both the diffusion and active use of a particular internet-based price transparency platform. The platform allows consumers to search for personalized and provider-specific negotiated prices for over 1000 medical procedures. It also displays information on provider quality, satisfaction ratings, and provides educational content on common diseases and conditions. Consumers gain access to the price transparency platform through their employer. At the end of the sample, approximately eight million individuals had access to the price transparency platform.

I supplement the price transparency data with unique and detailed administrative data on negotiated prices between providers and insurers. A key piece of this paper's identification strategy is the availability of provider-specific pricing data over the entire 2010–2014 period. The structure of the data allows me to construct a five-year longitudinal panel of quarterly provider prices for over 16,000 laboratory test providers and 90,000 office visit clinicians. This data contains the actual negotiated prices between a specific provider and insurer for a given procedure, rather than the chargemaster prices that have previously been used to evaluate provider responses to price transparency.

I combine both sources of data to estimate the within-provider price changes as access to price information becomes more widespread in each market. At the beginning of the panel, 2010, no providers faced consumers with access to the price transparency platform. However, by 2014, all provider markets contained at least some consumers with access to price transparency. At the end of the sample, 22% of the markets have penetration rates of at least 5% of the commercially insured population and in 10% of the markets, at least 10% of the commercially insured population has access to the price transparency platform.

The staggered diffusion of the transparency platform creates market-level variation in both the timing and the intensity of consumer access to price information and provider exposure to consumer price-shopping. This variation is driven by each employer's decision to purchase access to the price transparency platform and the corresponding decisions of neighboring firms. It is further driven by the types of firms that purchase the platform in each area. Contributing employers include large, self-insured employers from multiple industries and multiple geographic scopes. Some firms are concentrated in a single market while employees from other firms are spread across multiple markets. The variation in each employer's purchasing decision and the type of employer creates the identifying variation that I use to estimate provider responses to price transparency.

The most obvious way for price transparency to lead to lower prices is by allowing consumers to shop for low-price, high-quality providers. Lieber (2015) finds a 10–17% reduction in prices for consumers who use a telephone-based price transparency platform. Likewise, Wu et al. (2014) find an 18% reduction in MRI prices when price transparency information was combined with a prior-authorization program. In the same setting as this paper, Whaley et al. (2014) and Whaley (2015) show how price transparency allows consumers to shop for less expensive providers.[4] Both papers find that searching for providers leads to an approximately 15% reduction in prices for homogenous services, laboratory tests, but a smaller, approximately 1%, reduction in prices for more heterogeneous services, office visits. These differences in the consumer responses are important to this paper. If providers respond to patient behavior, then we should expect little to no price changes for office services but larger price changes for laboratory tests. On the other hand, Desai et al. (2016) finds no meaningful change in spending following the introduction of a price transparency platform.

Anecdotal evidence from the hospital industry trade literature suggests that providers are aware of the potential effects of price transparency on consumer demand. One report warns that "hospital finance leaders should prepare for a potentially adverse revenue impact from . . . increasing demand for greater price transparency" (Myers, 2015). Empirical evidence supporting a reduction in provider prices can also be seen from the effect of the internet on firm prices for other goods. For example, Brynjolfsson and Smith (2000) find that book and CD prices are 9-16% lower for internet-based firms than for non-internet firms. In addition, Kolstad (2013) shows how disclosing provider quality information can lead to large provider changes even in the face of small consumer responses when health care providers are sensitive to reputational concerns inherent with price rankings.

At the same time, several economic concepts actually support the benefits of price obfuscation. Most notably, price transparency may facilitate tacit collusion. In markets with negotiated prices, price disclosure may provide firms with additional bargaining leverage to use against payers. Low-cost providers can use price transparency information to obtain an insurer's maximum willingness to pay. This information can thereby reduce the ability of insurers to selectively contract and thus lead to an increase in prices. This problem is exacerbated in markets with a small number of firms and markets with inelastic consumer demand (Stigler, 1964; Mollgaard and Overgaard, 1999).[5] For this reason, many insurance contracts contain "gag clauses" that prohibit providers from disclosing prices.[6]

As shown theoretically in Schultz (2009), the disconnect between the two potential effects of price transparency depends

[3] "Chargemaster" prices are typically not correlated with actual negotiated prices and usually only apply to the uninsured population.

[4] Multiple papers examine how reducing search costs through providing online or other information can lead to lower prices. Brown and Goolsbee (2002) show internet access leads to lower prices for life insurance policies. Similarly, Morton et al. (2001) and Zettelmeyer et al. (2001, 2005) show that the ability to use online information to comparison shop leads to an approximately 2% reduction in automobile prices. In health and other settings, well-known "report card" papers demonstrate how ratings of firm quality or price allow consumers to select lower-cost or higher-quality firms (Chernew and Scanlon, 1998; Scanlon et al., 2002; Dranove et al., 2003; Jin and Leslie, 2003; Jin and Sorensen, 2006; Dafny and Dranove, 2008).

[5] Price transparency information also increases the applicability of punishment strategies by allowing other firms to know when one firm deviates from a collusive strategy.

[6] Price transparency can also undermine most-favored customer (MFC) contracts. As discussed in Gaynor and Vogt (2000), the competitive effects of MFN are mixed. Morton (1996) finds little effect of MFC contracts on prescription drug prices.

crucially on consumer price elasticities and product differentiation. If demand for medical services is price inelastic, then providers do not need to compete based on price. In such a case, revealing prices may have the unintended effect of enabling tacit collusion by setting benchmark prices. Similarly, if products are substantially differentiated, price transparency may not lead to price competition. Both factors are relevant to health care markets, which exhibit both low price elasticity and substantial product differentiation. In addition, the presence of insurance coverage further reduces consumer price sensitivity and thus increases the potential for price collusion among providers.[7] The possibility that providers might respond to price transparency by raising prices has led some economists to warn against potential adverse effects of price transparency for health care markets (Cutler and Dafny, 2011).[8,9]

I examine changes in provider prices for two of the most common health care services, laboratory tests and office visit services.[10] Laboratory tests account for 6.3% of medical spending among the commercially insured population and the services included in this analysis account for 32.9% (32.3%) of that share.[11] Similarly, office visits account for 16.5%% of total spending and the procedure codes used in this study account for 32.3% of office visit spending. Office visit and laboratory services were chosen for two reasons. First, the previous consumer analysis shows large responses for lab tests and smaller responses for office visits. Because a conceptual model shows that the magnitude of the provider response depends on the magnitude of the consumer response, office-based clinicians serve as a falsification test for lab test providers. Second, the two types of providers vary in ways that influence how the literature suggests they should respond to price transparency. Office visit services are highly differentiated and include a meaningful quality component. In contrast, laboratory tests are homogenous, commodity-like services.[12]

Similar to the consumer responses, I find small price changes for office visits but meaningful price reductions for laboratory tests. My main results imply that every 10 percentage point (10%) increase in access to the online price transparency platform leads to a 1.7% (0.3%) decrease in laboratory test prices, but does not lead to a change in office visit prices. These results are robust to a variety of specifications. I provide evidence that supports that these effects are driven by the price transparency platform's diffusion, and not other employer programs that may have been implemented contemporaneously. As a test of the underlying mechanism that leads to the provider price changes, I also add data on the share of individuals in each market that have created an account and actively used the price transparency platform. I find that provider responses to active use of the platform are larger in magnitude than responses to consumer access to the platform. Every 10% increase in the market-level share of the population that has actively created an account to the platform leads to a 0.5% reduction in laboratory test provider prices. This result suggests that providers do not simply respond to access to price transparency, but instead respond to consumers actively using price information.

This paper makes two main contributions to the economics literature. First, it provides the first look at the dynamic effects of a nascent technology in one of the largest and most complex sectors of the U.S. economy. This paper's results suggest that the broader move towards health care price transparency are warranted and have consumer benefits beyond just the consumer uses of technology. Second, this paper also addresses an important issue in economics. Starting with Stigler (1961) and Arrow (1963), economists have long recognized the importance of information asymmetries in health and other markets. From a policy perspective, this paper demonstrates how reducing consumer search costs spurs firm price competition in health care markets. This paper also demonstrates the limitations of health care price transparency as a means of reducing provider prices. While the reductions are in laboratory test prices are robust, they are relatively modest. I also find no change in prices for office visits.

The paper proceeds as follows. First, Section 2 provides an overview of the data and institutional setting. Section 3 provides the empirical tests of price transparency on provider prices. Section 4 estimates several alternative specifications and robustness tests. Section 5 examines the underlying mechanisms surrounding the provider responses and Section 6 concludes.

2. Data and setting

2.1. Price data

To estimate provider responses to price transparency, I rely on data from two sources, medical claims and online price transparency access and use information. Both data sources are provided by a company that offers an online price transparency platform. For self-insured firms that purchase access, the web-based price transparency platform allows employees and their adult dependents to search for provider prices, quality, location, and other information. Prices are linked to a consumer's benefit design and insurance network to display predicted negotiated prices specific to a consumer's insurance plan. The displayed prices take into account deductibles, out-of-pocket maximums, and other benefit design features. Both consumer out-of-pocket prices and the total prices are shown. The firms that purchase access to the price transparency firm include employers in industries ranging from retail, manufacturing, to local government and are spread through multiple geographies. These employers offer a variety of insurance options, including high-deductible, preferred provider organization, and narrow network plans.

When individual firms purchase access to the online price transparency platform, they provide medical claims data to the price transparency provider. The medical claims data are used to create predicted prices and support population health programs and are provided for the two-year period before the first access date and all periods following access. As a result, I have detailed medical information in the periods before and after each employee population gained access to the price transparency platform. Relevant for this study, the medical claims data contain information on procedure types, which are identified using Current Procedural Terminology (CPT) codes, patient and provider geographic locations, and the transacted price of each procedure (commonly referred to as the claim's "allowed amount"). The data also contains unique

[7] Also unlike other markets, provider prices are established through negotiations with insurers. In fact, many of the price disclosure clauses in pricing contracts between providers and insurers are insisted upon by insurers as a means to limit provider price coordination.

[8] A Federal Trade Commission (FTC) statement on health care price transparency warns that "without appropriate safeguards, information exchanges among competing providers may facilitate collusion or otherwise reduce competition on prices or compensation, resulting in increased prices, or reduced quality and availability of health care services" (FTC, 1996). A more recent, FTC statement reiterates the anti-competitive concerns about price transparency in health care markets and urges caution by policymakers in mandating disclosure of negotiated prices (Koslov and Jex, 2015).

[9] Anecdotal evidence suggests that when a large insurer publicly ranked hospital prices, from "$" to "$$$$", low-cost hospitals used the information to push for higher reimbursements (Ginsburg, 2007).

[10] I do not examine provider responses for imaging services, which were included in the consumer analysis, due to sample size concerns.

[11] Source: Analysis of nationwide sample of medical claims provided by Health Care Cost Institute.

[12] Based on the differences between these provider types, the model presented in Schultz (2009) suggests that tacit collusion may arise for office visits and the competitive effects of price transparency are most likely to be observed for lab test providers.

insurer and provider identifiers. Multiple insurers are represented in the data and each has its own provider identifiers. The price transparency firm maps the overlapping provider identifiers into a unique provider identifier. Because prices are set at the provider-insurer level and not at the employer level, the staggered addition of employers should not impact observed provider prices. I exclude medical claims from emergency department, inpatient hospital, and other intensive care providers because patients are unlikely to shop for care received in these settings.

I use the unique provider identifiers across multiple insurers to create a 2010–2014 longitudinal panel of providers. I do not separately analyze office visit specialties but rather pool all clinicians. I also include the multiple types of providers (e.g. physicians, nurses practitioners, and physician assistants) that perform these common office visits. I further identify cells at the provider, CPT code, and insurer level and only include cells with observations in all five years. These restrictions leave a provider population of 93,974 office visit and 16,502 laboratory test providers.

For each provider included in the panel, I calculate the procedure code and insurer-specific mean quarterly price for common office visits and lab tests.[13] The provider's negotiated price within each insurer, quarter, and procedure code cell is the key dependent variable used in this study. Due to the inclusion of data from the pre-access period, this sample contains provider prices before and after subscribing firms provided access to the price transparency platform and spans 2010, when few individuals had access, to 2014, when access to the platform is much more widespread.

Table 1 presents the basic descriptive statistics of the price data. The mean provider price for office visits is about twice the mean price for lab test providers but price dispersion is much greater for lab providers. The coefficient of variation, the standard deviation divided by the mean, for office visit prices is 0.45 compared to 1.53 for lab providers. This dispersion is further seen in the differences between the above and below their mean HSA-level prices. Prices for office visits above the mean HSA price are 40% higher than those below the mean price. For lab test providers, the ratio is 446%.

2.2. Price transparency diffusion data

The empirical strategy of this paper is to measure how provider prices change in concordance with the diffusion of the price transparency platform. This strategy uses geographic and temporal variation in the timing and intensity of when subscribing firms purchased the price transparency platform. This variation in turn causes variation in each provider's exposure to the price transparency platform. To measure exposure to the price transparency platform, I construct the share of the commercially insured population that has access to the platform in each quarter and local market. The number of individuals with access to the platform comes from demographic data provided by the employers combined with the dates when each employer provided access to the platform. Using the date at which each employer launched the platform, I can then obtain the number of individuals in each geographic market that has access to the platform.

The commercially insured denominator population data comes from the 2010–2014 Health Leaders InterStudy survey of insurers. The InterStudy data reports the total number of enrollees in each zip code by specific insurance carrier and plan. I exclude Medicare and Medicaid enrollment through a commercial insurer (e.g. Medicare Part C or Medicaid HMO) from the total commercially

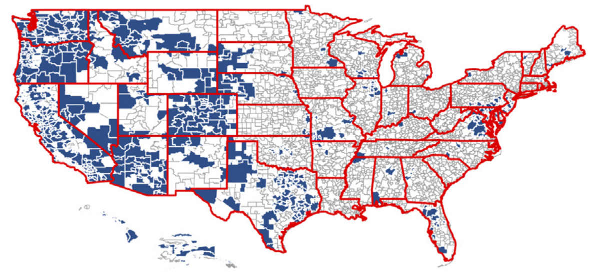

Fig. 1. Penetration: Q4 2010. Shaded regions represent Hospital Service Areas with any entry in the fourth quarter of 2010.

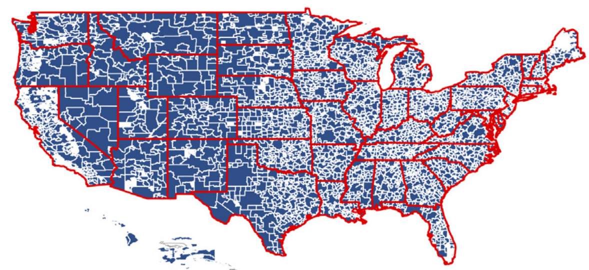

Fig. 2. Penetration: Q4 2014. Shaded regions represent Hospital Service Areas with any entry in the fourth quarter of 2014.

insured population denominator. While the InterStudy data contains the commercial population by insurer, I am unable to calculate each insurer's penetration rate because the insurance identifiers in the claims data are encrypted. As additional sources of data, I use the American Hospital Association's 2010 Annual Survey to construct hospital concentration measures, respectively. Construction of each measure is discussed below. Table A1 lists each data source used in this study.

I aggregate the zip code-level commercially insured population into markets using Hospital Service Areas (HSAs). As a robustness test, I also use the larger Hospital Referral Regions (HRRs) as the market definition.[14] As shown in the Appendix (Tables C1–C3), both results are similar. The HSA results are slightly more conservative and are more precisely estimated than when using HRRs as the market definition.

Table 2 describes the trends in the diffusion rate of the online price transparency platform. At the end of 2010, the mean diffusion rate was approximately 0.2%. By the end of 2014, the diffusion rate increased to 5.6%. The diffusion rate in the 90th percentile markets is approximately 11 times larger than the diffusion rate in the 10th percentile markets, while the diffusion rate in the 75th percentile HSA is three times the diffusion rate in the 25th percentile HSA. Figs. 1 and 2, which show dichotomous entry by HSA, show the increase in exposure over the 2010–2014 time period. At the end of 2010, access to the transparency platform was clustered in the Western U.S. and in a few number metropolitan areas in other parts of the country. By the end of 2014, the platform had eligible individuals in nearly all U.S. HSAs. Fig. 3 plots the density of penetration in HSA-specific access in the fourth quarter of 2014. While many HSAs have a small share of access, in a sizable share of markets, at least 5% of the commercially insured population has access to the platform.

[13] For each of the two services, I use the 10 most frequently observed procedure codes. Office visits: 99213, 99214, 99212, 99203, 99396, 99386, 99204, 99202, 99395, and 99215. Lab test providers: 85025, 80061, 80053, 84443, 83036, 88305, 80050, 82306, 81001, 80048.

[14] Counties and HSAs are of similar size while HRRs are considerably larger and approximate Metropolitan Statistical Areas (MSAs). Across the U.S., there are 3273 counties, 3436 HSAs, 306 HRRs, and 381 MSAs. Both HSAs and HRRs are defined by the Dartmouth Atlas of Health Care as local health care markets.

Table 1
Summary statistics: price characteristics.

	Office visits				Laboratory tests			
	Mean	Median	SD	Obs.	Mean	Median	SD	Obs.
All providers	$99.33	$90.77	$44.73	1,886,732	$51.58	$24.64	$78.82	707,798
Below mean HSA price	$81.15	$75.52	$30.34	819,385	$20.69	$14.77	$22.50	402,513
Above mean HSA price	$113.28	$103.24	$48.80	1,067,347	$92.31	$62.33	$104.01	305,285

This table presents the price mean, median, standard deviation, and number of observations for office visits and laboratory tests.

Table 2
Summary statistics: diffusion characteristics.

	Mean	SD	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
2010	0.21%	0.57%	<0.01%	0.01%	0.05%	0.17%	0.89%
2011	0.27%	0.54%	0.01%	0.02%	0.07%	0.29%	1.15%
2012	0.72%	2.55%	0.04%	0.09%	0.23%	0.59%	2.15%
2013	3.02%	4.06%	0.57%	1.13%	2.18%	3.61%	8.01%
2014	5.58%	8.39%	0.99%	1.84%	3.12%	5.22%	21.49%

This table presents the mean, standard deviation, 10th percentile, 25th percentile, 50th percentile, 75th percentile, and 90th percentile of the diffusion rate of the online price transparency platform. For each year, the diffusion rate in the fourth quarter of the calendar year is used. The diffusion rate is defined as the share of the commercially insured population that has access to the price transparency platform.

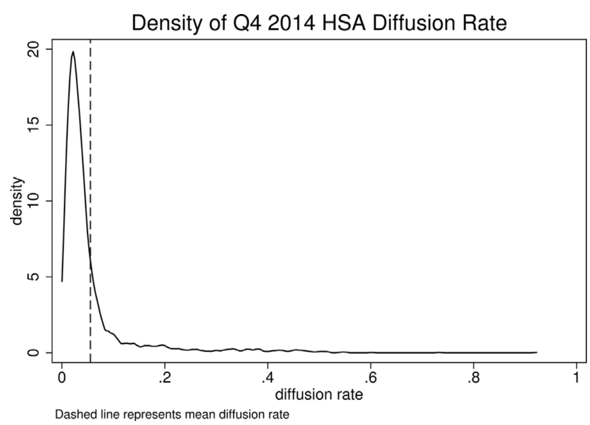

Fig. 3. Density of penetration: Q4 2014. This figure plots the density of the Hospital Service Area-specific share of commercially insured individuals who have access to the price transparency platform in the fourth quarter of 2014.

3. Provider responses to consumer access to price transparency

3.1. Estimation

To estimate provider price responses to the diffusion of the price transparency platform, I regress provider j's negotiated price with insurer h for CPT code k in date t on the share of individuals in market g who have access to the platform in that quarter:

$$\ln(price_{jghtk}) = \alpha + \beta_1 eligible_{tg} + \sum_t \tau_t date_t + \sum_k \lambda_k CPT_k + \sum_j \delta_j provider_j + \varepsilon_{jghtk}. \quad (1)$$

In this expression, $eligible_{tg}$ captures the share of the commercially insured population that has access to the platform in each market and time-period. Separate fixed effects for each quarter (i.e. 20 separate fixed effects) control for temporal trends while CPT code fixed effects, CPT_k, control for differences in prices between procedures. The provider fixed effects, $provider_j$, control for unobserved differences in prices and allow me to estimate the within-provider change in prices over time.[15] Each provider is linked to a single zip code and so geographic market fixed effects are not required. I iteratively add additional controls to this regression. First, average patient cost-sharing in each cell, OOP_{jthk}, controls potential changes in benefit designs that might influence prices. Second, insurance company fixed effects, $insurance_h$, control for payment differences between insurers. I also include $year_t \times insurance_h$ and $year_t \times CPT_k$ interactions to control for unobserved changes in insurer or procedure-specific policies or behaviors that influence prices. In the preferred specification, I include the full set of controls and both of the insurer and CPT code time trends. I estimate this equation using OLS with robust standard errors clustered at the HSA-level.

The identification of Eq. (1) comes from the variation in the diffusion of the price transparency platform. The variation occurs both temporally and in intensity as additional employers provide access to the platform. This approach follows the methodologies used in both Baker (1997) and Baker and Brown (1999) to measure the influence of insurance designs on provider technology adoption. Employers provide access to the price transparency platform at different points in time and the employers and employee population are geographically dispersed throughout the country. The variation in access is further driven by variation in the sales and implementation cycle for each employer and the decisions of neighboring firms to offer access to the platform to their employees. As a result, the number of consumers with access to the platform in each local market is plausibly quasi-randomly assigned.

One limitation of using claims data from employers who purchased access to the platform is the potential for bias due to other changes by the employer. I implicitly assume that the same employers who implement the transparency platform do not contemporaneously make other benefit design changes that lead to provider price changes. However, the employers who purchase the price transparency platform do so largely out of motivation to control health care spending and thus may also be more likely to implement other cost-reducing mechanisms, such as a high-deductible health plan. The variation in the timing, intensity, and location of the platform's introduction helps to alleviate but does not eliminate these concerns. In light of the identification assump-

[15] Alternate specifications that include fixed effects for the interaction of providers and insurance companies, and thus estimate the within provider and insurer change in prices, yield nearly identical results.

Table 3
Provider price responses to online price transparency.

(a) Office visits

	(1)	(2)	(3)	(4)	(5)	(6)
Share eligible	0.0463***	0.0469***	0.0469***	0.00458	0.0511***	0.00712
	(0.0147)	(0.0148)	(0.0148)	(0.0108)	(0.0144)	(0.0107)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

(b) Laboratory tests

	(1)	(2)	(3)	(4)	(5)	(6)
Share eligible	−0.159	−0.160	−0.160	−0.176*	−0.162	−0.179*
	(0.101)	(0.101)	(0.101)	(0.0946)	(0.101)	(0.0950)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.550	0.551	0.556	0.558	0.551	0.558
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the $eligible_{tg}$ coefficients from Eq. (1), which is estimated using OLS. In each regression, $eligible_{tg}$ is defined as the share of each HSA's commercially insured population with access to the price transparency platform in each quarter. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta)-1$.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

tions, I perform several placebo and robustness tests. In addition, I estimate price changes for both office visits and lab tests. Any broader changes should influence prices for both services but I only find price responses for laboratory tests. A conceptual model of how consumer access to price transparency information can impact the price negotiation process between providers and insurers is presented in the Appendix.

3.2. Results

Table 3 shows provider responses to consumer access to the online price transparency platform. Panel A shows provider price responses for office visits while Panel B shows responses for laboratory tests. Within each service, I iteratively add controls for patient cost-sharing, insurance company fixed effects, year by insurer fixed effects, year by CPT code fixed effects, and year interactions with both insurer fixed effects and CPT fixed effects. For office visits, adding these controls substantially changes the magnitude and precision of the coefficients. Without the insurance company-year interactions, the coefficients in columns 1–3 and 5 imply that every 10 percentage point increase in the share of the population with access to the price transparency platform leads to an approximately 0.5% increase in provider prices.[16] However, after adding the insurer-specific time trends (columns 4 and 6), this effect disappears. This change in the results suggests that there may be changes in the how insurers set prices for office visits over this time period.

Panel B show sizable reductions in prices for laboratory test providers. The coefficients do not substantially change based on the inclusion of additional controls. The preferred specification in column 6 implies that every 10 percentage point increase in access to the transparency platform leads to a 1.8% reduction in laboratory test prices. This coefficient is close to statistical significance at conventional levels (p-$value = 0.06$). At the mean penetration rate in the fourth quarter of 2014, the lab test results imply an approximately 1% reduction in lab provider prices due to the entry of the platform.

These results in each of these tables show the link between provider responses and the consumer uses of the price transparency platform found in Whaley et al. (2014) and Whaley (2015). For the service that consumers actively use the platform to price shop, lab tests, providers lower prices. On the other hand, providers do not meaningfully change prices for the service that consumers are less likely to change behavior based on price information, office visits.

3.3. Alternative specifications

The previous results use the raw share of the eligible population to measure access to the price transparency platform. This measure is highly skewed and so I estimate specifications that use alternative measures of access. Table 4 uses the natural log of $eligible_{tqg}$. Using the log-transformation has two advantages. First, it allows for an elasticity interpretation of provider price responsiveness to the diffusion of the platform. Second, as shown in Fig. C1, the log-transformed penetration rate is close to normally distributed. For office visits, the results columns 1–3 and 5 in Panel A show a precisely estimated elasticity of that is positive but close to zero, 0.04. After adding the insurer-specific time trends (columns 4 and 6), the elasticity is smaller and is not distinguishable from zero. For lab tests, all six specifications estimate an elasticity of −0.026 that is precisely estimated. To put the lab test elasticity in perspective, moving from the 25th to the 75th percentile log-diffusion rate in the fourth quarter of 2014 is an increase of 78%. Thus, applying the −0.026 elasticity implies that provider prices for laboratory tests are 1.9% lower in the 75th percentile HSA than in the 25th percentile HSA.

To test for non-linear effects, I categorize $eligible_{tg}$ into 1 percentage point increments: $\{0\%, (0-1\%], (1-2\%], (2-3\%], (3-4\%], (4-5\%] > 5\%\}$. By the end of the sample, the share of HSAs in each

[16] Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta)-1$.

Table 4
Provider price responses to online price transparency: log diffusion.

(a) Office visits

	(1)	(2)	(3)	(4)	(5)	(6)
ln(share eligible)	0.00363***	0.00368***	0.00369***	0.00127	0.00415***	0.00153
	(0.00133)	(0.00135)	(0.00134)	(0.00119)	(0.00130)	(0.00117)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

(b) Laboratory tests

	(1)	(2)	(3)	(4)	(5)	(6)
ln(share eligible)	−0.0249***	−0.0250***	−0.0248***	−0.0258***	−0.0252***	−0.0260***
	(0.00859)	(0.00858)	(0.00856)	(0.00773)	(0.00860)	(0.00774)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.551	0.556	0.558	0.551	0.559
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the log-transformed $eligible_{tg}$ coefficients from Eq. (1). In each regression, $\ln(eligible_{tg})$ is defined as the log of the share of each HSA's commercially insured population with access to the price transparency platform in each quarter. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

diffusion category is 10.2%, 18.1%, 19.6%, 15.4%, 10.3%, and 26.4%, respectively. The non-linear specifications test for a dose-response relationship. The diffusion categories are also relevant because no HSAs have full access to price transparency and thus limit the need to linearly extrapolate the β_1 coefficient. Thus, these results offer a more realistic estimate of the effects of the diffusion of the price transparency platform on provider prices. As shown in Table 5, the diffusion effect on office visits is small in magnitude and intermittently switches signs based on the diffusion increment. The only consistently significant result is an approximately 1% reduction in prices for the 4–5% diffusion category. However, for lab tests, there is a general increasing relationship between the share of commercially insured individuals with access to the platform and reductions in provider in prices. Every one percentage point increase in the share eligible leads to an approximately one percentage point reduction in lab test provider prices. Evidence of a dose-response further supports the causal relationship between provider prices and the diffusion of price transparency. At the median fourth quarter 2014 diffusion rate, the results in Table 5 indicate a 4.0% reduction in lab test provider prices. At the mean and median lab test prices, this reduction represents a \$1.76 to \$0.84 reduction in prices, respectively.[17]

4. Robustness and alternative explanations

4.1. High vs. low diffusion markets

As an additional test, I categorize markets as those with high and low diffusion at the end of the sample. I use the distribution of the diffusion rate at the end of the sample, the end of 2014, and define the "low" diffusion markets as the 853 HSAs with a diffusion rate below the 25th percentile of 1.8%. I likewise define the "high" diffusion markets as the 852 HSAs above the 75th percentile of 5.2%.

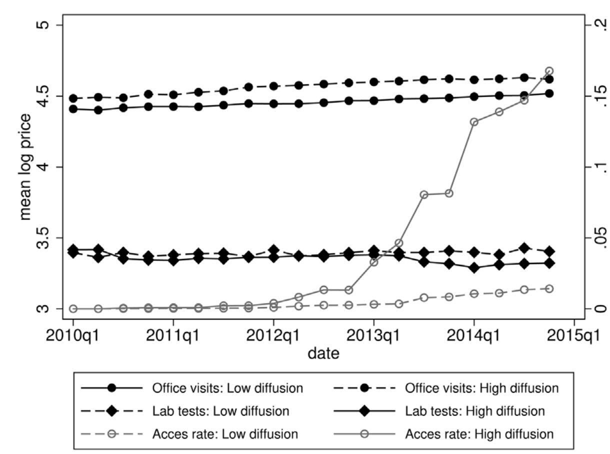

Fig. 4. Office visit and laboratory test provider price trends in high and low diffusion markets. This graph shows trends in price transparency diffusion and log-transformed prices for office visit and laboratory test services. For both services, Hospital Service Areas are categorized as "high" diffusion markets and "low" diffusion markets. The high diffusion markets are defined using the 75th percentile of the diffusion rate in the fourth quarter of 2014 and the low diffusion markets are defined using the 25th percentile.

At the beginning of the sample, 2010, both market classifications had no diffusion.

The unadjusted price trends and trends in the diffusion of the platform between the two markets are presented in Fig. 4, which shows constant trends for office visits but a noticeable divergence in prices for lab tests starting in 2013, which is also when diffusion of the price transparency platform begins to substantially increase. As a more formal test, I estimate the differential time trends between low and high-penetration HSAs as

$$\ln(price_{jthk}) = \alpha + \sum_t \gamma_t year_t \times high_g + \sum_t \tau_t date_t + \sum_k \lambda_k CPT_k + \sum_j \delta_j provider_j + \varepsilon_{jthk}. \quad (2)$$

[17] Using the classic price elasticity of 0.2 found in the RAND Health Insurance Experiment, the price reduction equates to a \$1.91 increase in consumer surplus (Manning et al., 1987).

Table 5
Provider price responses to online price transparency: diffusion categories.

(a) Office visits

	(1)	(2)	(3)	(4)	(5)	(6)
(0 – 1]% share eligible	−0.00407*	−0.00409*	−0.00411*	−0.000127	−0.00415*	−0.000469
	(0.00246)	(0.00247)	(0.00247)	(0.00216)	(0.00244)	(0.00214)
(1 – 2]% share eligible	−0.00375	−0.00372	−0.00373	0.00226	−0.00357	0.00215
	(0.00387)	(0.00387)	(0.00387)	(0.00278)	(0.00385)	(0.00277)
(2 – 3]% share eligible	−0.00596	−0.00593	−0.00596	0.000638	−0.00573	0.000515
	(0.00370)	(0.00369)	(0.00369)	(0.00269)	(0.00367)	(0.00268)
(3 – 4]% share eligible	−0.0121***	−0.0121***	−0.0121***	−0.00427	−0.0117***	−0.00429
	(0.00413)	(0.00412)	(0.00412)	(0.00314)	(0.00410)	(0.00313)
(4 – 5]% share eligible	−0.0150***	−0.0150***	−0.0150***	−0.00814**	−0.0145**	−0.00815**
	(0.00566)	(0.00567)	(0.00568)	(0.00343)	(0.00565)	(0.00343)
>5% share eligible	0.000609	0.000709	0.000712	0.00494	0.00160	0.00506
	(0.00349)	(0.00349)	(0.00349)	(0.00353)	(0.00349)	(0.00348)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

(b) Laboratory tests

	(1)	(2)	(3)	(4)	(5)	(6)
(0 – 1]% share eligible	−0.00124	−0.00167	−0.00139	0.00618	−0.00156	0.00632
	(0.00607)	(0.00607)	(0.00605)	(0.00606)	(0.00610)	(0.00609)
(1 – 2]% share eligible	−0.0116	−0.0121	−0.0117	−0.00491	−0.0116	−0.00440
	(0.00762)	(0.00762)	(0.00760)	(0.00739)	(0.00766)	(0.00741)
(2 – 3]% share eligible	−0.0169	−0.0175	−0.0170	−0.0112	−0.0172	−0.0108
	(0.0108)	(0.0108)	(0.0108)	(0.0112)	(0.0108)	(0.0112)
(3 – 4]% share eligible	−0.0420***	−0.0428***	−0.0420***	−0.0353***	−0.0427***	−0.0351***
	(0.0118)	(0.0117)	(0.0117)	(0.0124)	(0.0118)	(0.0124)
(4 – 5]% share eligible	−0.0299	−0.0305	−0.0292	−0.0212	−0.0305	−0.0211
	(0.0188)	(0.0188)	(0.0188)	(0.0178)	(0.0188)	(0.0178)
>5% share eligible	−0.0664***	−0.0670***	−0.0659***	−0.0572***	−0.0672***	−0.0574***
	(0.0146)	(0.0145)	(0.0146)	(0.0140)	(0.0144)	(0.0139)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.551	0.557	0.558	0.551	0.559
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the categorized $eligible_{tg}$ coefficients from Eq. (1), which is estimated using OLS. In each regression, $eligible_{tg}$ is defined as the share of each HSA's commercially insured population with access to the price transparency platform in each quarter. The $eligible_{tg}$ diffusion measure is categorized into one percentage-point increments: {0%, (0 – 1%], (1 – 2%], (2 – 3%], (3 – 4%], (4 – 5%] >5%}. By the end of the sample, the share of HSAs in each diffusion category is 10.2%, 18.1%, 19.6%, 15.4%, 10.3%, and 26.4%, respectively. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

As above, I iteratively add controls to this baseline regression.

The $year_t \times high_g$ interaction coefficients from this regression are shown in Table 6. Consistent with the previous results, for office visits, I do not find a consistent price effect. Office visit prices increase at approximately the same rate, approximately 2 percentage points per year, in the high and low-diffusion markets. However, for lab test providers, consistent with the unadjusted graphs, there is a sizable reduction in within-provider prices. Relative to the 2010 baseline year, in 2012, the high-diffusion markets have prices that are approximately 2.7% lower than in the low-diffusion markets in the specifications that include year-by-insurer interactions (columns 4 and 6). In 2013, the difference increases to 4.5%, and by 2014, the difference increases to 7.0% and becomes more precise. At the mean and median prices, the 2013 and 2014 differences imply a $3.61 and $1.45 reduction laboratory test prices, respectively.

Importantly, there is no difference in laboratory test price trends in 2011, when there very little diffusion of the platform, and only a small difference in 2012, when diffusion of the platform first becomes meaningful. Because nearly all of the growth of the price transparency platform occurred in 2013 and 2014, the lack of any sizable effect in 2011 and 2012 supports the parallel pre-trends assumption. It also suggests that the price transparency platform was not selectively deployed in markets with differing price trends.

Table 6
Price transparency access: high and low diffusion markets.

(a) Office visits

	(1)	(2)	(3)	(4)	(5)	(6)
High access × 2011	0.0130***	0.0130***	0.0131***	0.00561*	0.0143***	0.00660**
	(0.00365)	(0.00365)	(0.00362)	(0.00290)	(0.00371)	(0.00295)
High access × 2012	0.0282***	0.0282***	0.0282***	0.00965**	0.0308***	0.0114***
	(0.00546)	(0.00546)	(0.00543)	(0.00413)	(0.00546)	(0.00417)
High access × 2013	0.0315***	0.0317***	0.0317***	0.00844*	0.0340***	0.00984*
	(0.00631)	(0.00634)	(0.00631)	(0.00504)	(0.00630)	(0.00504)
High access × 2014	0.0156**	0.0158**	0.0157**	0.00429	0.0180**	0.00543
	(0.00735)	(0.00737)	(0.00735)	(0.00566)	(0.00733)	(0.00558)
Observations	864,977	864,977	864,977	864,977	864,977	864,977
Number of providers	39,909	39,909	39,909	39,909	39,909	39,909
Adjusted R^2	0.749	0.749	0.750	0.758	0.750	0.759
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

(b) Laboratory tests

	(1)	(2)	(3)	(4)	(5)	(6)
High access × 2011	−0.00511	−0.00534	−0.00636	−0.0153	−0.00457	−0.0144
	(0.0126)	(0.0126)	(0.0126)	(0.0127)	(0.0125)	(0.0127)
High access × 2012	−0.0100	−0.0105	−0.0102	−0.0292**	−0.00919	−0.0277**
	(0.0143)	(0.0142)	(0.0144)	(0.0140)	(0.0143)	(0.0140)
High access × 2013	−0.0319	−0.0325	−0.0314	−0.0470**	−0.0316	−0.0461**
	(0.0200)	(0.0200)	(0.0201)	(0.0193)	(0.0201)	(0.0195)
High access × 2014	−0.0785***	−0.0789***	−0.0779***	−0.0727***	−0.0794***	−0.0731***
	(0.0279)	(0.0279)	(0.0281)	(0.0276)	(0.0283)	(0.0279)
Observations	320,548	320,548	320,548	320,548	320,548	320,548
Number of providers	6,732	6,732	6,732	6,732	6,732	6,732
Adjusted R^2	0.583	0.583	0.588	0.591	0.583	0.591
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the high and low access results. HSAs are categorized as having "low" and "high" eligibility rates using the share of the commercially insured population that has access to the price transparency platform by the fourth quarter of 2014. Low eligibility rates are defined using the 25th percentile of the diffusion rate and high registration rates are defined using the upper quartile of the diffusion rate. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

4.2. Placebo tests

The second, and more challenging, concern is the presence of other employer programs designed to reduce health care spending. I use several strategies to address this point. First, the previous section does not find pre-trend price differences between high and low-diffusion markets. I also test if the diffusion of the platform is correlated with changes in consumer cost-sharing and if changes in consumer cost-sharing lead to changes in provider prices. I find no evidence supporting either alternative explanation.

One threat to the validity of these results is the potential that the employers that purchase access to the price transparency platform may also be engaged in other activities that encourage patients to receive care from less expensive providers. Most notably, as a means of constraining health care spending, many employers have shifted to high-deductible health plans (HDHPs), which require consumers to bear a large portion of initial medical spending.[18] If the same employers that purchase access to the price transparency platform used in this study also implement HDHPs or other programs that incentivize consumers to seek less expensive care, then provider responses to these other programs may be the true cause of any provider price changes I observe. However, while a key aim of HDHPs is to incentivize consumers to shop for less expensive providers, recent evidence suggests that for "shoppable" services, HDHP enrollees are not more likely to receive care from less expensive providers (Sood et al., 2013; Huckfeldt et al., 2015; Brot-Goldberg et al., 2017). Likewise, the results of Brot-Goldberg et al. (2017), suggest that providers do not lower prices in response to employer implementation of HDHPs.[19]

While the main results find that controlling for patient cost-sharing does not change the results, I also conduct two robustness tests that examine if other programs from these "motivated" employers might be leading to the price responses I observe in the

[18] In 2014, 84% of individuals with employer-sponsored insurance had a deductible and the average deductible amount was $1353 (Source: 2014 MEPS Insurance Component Tables I.F.1 and I.F.2). As shown in the 2013 MEPS consolidated file, the median level of medical spending for the commercially insured population in 2013 was $525 and so it is likely that most HDHP enrollees do not receive any insurance coverage through their HDHP.

[19] However, Whaley and Brown (2018) finds that surgical providers lower prices lower prices in response to a targeted cost-sharing program that imposes differential cost-sharing for high-priced providers. Similar programs may have been implemented by employers in the study population.

main results. First, I use an event study approach to estimate if the launch of the price transparency platform is correlated with changes in patient cost-sharing. If other benefit design changes occur contemporaneously with the diffusion of the platform, then patient cost-sharing should likewise change. The most notable example would be implementing a high-deductible health plan and then offering the price transparency platform to help consumers navigate the increase in cost-sharing. Such a scenario raises the possibility that the effects I observe are due to the underlying change in insurance benefit design rather than provider responses to price transparency. For each employer, I measure changes in patient cost-sharing in the 18 months before and after when each employer launched the price transparency platform. Changes in patient cost-sharing are indicative of other changes in benefit design, which may be leading to changes in laboratory test prices. To do so, I estimate the changes in patient cost-sharing at each employer as

$$oop_{mkt} = \alpha + \sum_{t=-q}^{t=6} \beta_t launch_t + \sum_k \lambda_k CPT_k + \sum_m \psi_m employer_m + \sum_t \tau_t date_t + \varepsilon_{mkt}. \tag{3}$$

Here, oop_{mkt} measures the median cost-sharing share among employer m for CPT code k during quarter t. This variable is different from the patient cost-sharing variable used in the main analysis, OOP_{jtqhk}, in that it is at the employer-procedure-quarter level rather than at the provider-insurer-CPT code-quarter level. This measure of cost-sharing includes all patient cost-sharing (e.g. deductibles, copays, and coinsurance). I include fixed effects for each employer, and thus this test measures the within-employer change in patient cost-sharing in the months preceding and following the employer's decision to provide access to the price transparency platform to its employee population. I separately estimate this regression for laboratory tests and office visits. Time fixed effects control for differences in when each employer provided access to the platform.

Fig. 5 presents the results using the combined cost-sharing variable. For both office visits and laboratory tests, the confidence intervals are large and I fail to reject any change in patient cost-sharing that is dependent on the launch of the price transparency platform. For both office visits and laboratory tests, patient cost sharing 18 months prior to the implementation of the price transparency platform is the same as in the 18 months following implementation. These results support the underlying hypothesis that the changes in provider prices are not due to changes in insurance designs. The null finding matches anecdotal evidence of how the transparency platform is operated. Within a given employer, the exact implementation date of the platform is dependent on an idiosyncratic sales cycle between the transparency firm and the employer. Once a sales deal is completed, the transmission of medical claims data from the employer's insurer to the price transparency firm and the implementation of the platform for each employer's population is also highly idiosyncratic. Even if employers wanted to contemporaneously time benefit design changes with the launch of the platform, these logistical hurdles make such timing challenging.

The second test examines the link between changes in patient cost-sharing and provider prices. I estimate a similar model as Eq. (1), but omit the price transparency diffusion measure and instead focus on the patient cost-sharing variable. As shown in Table 7, across both procedures and specifications, I do not find that increases in patient cost-sharing are associated with meaningful reductions in provider prices. If anything, the laboratory test results imply a positive relationship between patient cost-sharing and provider prices, which is in the opposite direction of any potential bias.

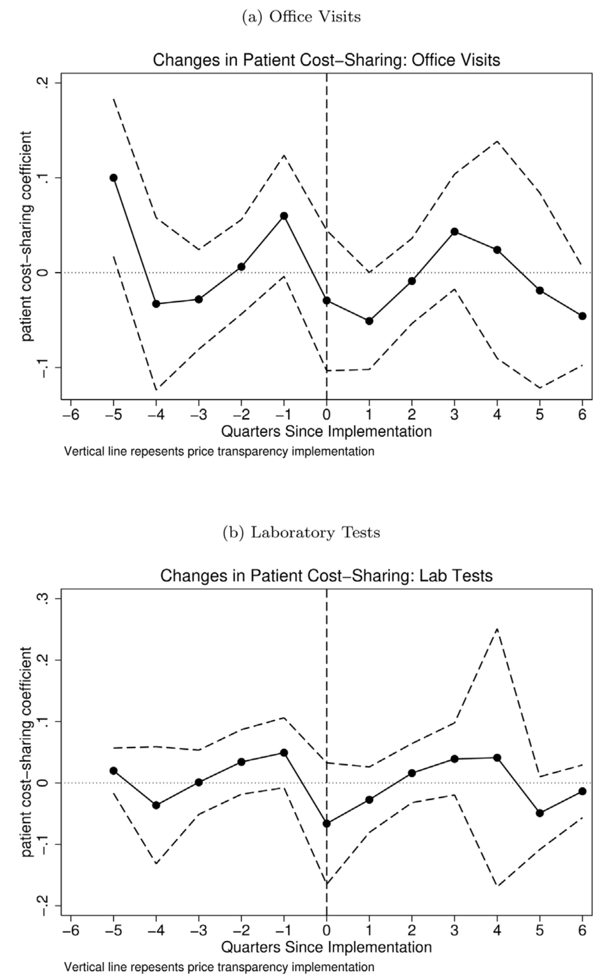

Fig. 5. Patient cost-sharing placebo test. These figures present the placebo test results that test for contemporaneous changes in consumer cost-sharing and the implementation of the price transparency platform (Eq. (3)). The dashed lines represent 95% confidence intervals that are clustered at the employer level.

4.3. *Heterogeneity in laboratory test provider responses to price transparency information*

As a test of heterogeneous provider responses to price transparency, I examine price changes for providers that only provide laboratory tests compared to providers that offer both office visit services and laboratory tests. Laboratory-specific facilities, led by nationwide chains, tend to be much less expensive than physician offices and hospitals that offer laboratory tests in addition to more traditional types of medical services (Kricka et al., 2015). One of the aims of price transparency initiatives is to shift laboratory test demand from hospital-based laboratories to low-cost laboratory facilities. As a result, traditional health care providers may show stronger responses to price transparency information as they compete with new entrants. Especially relevant to this paper, a recent trade-press article states that "payers are using price transparency in an attempt to steer business away from hospital-based laboratories and towards national laboratories" (Myers, 2015).

To test differential responses, I categorize providers as either laboratory-specific providers ("specialists") or providers who perform both lab and office visit services ("generalists"). Because I do not observe provider classifications, I instead identify providers who during the 2010–2014 period perform only laboratory services and providers who perform both types of services. Using this classification, approximately 60% of providers who perform lab tests are

Table 7
Patient cost-sharing placebo test.

(a) Office visits

	(1)	(2)	(3)	(4)	(5)
Patient share	−0.00236	−0.00223	−0.00454**	−0.00185	−0.00417**
	(0.00205)	(0.00206)	(0.00180)	(0.00212)	(0.00186)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.750	0.746	0.751
Controls		Insurer	Insurer × year	CPT × year	Insurer/CPT × year

(b) Laboratory tests

	(1)	(2)	(3)	(4)	(5)
Patient share	0.0291***	0.0338***	0.0296***	0.0291***	0.0296***
	(0.00452)	(0.00429)	(0.00413)	(0.00453)	(0.00414)
Observations	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.556	0.558	0.551	0.558
Controls		Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the placebo test results that test if changes in consumer cost-sharing lead to changes in provider prices. In each regression, the patient share is defend as the mean consumer cost-sharing rate. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
Provider laboratory price responses to price transparency: specialists vs. generalists.

	Generalists (1)	Specialists (2)	Both (3)
Share eligible	−0.158	−0.102	−0.0433
	(0.117)	(0.0626)	(0.0648)
Specialist × share eligible			−0.188*
			(0.0960)
Observations	383,937	323,602	707,539
Number of providers	9975	6527	16,502
Adjusted R^2	0.576	0.549	0.558

This table categorizes laboratory test providers as those that only perform laboratory tests, “specialists,” and those that perform both laboratory tests and clinician services, “generalists.” In each regression, $eligible_{tg}$ is defined as the share of each HSA’s commercially insured population with access to the price transparency platform in each quarter. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Column 1 only includes generalist providers, column 2 includes only specialist lab test providers, and column 3 includes both but interacts the provider classification with $eligible_{tg}$. All columns include provider, CPT code, year, quarter, insurance company, insurance company interacted with year fixed effects, and CPT code interacted with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

generalists and 40% are specialists. The mean 2010 price for laboratory tests performed at generalists ($61.50) is 50% higher than the mean 2010 price for tests performed by specialists ($40.91). I then estimate separate price responses for each provider type (Eq. (1)) and also interact the provider classification $eligible_{tqg}$. I only report results include the full set of controls but the results are robust to the inclusion of each control.

As shown in Table 8, I find that price transparency information leads to reductions in lab test prices for both specialized and general providers. However, the price reductions are larger for generalists than they are for specialized lab test providers. I find a 14.6% reduction in prices for generalist providers (column 1) and a 9.7% reduction in prices for specialist provides (column 2). As shown in column 3, the difference between the two effects translates into a 17.1% larger reduction in prices for the generalist providers relative to the specialist providers. This result is consistent with price transparency spurring price competition for traditional firms as consumers shift demand from incumbent firms to alternative providers.

5. Underlying mechanism: consumer access or active consumer use?

While the previous results show meaningful reductions in provider prices for laboratory tests following access to the price transparency platform, they do not identify the underlying mechanisms of why providers lower prices. Two possible mechanisms may lead to provider price reductions. First, providers may respond to changes in consumer demand. Even if the share of consumers who shift demand from high-priced to low-priced provides is small, if providers set prices based on the marginal consumer, who is likely to make provider decisions based on price transparency information, then we may see a large reduction in provider prices. At the same time, the intrinsic motivation mechanism underlying the results in Kolstad (2013) may lead providers to change prices in the absence of any consumer demand responses.

To explore these mechanisms, I measure the share of consumers who have created an account for the platform and add this variable to Eq. (1). This share identifies the fraction of consumers that are active users of price transparency information rather than simply those who have access to the platform. Each market’s registration rate comes from the individual-level registration data provided by the price transparency firm. While the average usage rate across all markets is less than one percent, there is substantial variation. By the end of the sample, 697 HSAs have a registration rate above one

Table 9
Provider responses to active use of price transparency information.

(a) Office Visits						
	(1)	(2)	(3)	(4)	(5)	(6)
Share eligible	0.104***	0.104***	0.104***	0.0428***	0.104***	0.0427***
	(0.0198)	(0.0199)	(0.0199)	(0.0162)	(0.0197)	(0.0161)
Share registered	−0.341***	−0.340***	−0.339***	−0.205***	−0.316***	−0.191***
	(0.0785)	(0.0780)	(0.0780)	(0.0634)	(0.0761)	(0.0620)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year
(b) Laboratory tests						
	(1)	(2)	(3)	(4)	(5)	(6)
Share eligible	−0.0180	−0.0188	−0.0222	−0.0790	−0.0205	−0.0812
	(0.0887)	(0.0888)	(0.0883)	(0.0972)	(0.0892)	(0.0974)
Share registered	−0.927**	−0.923**	−0.901**	−0.580	−0.927**	−0.583
	(0.423)	(0.425)	(0.421)	(0.380)	(0.427)	(0.382)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.551	0.556	0.558	0.551	0.558
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table includes the share of the commercially insured population with access to the price transparency platform (share eligible) and the share that has created an account (share registered). Both are defined at the HSA and quarter level. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

percent, 237 have a registration rate of at least two percent, and 31 HSAs have a registration rate of at least five percent.

Table 9 presents these results for level changes in the share of the population with access to the platform and the share registered. For office visits (Panel A), the share eligible result are positive and statistically significant. However, the share registered coefficients are negative and much larger in magnitude. In the preferred specification in column 6, a 10 percentage-point increase in the share with access to the platform leads to a 0.4% increase in office visit prices, while a 10 percentage-point increase in the share of the population that actively uses the platform leads to a 1.7% reduction in prices. These two countervailing effects net out in the main results in Table 3. For laboratory tests (Panel B), there is a negative effect for both the share of the population eligible and the share that has created an account. In column 6, the access effect is much smaller than the use effect, but neither are statistically significant.

Table 10 presents similar results but uses the log access and registration rates to estimate an elasticity response. For office visits (Panel A), the implied elasticities are small in all specifications. In column 6, there is an approximately 1% positive elasticity between the population share with access to the platform and office visit prices. When looking at the share of the population that uses the platform, there is an offsetting negative 1% elasticity. For laboratory tests, there is not a statistically significant or economically meaningful effect for the share of the population with access to the platform. However, there is a negative 5% elasticity between the share of the population that has created an account and laboratory test prices. This elasticity is approximately twice as large as the elasticity presented in Table 4 that only examines the share eligible to use the platform. The absence of an effect for the eligibility coefficient when controlling for active use suggests that laboratory test providers respond not to the potential use of the platform by consumers, but to active engagement.

6. Conclusion

Recent years have seen a large increase in the availability of price information available to health care consumers. While consumer responses to price transparency are becoming well-understood, how providers respond to price transparency remains less developed but is an equally important question. Because provider price changes apply to all consumers, not just those who price-shop, provider responses to price transparency have the potential to impact a far greater share of health care expenditures than consumer responses alone. In addition, the economics literature raises the potential of anti-competitive effects to price transparency. Using data from a leading online price transparency platform, I find substantial price reductions for lab test providers and small reductions for office visits. The differing results follow economic intuition as lab tests are much more homogenous than highly differentiated office visit providers.

These results raise the natural question of why providers change their prices in response to price transparency when a relatively small share of the total population has access to the platform. Of the consumers with access, not all are actively shopping and so the engaged consumer share is even smaller. I find that provider responses to the actively engaged population are much larger than the provider responses to access to the price transparency platform alone. The consumers who are actively shopping and making provider decisions based on their shopping results likely constitute the marginal consumers upon whom providers set prices. Even if the marginal consumers constitute a small share of the

Table 10
Provider responses to active use of price transparency information: log registration rate.

(a) Office visits

	(1)	(2)	(3)	(4)	(5)	(6)
ln(share registered)	−0.0145***	−0.0144***	−0.0143***	−0.0125***	−0.0133***	−0.0118***
	(0.00426)	(0.00425)	(0.00425)	(0.00322)	(0.00423)	(0.00316)
ln(share eligible)	0.00969***	0.00969***	0.00967***	0.00680***	0.00967***	0.00671***
	(0.00209)	(0.00209)	(0.00209)	(0.00179)	(0.00208)	(0.00178)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

(b) Laboratory tests

	(1)	(2)	(3)	(4)	(5)	(6)
ln(share registered)	−0.0604***	−0.0603***	−0.0595***	−0.0480***	−0.0608***	−0.0484***
	(0.0179)	(0.0179)	(0.0179)	(0.0164)	(0.0180)	(0.0166)
ln(share eligible)	−0.00284	−0.00293	−0.00307	−0.00705	−0.00299	−0.00711
	(0.00545)	(0.00545)	(0.00542)	(0.00595)	(0.00547)	(0.00595)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.551	0.557	0.558	0.551	0.559
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table includes the log-transformed share of the commercially insured population with access to the price transparency platform (ln(share eligible)) and the log-transformed share that has created an account (ln(share registered)). Both are defined at the HSA and quarter level. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta)-1$.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

overall market, their price shopping behavior should disproportionately influence provider pricing. Additionally, and similar to Kolstad (2013), providers may be changing prices for reputational reasons.

This paper is not without limitations. For one, I rely on data from a set of firms who have chosen to purchase access to price transparency information for their employees and dependents. These firms may be contemporaneously engaged in other activities that influence provider prices, such as benefit design changes. In such a case, the provider price changes that I attribute to price transparency will be misspecified. Further work should pair the diffusion metrics with a broader sample of provider prices. Similarly, I only use the diffusion of a particular price transparency firm. In addition to state-based efforts, there are multiple firms that provide price transparency services that I do not observe. If these other firms have a presence in the same markets that I measure, then my results may be biased. However, a single employer typically only purchases the services of one price transparency firm and so it is likely that the presence of other firms is captured in the control group markets. In this case, my results may actually be understated if there is a price decrease in the control markets due to other price transparency efforts. Finally, these effects are the short-run responses to price transparency. Providers may have over-reacted to price transparency, and thus these results may not be sustainable.

Future work should examine provider responses for multiple services and across the spectrum of care. Spillovers may occur if providers lower prices for all procedures but may also lead to higher prices in cases where providers lower prices only for services with high elasticities or consumer responses to price information and then raise prices for other services. Future studies should also examine provider responses to other commercially-supplied price transparency information and state price transparency laws. Finally, these results provide an early view of the dynamic effects of price transparency. As price transparency information becomes more common and widely used, it will be important to test if these initial findings still hold. Despite these limitations, this paper provides initial evidence of the effects of online price transparency on provider prices. As the popularity and consumer use of price transparency information grow, these results suggest that there may be limited price competition among certain types of providers.

Appendix A. Data sources

Table A1
Data sources.

Data source	Years	Key variables
Price transparency diffusion	2010–2014	$eligible_{tg}$: Share of HSA g's commercially insured population with access to price transparency platform in year t and quarter q.
Insurer-provider negotiated prices	2010–2014	$price_{jthkg}$: Negotiated price between provider j and insurance company h for procedure code k in each quarter t. Negotiated are based on each claims allowed amount (i.e. the sum of consumer cost-sharing and employer or insurer payments). $price_{thkg}$: Mean market-level negotiated price for consumer market g for procedure k in year t and quarter q.
HealthLeaders Interstudy Survey	2010–2014	Population size of commercially insured population.

Appendix B. Conceptual model

If providers set prices directly based on consumer demand and consumer responses to price information, as is the case in most markets, then the advertising models of Varian (1980) and Stahl (1989) can be used to show provider responses to consumer price transparency. However, health care prices for the commercially insured population are set through negotiations between insurance companies and providers. To describe how consumer price transparency can lead to lower negotiated prices between insures and providers, I present a bargaining model that closely follows previous models that have examined health care negotiations (Capps et al., 2003; Ho, 2009; Grennan, 2013; Ho and Lee, 2013), but especially follows the insurer-hospital bargaining model in Gowrisankaran et al. (2015). I start with consumer utility but unlike other insurer-provider bargaining models, I follow Varian (1980) and consider a market with both informed and uninformed consumers. The comparative statics of this model show that as consumers gain more information about providers, thereby becoming more price sensitive, insurer bargaining power with providers increases.

I assume each consumer i enrolled in an insurance plan h purchases a single unit of medical care from provider $j \in J$. After receiving care, the patient's utility from provider j is given by

$$U_{ijh} = \underbrace{\beta X_{ijh} - \gamma p_{jh}}_{\delta_{ijh}} + \epsilon_{ijh}. \tag{4}$$

In this expression, X_{ijh} measures the non-price patient and provider characteristics that influence the benefits of receiving care from a particular provider (e.g. distance, quality of care, and overall fit with patient). The provider's negotiated price with the insurer is given by p_{jh}. The β and γ terms thus measure patient responsiveness to the price and non-price attributes, respectively. I assume that ϵ_{ijh} is an error term with an extreme value type 1 distribution.

A given patient faces a cost of searching for providers of v_{ih}. For any given search cost value, $\bar{v}_{ih}$, the patient will maximize expected utility among the set of providers such that the expected incremental benefit of an additional provider is greater than the search costs. For a given provider $k \in J$, the patient will decide to continue searching as long as the expected benefit of searching is greater than the costs:

$$E[\max_{j=1\ldots J}(U_{ijh})|X_{ijh}] - u_{ikj} > \bar{v}_{ih}. \tag{5}$$

If we let U^*_{ijh} solve Eq. (5) for a given search cost $\bar{v}_{ih}$, then

$$j^*_{\bar{v}_{ih}} = \mathrm{argmax}_{j \in J} U_{ijh}.$$

Now consider a market with two types of consumers, uninformed and informed, that have different search costs such that $v^I < v^U$ and similar to Varian (1980), within a given market, let the share of informed consumers be given by $\mu = \frac{N_I}{N_I + N_U}$. By Eq. (5), $\delta^*_I \geq \delta^*_U$. Likewise, conditional on non-price attributes, the chosen provider's price for the informed group will be less than the uninformed population: $E[p^*_{jI}|X_{ijh}] \leq E[p^*_{jU}|X_{ijh}]$. Intuitively, as reduced search costs expand the choice set available to consumers, consumers are less likely to select a high-priced provider.

Due to the logit demand assumption, provider market shares from a set of providers $G \subseteq J$ are given by

$$s_{ijh} = \mu \frac{\exp(\delta_{ijh})}{\sum_{g \in G^I} \exp(\delta_{igh})} + (1-\mu)\frac{\exp(\delta_{ijh})}{\sum_{g \in G^U} \exp(\delta_{igh})}.$$

In this expression, G^I represents the set of providers such that $E[\max_{j=1\ldots J}(U_{ijh})|X_{ijh}] - u_{ikj} > v^I$ and G^U represents the set of providers such that $E[\max_{j=1\ldots J}(U_{ijh})|X_{ijh}] - u_{ikj} > v^U$. Because $v^I < v^U$, $G^U \subseteq G^I$. A given provider's market share is decreasing in price but is further decreasing in the share of informed consumers:

$$\frac{\partial^2 s_{ijh}}{\partial p_{jh} \partial \mu} < 0$$

With N consumers in the market, quantities are given by $q_{jh} = N\sum_i^N s_{ijh}$ and thus $\frac{\partial^2 q_{jh}}{\partial p_{jh} \partial \mu} < 0$.

Following Capps et al. (2003), the monetary consumer value of access to a given network is given by

$$V_{Gh} = \frac{1}{\gamma} \ln \sum_{g \in G} \exp(\delta_{igh}). \tag{6}$$

By the logit demand assumption, the utility values, $\ln \sum_{g \in G} \exp(\delta_{igh})$, can be converted to monetary values by dividing by the γ coefficient. Thus, an individual provider j's contribution to the value of the network is given by the incremental value that the provider adds to the network:

$$\mathcal{C}_{jh} = \mu \frac{1}{\gamma}\frac{1}{1 - s^I_{ijh}} + (1-\mu)\frac{1}{\gamma}\frac{1}{1 - s^U_{ijh}}. \tag{7}$$

The comparative statics show that the consumer value of the network is decreasing in price but the rate of the decrease is increasing in the share of informed consumers. However, the incremental gains in each provider's value to the network is more responsive to provider prices for the informed population than it is for the uninformed population. Thus, increasing the informed share of the population, μ, increases the price responsiveness of each provider's contribution the equilibrium network:

$$\frac{\partial^2 V_h}{\partial p_{jh} \partial \mu} > 0 \tag{8}$$

and

$$\frac{\partial^2 \mathcal{C}_{jh}}{\partial p_{jh} \partial \mu} < 0 \tag{9}$$

This feature provides the mechanism for reductions in negotiated prices. Following price transparency, expensive providers provide less value to the network than other competitors. Of course, this change in value depends on the degree of product differentiation and consumer price responses to transparency. The larger the consumer response to price transparency, the larger the reduction in the value expensive providers provide to an insurer's network.

Bargaining

For a given provider, profits are a function of the negotiated prices and volume, which depend on negotiated prices:

$$\pi_{jh}(\vec{p_h}) = \vec{p}_h q_j(\vec{p}_h).$$

In this expression, $\vec{p_h}$ represents a vector or price offered by an insurance network h. For simplicity, I assume that all providers have the same cost structure, which allows me to only consider revenue maximization.

The Nash bargaining problem solves

$$p^*_{jh} = \max_{p_{jh}} \left(q_{jh}(\vec{p_h})p_{jh}\right)^{b_{j(h)}} \left(\mathcal{C}_{jh}(\vec{p_h})\right)^{b_{h(j)}} \tag{10}$$

where $\left(\mathcal{C}_{jh}(N_h, \vec{p_h})\right)^{b_{h(j)}} = \left(V_h(N_h, \vec{p_h}) - V_h(N_h \backslash J_s, \vec{p_h})\right)^{b_{h(j)}}$ captures each provider's contribution to the equilibrium network's value. The $b_{h(j)}$ and $b_{j(h)}$ terms represent the bargaining abilities of providers with insurers and insurers with providers, respectively. The equilibrium set of providers in insurance plan h's network are denoted by N_h and J_s denotes any subset of N_h. The bargaining game jointly maximizes provider revenue and the consumer value of each insurance plan's network.

As shown in Gowrisankaran et al. (2015), by taking logs and maximizing, the first order conditions give

$$b_j(h)\frac{q_{hj}+\sum_{k\in J_s}\frac{\partial q_{jh}}{\partial p_{jh}}(p_{hj})}{\sum_{k\in J_s}q_{jh}p_{jh}} = -b_{h(j)}\frac{\partial V_h/\partial p_{jh}}{\mathcal{C}_h(\vec{p_h})} \tag{11}$$

For a single provider, this translates into

$$p^*_{jh} = -q_{jh}\left(\frac{\partial q_{jh}}{\partial p_{jh}} + q_{jh}\frac{b_h(j)}{b_j(h)}\frac{\partial V_h}{\partial p_{jh}}\frac{1}{\mathcal{C}_h}\right)^{-1} \tag{12}$$

From this formula, the negotiated price depends on the provider's own price elasticities, bargaining abilities, and the economic value each provider adds to the network. Tying in the results from Eqs. (8) and (9), because the marginal contribution of a high-priced provider to the network is decreasing in the share of informed consumers, the equilibrium price is also decreasing as more consumers gain access to price information:

$$\frac{\partial p^*_{jh}}{\partial \mu} < 0 \tag{13}$$

Qualitatively, increasing the share of informed consumers has the same effect as increasing insurer bargaining power. The magnitude of the increase in bargaining power depends on the consumer responses to price information. According to this model, for services where consumers do not shift demand to less expensive providers, there should be no change in provider prices but services for which price information leads to a large shift should see a decrease in provider prices. Tying in the previously estimated consumer results, this model implies that there should be little to no provider price response for services like office visits but there may be a substantial effect for services like lab tests.

One issue that remains ambiguous from these comparative statics is the potential effect of price transparency both increasing provider bargaining power (i.e. p^*_{jh} is increasing in $b_{h(j)}$, which may be increasing in μ), which would lead to higher prices, and making consumers more price sensitive, which leads to lower negotiated prices. The concerns about price transparency stem from the possibility that the increase in provider bargaining power outweighs the increase in insurer bargaining power, leading to an increase in prices. Which effect dominates cannot be determined from this model but underlies the empirical tests.

B.1 Model derivations

Proposition 1. *Patient utility is decreasing with respect to search costs.*

Proof. Let $\nu_1 < \nu_2$. Based on the optimal stopping rule, $E[U_1] = E[\max(U_{ijh})|X_{ijh}] - u_{ikj} > \nu_1$ and $E[U_2] = E[\max(U_{ijh})|X_{ijh}] - u_{ikj} > \nu_2$. Thus $\nu_1 < \nu_2 \Rightarrow E[U_1] > E[U_2]$. □

Proposition 2. *Provider market share is decreasing with respect to price and is further decreasing following searching.*

Proof

I start by noting that differentiating market share with respect to provider prices gives

$$\begin{aligned}
\frac{\partial s_{ijh}}{\partial p_{jh}} &= \mu\frac{-\gamma\exp(\delta_{ijh})\sum_{g\in G^I}\exp(\delta_{igh})+\gamma\exp(\delta_{ijh})^2}{\underbrace{\sum_{g\in G^I}\exp(\delta_{igh})^2}_{S_I^2}} \\
&\quad +(1-\mu)\frac{-\gamma\exp(\delta_{ijh})\sum_{g\in G^U}\exp(\delta_{igh})+\gamma\exp(\delta_{ijh})^2}{\underbrace{\sum_{g\in G^U}\exp(\delta_{igh})^2}_{S_U^2}} \\
&= \mu\frac{\gamma\exp(\delta_{ijh})(\overbrace{\exp(\delta_{ijh})-S_I}^{<0})}{S_I^2} \\
&\quad +(1-\mu)\frac{\gamma\exp(\delta_{ijh})(\overbrace{\exp(\delta_{ijh})-S_U}^{<0})}{S_U^2} \\
&< 0
\end{aligned}$$

Likewise, differentiating this expression with respect to the share of informed consumers, μ, is also decreasing

$$\begin{aligned}
\frac{\partial^2 s_{ijh}}{\partial p_{ijh}\partial\mu} &= \frac{\gamma\exp(\delta_{ijh})(\exp(\delta_{ijh})-S_I)}{S_I^2} - \frac{\gamma\exp(\delta_{ijh})(\exp(\delta_{ijh})-S_U)}{S_U^2} \\
&= \frac{S_U^2\gamma\exp(\delta_{ijh})(\exp(\delta_{ijh})-S_I) - S_U^2\gamma\exp(\delta_{ijh})(\exp(\delta_{ijh})-S_U)}{S_I^2S_U^2} \\
&= \frac{\gamma\exp(\delta_{ijh})\left(S_U^2(\overbrace{\exp(\delta_{ijh})-S_I}^{<0}) + S_I^2(\overbrace{\exp(\delta_{ijh})-S_I}^{<0})\right)}{S_I^2S_U^2} \\
&< 0
\end{aligned}$$

□

Proposition 3. *The value of a given network is decreasing in price but is further increasing as the share of informed consumers increases.*

Proof

The value of a network G is given by

$$\begin{aligned}
V_{Gh} &= \frac{1}{\gamma}\ln\sum_{g\in G}\exp(\delta_{igh}) \\
&= \mu\frac{1}{\gamma}\ln\sum_{g\in G^I}\exp(\delta_{igh}) + (1-\mu)\frac{1}{\gamma}\ln\sum_{g\in G^U}\exp(\delta_{igh})
\end{aligned}$$

Differentiating the value of the network with respect to p_{jh} gives

$$\begin{aligned}
\frac{\partial V}{\partial p_{jh}} &= -\mu\frac{\exp(\delta_{jh})}{S^I} - (1-\mu)\frac{\exp(\delta_{jh})}{S^U} \\
&< 0
\end{aligned}$$

Differentiating this with respect to μ gives

$$\begin{aligned}
\frac{\partial^2 V}{\partial p_{jh}\partial\mu} &= -\frac{\exp(\delta_{jh})}{S^I} + \frac{\exp(\delta_{jh})}{S^U} \\
&= \frac{\exp(\delta_{jh})}{S^U} - \frac{\exp(\delta_{jh})}{S^I} \\
&> 0
\end{aligned}$$

□

Proposition 4. *The incremental gain in each provider's value to the network is decreasing in price and is further decreasing as the share of informed consumers increases.*

Proof

A provider's contribution to the network is given by

$$\mathcal{C}_{jh} = \frac{1}{\gamma}\frac{1}{1 - s_{ijh}(\delta_{ijh})}.$$

Differentiating each provider's contribution to the provider's price with respect to that provider's price gives

$$\begin{aligned}\frac{\partial \mathcal{C}_{jh}}{\partial p_{jh}} &= \frac{\partial \mathcal{C}_{jh}}{\partial s_{ijh}} \cdot \frac{\partial s_{ijh}}{\partial p_{jh}} \\ &= \underbrace{\frac{\gamma}{(\gamma - s_{ijh}(\delta_{ijh}))^2}}_{>0} \cdot \underbrace{\frac{\partial s_{ijh}}{\partial p_{jh}}}_{<0} \\ &< 0\end{aligned}$$

Similarly, each provider's contribution to the network is increasing in the share of informed consumers provider's market share:

$$\frac{\partial \mathcal{C}_{jh}}{\partial \mu} = \frac{1}{\gamma - \gamma s_I} - \frac{1}{\gamma - \gamma s_U}$$

Differentiating this with respect to prices gives

$$\begin{aligned}\frac{\partial^2 \mathcal{C}_{jh}}{\partial \mu \partial p_{jh}} &= \frac{\gamma \frac{\partial s_I}{\partial p}}{(\gamma - \gamma s_I)^2} - \frac{\gamma \frac{\partial s_U}{\partial p}}{(\gamma - \gamma s_U)^2} \\ &= \frac{\overbrace{(\gamma - \gamma s_U)^2}^{>0}\ \gamma\ \overbrace{\frac{\partial s_I}{\partial p}}^{<0} - \overbrace{(\gamma - \gamma s_I)^2}^{>0}\ \gamma\ \overbrace{\frac{\partial s_U}{\partial p}}^{<0}}{(\gamma - \gamma s_I)^2 (\gamma - \gamma s_U)^2} \\ &< 0\end{aligned}$$

□

Proposition 5. *Equilibrium prices decrease as the share of informed consumers increases.*

Proof

I start by noting the following:

$$\begin{aligned}\frac{\partial p_{jh}}{\partial \mu} &= -\overbrace{\frac{\partial q_{jh}}{\partial \mu}}^{<0}\left(\overbrace{\frac{\partial q_{jh}}{\partial p_{jh}} + q_{jh}\frac{b_{ht}(j)}{b_{jt}(h)}\frac{\partial V_h}{\partial p_{jh}}\frac{1}{\mathcal{C}_{jh}}}^{<0}\right)^{-1} \\ &\quad -q\left(\underbrace{\frac{\partial q_{jh}}{\partial p_{hjt}} + q_{jh}\frac{b_{ht}(j)}{b_{jt}(h)}\frac{\partial V_h}{\partial p_{jh}}\frac{1}{\mathcal{C}_{jh}}}_{<0}\right)^{-1} \\ &\quad \left(\underbrace{\frac{\partial q}{\partial p}\frac{b_{ht}(j)}{b_{jt}(h)}\frac{\partial V}{\partial p}\frac{1}{\mathcal{C}_{jh}}}_{>0} + \underbrace{q_{jh}\frac{b_{ht}(j)}{b_{jt}(h)}\frac{\partial^2 V_h}{\partial p_{jh}\partial \mu}\frac{1}{\mathcal{C}_{jh}}}_{>0} + \underbrace{q_{jh}\frac{b_{ht}(j)}{b_{jt}(h)}\frac{\partial V_h}{\partial p_{jh}}\frac{\partial \frac{1}{\mathcal{C}_{jh}}}{\partial \mu}}_{>0}\right) \\ &\quad \left(\underbrace{\frac{\partial q_{jh}}{\partial p_{jh}} + q_{jh}\frac{b_{ht}(j)}{b_{jt}(h)}\frac{\partial V_h}{\partial p_{jh}}\frac{q_{jh}}{\mathcal{C}_{jh}}}_{<0}\right)^{-1} \\ &< 0\end{aligned}$$

□

Appendix C. Additional tables and figures

Log-transformed diffusion rate

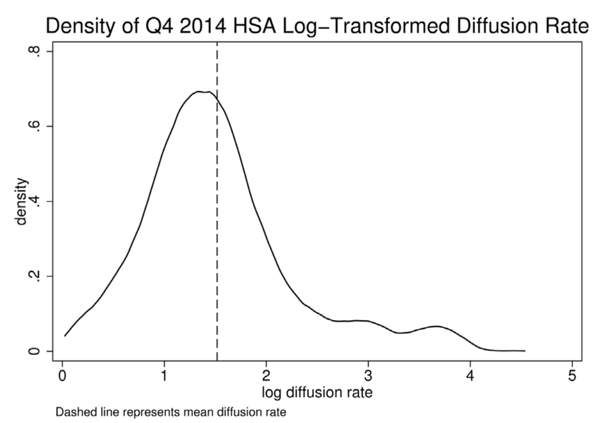

Fig. C1. Log-transformed penetration rate. This figure plots the density of the Hospital Service Area-specific log-transformed share of commercially insured individuals who have access to the price transparency platform in the fourth quarter of 2014.

Robustness test using hospital referral regions (HRRs) as alternative geographic market

Table C1
Provider price responses to online price transparency-HRR robustness test.

(a) Office visits						
	(1)	(2)	(3)	(4)	(5)	(6)
Share eligible	0.0939*	0.0940*	0.0942*	0.0313	0.0971**	0.0326*
	(0.0488)	(0.0490)	(0.0490)	(0.0199)	(0.0460)	(0.0188)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year
(b) Laboratory tests						
	(1)	(2)	(3)	(4)	(5)	(6)
Share eligible	−0.173	−0.173	−0.174	−0.225	−0.175	−0.227
	(0.235)	(0.234)	(0.231)	(0.174)	(0.235)	(0.175)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.550	0.551	0.556	0.558	0.551	0.558
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the $eligible_{tg}$ coefficients from Eq. (1), which is estimated using OLS. In each regression, $eligible_{tg}$ is defined as the share of each HRR's commercially insured population with access to the price transparency platform in each quarter. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Service Area level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

C2

Table C2
Provider price responses to online price transparency: log diffusion-HRR robustness test.

(a) Office visits						
	(1)	(2)	(3)	(4)	(5)	(6)
ln(share eligible)	0.00568	0.00572	0.00573	0.00291	0.00613*	0.00309*
	(0.00344)	(0.00349)	(0.00349)	(0.00187)	(0.00331)	(0.00179)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPTX × year	Insurer/CPT × year
(b) Laboratory tests						
	(1)	(2)	(3)	(4)	(5)	(6)
ln(share eligible)	−0.0251	−0.0251	−0.0250	−0.0269**	−0.0253	−0.0271**
	(0.0164)	(0.0163)	(0.0161)	(0.0112)	(0.0164)	(0.0112)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.551	0.556	0.558	0.551	0.558
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the log-transformed $eligible_{tg}$ coefficients from Eq. (1). In each regression, $\ln(eligible_{tg})$ is defined as the log of the share of each HRR's commercially insured population with access to the price transparency platform in each quarter. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Referral Region level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table C3
Provider price responses to online price transparency: diffusion categories-HRR robustness test.

(a) Office visits	(1)	(2)	(3)	(4)	(5)	(6)
(0 – 1]% share eligible	−0.00280	−0.00284	−0.00287	0.00327	−0.00308	0.00290
	(0.00401)	(0.00403)	(0.00404)	(0.00309)	(0.00397)	(0.00308)
(1 – 2]% share eligible	−0.00283	−0.00282	−0.00285	0.00436	−0.00288	0.00420
	(0.00636)	(0.00635)	(0.00635)	(0.00343)	(0.00630)	(0.00344)
(2 – 3]% share eligible	−0.00403	−0.00401	−0.00405	0.00547	−0.00392	0.00529
	(0.00831)	(0.00829)	(0.00830)	(0.00434)	(0.00821)	(0.00435)
(3 – 4]% share eligible	−0.0132	−0.0132	−0.0132	−0.00379	−0.0130	−0.00383
	(0.00877)	(0.00873)	(0.00874)	(0.00435)	(0.00865)	(0.00435)
(4 – 5]% share eligible	−0.00959	−0.00952	−0.00953	−0.0000132	−0.00909	0.0000969
	(0.0104)	(0.0103)	(0.0103)	(0.00606)	(0.0102)	(0.00606)
>5% share eligible	0.00334	0.00343	0.00343	0.00937*	0.00416	0.00940*
	(0.00510)	(0.00509)	(0.00508)	(0.00504)	(0.00518)	(0.00503)
Observations	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223	1,886,223
Number of providers	93,974	93,974	93,974	93,974	93,974	93,974
Adjusted R^2	0.745	0.745	0.745	0.750	0.746	0.751
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year
(b) Laboratory tests	(1)	(2)	(3)	(4)	(5)	(6)
(0 – 1]% share eligible	−0.0128	−0.0130*	−0.0126	−0.00478	−0.0128	−0.00457
	(0.00776)	(0.00780)	(0.00779)	(0.00755)	(0.00781)	(0.00755)
(1 – 2]% share eligible	−0.0270***	−0.0272***	−0.0267***	−0.0207**	−0.0267***	−0.0201**
	(0.0100)	(0.0101)	(0.0100)	(0.00958)	(0.0101)	(0.00960)
(2 – 3]% share eligible	−0.0179	−0.0184	−0.0180	−0.0113	−0.0180	−0.0109
	(0.0130)	(0.0130)	(0.0130)	(0.0125)	(0.0132)	(0.0126)
(3 – 4]% share eligible	−0.0485***	−0.0489***	−0.0479***	−0.0406***	−0.0487***	−0.0403***
	(0.0150)	(0.0150)	(0.0149)	(0.0146)	(0.0151)	(0.0147)
(4 – 5]% share eligible	−0.0442**	−0.0447**	−0.0433**	−0.0387**	−0.0447**	−0.0387**
	(0.0193)	(0.0194)	(0.0194)	(0.0182)	(0.0195)	(0.0183)
>5% share eligible	−0.0676***	−0.0680***	−0.0668***	−0.0575***	−0.0681***	−0.0576***
	(0.0178)	(0.0177)	(0.0176)	(0.0140)	(0.0175)	(0.0139)
Observations	707,539	707,539	707,539	707,539	707,539	707,539
Number of providers	16,502	16,502	16,502	16,502	16,502	16,502
Adjusted R^2	0.551	0.551	0.556	0.558	0.551	0.559
Controls		OOP	Insurer	Insurer × year	CPT × year	Insurer/CPT × year

This table presents the categorized $eligible_{tg}$ coefficients from Eq. (1), which is estimated using OLS. In each regression, $eligible_{tg}$ is defined as the share of each HRR's commercially insured population with access to the price transparency platform in each quarter. The $eligible_{tg}$ diffusion measure is categorized into one percentage-point increments: {0%, (0 – 1%], (1 – 2%], (2 – 3%], (3 – 4%], (4 – 5%] >5%}. The dependent variable is the log-transformed mean quarterly provider price for each CPT code. Panel A presents results for office visits and Panel B presents results for laboratory tests. In each panel, column 1 includes fixed effects for date and procedure code. Column 2 adds average patient cost sharing, column 3 adds insurance company fixed effects, column 4 interacts the insurance company fixed effects with year fixed effects, column 5 interacts year and CPT code fixed effects, and column 6 includes fixed effects for both the insurer and CPT code interactions with year fixed effects. Robust standard errors clustered at the Hospital Referral Region level in parentheses. Because each regression uses the log-transformed price as the dependent variable, all coefficients can be interpreted as percent changes using $\exp(\beta) - 1$.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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