UC Berkeley
UC Berkeley Electronic Theses and Dissertations

Title
The effects of consumer information and cost-sharing on healthcare prices

Permalink
https://escholarship.org/uc/item/3s7333qw

Author
Whaley, Christopher

Publication Date
2015

Peer reviewed|Thesis/dissertation

eScholarship.org Powered by the California Digital Library
University of California

The effects of consumer information and cost-sharing on healthcare prices

by

Christopher Whaley

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Health Services and Policy Analysis

in the

Graduate Division
of the
University of California, Berkeley

Committee in charge:

Professor Benjamin R. Handel, Chair
Professor Paul J. Gertler
Professor James C. Robinson
Professor Steven Tadelis

Spring 2015

The effects of consumer information and cost-sharing on healthcare prices

Copyright 2015
by
Christopher Whaley

Abstract

The effects of consumer information and cost-sharing on healthcare prices

by

Christopher Whaley
Doctor of Philosophy in Health Services and Policy Analysis

University of California, Berkeley

Professor Benjamin R. Handel, Chair

Non-transparent information about prices is a key piece of many economic models. George Stigler's seminal work first formulated how 'search costs' lead to price dispersion in provider prices. For several decades, refining the relationship between search costs and prices was a key component of the economics literature. With growth of the internet, consumer information about prices has increased substantially. The growth of online retailers has led to substantial decreases in search costs by providing an easy mechanism to compare prices.

Recent technologies have expanded the internet's search-cost reducing powers to the healthcare sector. Compared to other markets, healthcare prices exhibit an enormous amount of price variation and have traditionally been among the most non-transparent of any market. The lack of meaningful price transparency has traditionally made price shopping for healthcare services nearly impossible. As consumer cost-sharing increases, led by the growth in high-deductible health plans, there is a strong imperative to provide the tools necessary for consumers to shop for care. Without accurate price information, increases in consumer cost-sharing will simply shift expenses from employers and insurers to consumers.

While the hope is that 'price transparency' information will encourage consumers to shop for care, little is known about how consumers actually use price information. The first chapter of this dissertation uses detailed data from a leading online price transparency firm to examine the consumer effects of price transparency. Large price effects are found for commodity-like services as consumers shift demand from expensive to less-expensive providers. For physician office visits, which entail a more personal relationship, the largest effects are for non-price information, such as provider gender and length of practice.

Even less is known about how providers will respond to consumers using price transparency information to shop for care. Healthcare providers have not traditionally had to account for consumers making decisions based on price and have simply negotiated prices with insures. With the growth of consumer cost-sharing and price transparency, this paradigm will undoubtedly change. The second chapter uses the same data to estimate an initial look at how providers respond to consumer price transparency. Following

the consumer analysis, large effects are found for non-differentiated products. Consistent with Stigler's observations, reducing consumer search costs leads to both reductions in consumer prices and the prices that providers charge.

The third chapter of this dissertation examines a similar topic as the second, how providers respond to increases in consumer-cost sharing. This chapter leverages the implementation of a Reference-Based Benefit (RBB) design by the California Public Employees Retirement System (CalPERS) that capped reimbursements for certain procedures. Previous work has documented large consumer effects to the RBB program but how providers respond has not been studied in detail. The results show large price reductions by providers who have the largest exposure to the CalPERS population.

As a means to reduce the growth in healthcare spending, employers and insurers have implemented innovative benefit designs and technologies. These changes are largely driven by the recognition that the current healthcare ecosystem has evolved into a market with substantial price variation and no link between price and quality. Consumer cost-sharing and price transparency provide both the incentive and the means to steer patients away from high-cost providers. As these innovations have their desired effects, this dissertation shows how providers respond accordingly. These tandem consumer and provider responses to price transparency and target cost-sharing result in general equilibrium effects that lead to less expensive healthcare and a more efficient healthcare market.

This dissertation is dedicated to my wife, Katherine Yang

Contents

List of Figures **iv**

List of Tables **v**

1 Searching for Health: Price Transparency and Online Search **1**
1.1 Introduction . . . 2
1.2 Literature . . . 4
1.2.1 How the internet reduces search costs . . . 4
1.2.2 Report cards . . . 5
1.2.3 Price Transparency . . . 6
1.3 Theoretical Framework . . . 6
1.4 Data and Setting . . . 9
1.4.1 Descriptive Characteristics . . . 10
1.5 Consumer Responses to Price Transparency . . . 11
1.5.1 Effect of Searching on Consumer Prices . . . 11
1.5.2 Endogeneity Concerns . . . 13
1.5.3 Searching and Market-level Price Variation . . . 14
1.5.4 Physician Choice . . . 15
1.5.4.1 Model and estimation . . . 16
1.5.4.2 Results . . . 17
1.6 Conclusion . . . 18

Bibliography **20**
1.7 Figures and Tables . . . 25
1.8 Appendix: Consumer Search Extensions . . . 38
1.8.1 Relative Prices . . . 38
1.8.2 Learning . . . 39
1.8.3 Downstream Effects . . . 40
1.9 Appendix: Searcher Non-searcher Comparisons . . . 42

2 Provider Responses to Price Transparency **43**
2.1 Introduction . . . 44

2.2 Theoretical Motivation 46
2.2.1 Bargaining 47
2.3 Data 48
2.3.1 Estimation 50
2.3.1.1 Heterogeneous Provider Responses 51
2.4 Results 52
2.4.1 Main Results 52
2.4.2 Heterogeneity Results 53
2.4.3 Provider Market Shares 54
2.4.4 Market-Level Effects 55
2.5 Conclusion 56

Bibliography **58**
2.6 Tables and Figures 63

3 Provider Responses to Consumer Incentives: Evidence from Reference Based Benefits **79**
3.1 Introduction 80
3.2 Institutional Background 81
3.3 Data and Methods 82
3.4 Results 84
3.4.1 Heterogeneity in Effect 84
3.5 Financial Savings 85
3.6 Discussion 85

Bibliography **87**
3.7 Figures and Tables 92

List of Figures

1.1 Metropolitan Statistical Area (MSA) Price Variation Distribution 27
1.2 County Price Variation Distribution 28
1.3 Time between access and searching 29

2.1 County Penetration: 2011 63
2.2 County Penetration: 2014 63

3.1 Distribution of Provider Prices 92
3.2 Provider Price Trends 93

List of Tables

1.1 Summary Statistics . . . 26
1.2 Main Effect: All claims following search . . . 30
1.3 Main Effect: Length of time between searching and claim . . . 30
1.4 Placebo Test . . . 31
1.5 Effect of Searching on Prices: Instrumental Variables Approach . . . 32
1.6 Price Variation: Weighted average share above mean cv_{gk} . . . 33
1.7 Price Variation: Weighted average share above median cv_{gk} . . . 34
1.8 Choice Results: Post Search . . . 35
1.9 Choice Results: Post Access . . . 36
1.10 Willingness-to-pay estimates . . . 37
1.11 Relative Prices: Probability above mean price MSA price . . . 38
1.12 Relative Prices: Probability above mean price county price . . . 39
1.13 Learning . . . 40
1.14 Downstream effects . . . 41
1.15 Searcher vs Non-Searcher Main Effect: All claims following search . . . 42
1.16 Searcher vs Non-Searcher Main Effect: Length of time between searching and claim . . . 42

2.1 Summary Statistics . . . 64
2.2 Physician Price Responses to Price Transparency . . . 65
2.3 Physician Price Responses to Price Transparency: Diffusion Categories . . . 66
2.4 Physician Price Responses to Price Transparency: Alternative Diffusion Categories . . . 67
2.5 Provider Responses to Price Transparency: Lagged Diffusion . . . 68
2.6 Physician Price Responses to Price Transparency: Sensitivity Test . . . 69
2.7 Physician Price Responses to Price Transparency: Zip Code Sensitivity Test 70
2.8 Physician Price Responses to Price Transparency: Hospital Referral Region Sensitivity Test . . . 71
2.9 Physician Price Responses to Price Transparency: Baseline Provider Prices 72
2.10 Physician Price Responses to Price Transparency: Market Characteristics . 73
2.11 Market Share Changes . . . 74
2.12 Market-level Average Price Changes: . . . 75

2.13 Market-level Average Price Changes: 76
2.14 Market-level Price Dispersion Changes: 77
2.15 Market-level Price Dispersion Changes: 78

3.1 Summary Statistics 94
3.2 Concentration of CalPERS Enrollees by Hospital Referral Region 94
3.3 Provider Responses to RBB 95
3.4 HOPD Responses to RBB 96
3.5 ASC Responses to RBB 97
3.6 Heterogeneity: CalPERS share 98
3.7 Heterogeneity: Baseline Price 99

Acknowledgments

This dissertation would not have been possible without the support of many individuals. First, Ghada Haddad has provided a tremendous amount of support and logistical expertise during my time at Berkeley. Without Ghada, my Berkeley experience would have been much less enjoyable. Eve Donavan at the Berkeley Center for Health Technology also provided the logistical support that helped get this dissertation completed. My classmates Abhay Aneja, Paulette Cha, Ritadhi Chakravarti, Courtnee Hamity, Heather Knauer, Jing Li, Lauren Harris, and Neil Sehgal helped me through grad school. Lunches and coffee with Armando Franco helped refine my research ideas. The broader UC Berkeley Health Services and Policy Analysis community also provided an excellent venue for learning about the healthcare system from a variety of perspectives. Many fellow students provided helpful feedback on early research ideas and encouragement throughout the program. Timothy Brown, Will Dow, Brent Fulton, Ann Keller, Richard Schefler, and Stephen Shortell all provided research mentorship and guidance.

I am indebted to the guidance and support of my dissertation committee: Professors Benjamin Handel, Paul Gertler, James Robinson, and Steven Tadelis. Professor Neeraj Sood at the Leonard D. Schaeffer Center for Health Policy and Economics also provided a tremendous amount of support and guidance. The insights and unique perspectives of each individual improved my work considerably.

Even greater acknowledgement belongs to those outside the research community who helped with this paper. My parents, Janet and Jim, encouraged an appreciation of learning and knowledge from an early age. My two brothers, Justin and Basil, who have provided a lifetime of joy. My in-laws, John and Terrie, have welcomed me into their family. Irene and Rob have provided great camaraderie throughout the process. Finally, being a graduate student requires spending a substantial amount of time away from home. This dissertation would not have been possible without the love, support, and encouragement of my wife, Katherine Yang. Our bundle of energy, Honey, has provided relief from the stresses inherent with academic work.

Chapter 1

Searching for Health: Price Transparency and Online Search

1.1 Introduction

High prices for the commercially insured population are a substantial contributor to higher healthcare spending in the U.S. relative to other OECD countries (Anderson *et al.* , 2003). In addition, the widespread variation in commercially insured prices for medical services is well documented (Rosenthal, 2013; Brill, 2013; Robinson, 2011; Baker *et al.* , 2013; Hsia *et al.* , 2014). Prices vary substantially both within the same region and between different geographic markets. For example, one piece of descriptive evidence shows that that the average price of an MRI of the lower back in San Francisco, CA is $2,244 but the range in prices is $851 to $3,410. Meanwhile, the average price in Los Angeles, CA is $1,201 and the range is $536 to $3,227.[1] Among other factors, the causes of this price variation range from provider-insurer bargaining differences, local practice patterns, and provider concentration. At the same time, there is no consistent documentation of a relationship between commercial prices and quality. The most expensive providers rarely have the highest quality (e.g. lowest complication, readmission, or mortality rates) or highest satisfaction ratings (Hussey *et al.* , 2013).

Given the level of price variation, a natural question arises of why consumers visit high-priced rather than low-priced providers, especially for elective or planned procedures. One reason is the presence of insurance. Insurance insulates consumers from high prices and so consumers have less financial incentive to choose low-cost providers. Coupled with an already inelastic demand, this moral hazard limits the economic incentives to seek less expensive care.

However, many employers have moved to high-deductible health plans (HDHPs), in which consumers are responsible for a substantial portion of medical costs. In 2013, 20% of U.S. residents with employer-sponsored insurance had a high deductible health plan, defined as a deductible of at least $1,000 for an individual plan and $2,000 for a family plan, up from 4% in 2006 (Claxton *et al.* , 2013). Considering that 2012 median per-capita medical spending in the U.S. for the under-65 population was $627, most individuals will not receive any insurance coverage through their high-deductible plan.[2] For those who do not reach their deductible, insurance coverage provides a barrier against catastrophic costs rather than a reduction in out-of-pocket costs for routine medical services. With the growth in high-deductible health plans, one may expect consumers to avoid high-priced providers. Yet several studies demonstrate that high-deductible plans do not led to lower prices for medical care (Sood *et al.* , 2013; Brot-Goldberg *et al.* , 2015; Huckfeldt *et al.* , 2015). Instead, much of the reduction in healthcare spending attributable to high-

[1]Source: Castlight Health. "Pricing for the Same Medical Services is All Over the Map". June 2014. Available from: http://www.castlighthealth.com/price-variation-map. Another recent examples include 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]Source: Medical Expenditure Panel Survey 2012 Full Year Consolidated Data File

deductible plans appears to be due to decreases in healthcare utilization, particularly utilization of routine, preventive services.

One potential reason why HDHPs have not led to reductions in per-unit prices for healthcare services is the lack of provider price information available to consumers. Even in high-deductible plans, consumers have little information about provider prices before receiving care. A variety of factors contribute to the lack of consumer information. For one, strong informational asymmetries exist between patients and their providers (Arrow, 1963; Stigler, 1961; Reinhardt, 2006). In addition, many insurance contracts legally prohibit disclosing negotiated rates. Finally, most commercial prices are determined through a complex negotiation process. Unlike Medicare, which reimburses providers based on a formulated price schedule, commercial prices are negotiated between providers and insurers. The price that a provider charges a given patient depends on the patient's insurance company, insurance network, and patient-specific benefits. Even if they wanted to provide prices, providers may not be able to readily assess these characteristics and thus may not even be able to provide accurate price quotes (Rosenthal *et al.* , 2013).

As a solution to the lack of commercial price information, a move towards healthcare "price transparency" has become increasingly advocated (Bloche, 2006; Mehrotra *et al.* , 2012; Emanuel *et al.* , 2012). The move towards greater price transparency has been particularly championed at the state-level. Most states require reporting of hospital charges or reimbursement rates and more than 30 states are pursuing legislation to enhance price transparency in health care (Sinaiko & Rosenthal, 2011; Kullgren JT *et al.* , 2013). For example, the state of New Hampshire publishes hospital-specific average charges and costs for common procedures.[3] However, much of the price information provided by state-administered platforms is based on billed charges rather than on transacted prices. Due to negotiated prices, restricted networks, and varying benefit designs, billed charges rarely represent actual prices for the privately insured population. In addition, use of the state-administered sites is low (Mehrotra *et al.* , 2014). Initial evidence suggests that such state-administered price transparency initiatives have had little success (Tu & Lauer, 2009; Cutler & Dafny, 2011a).

In recent years, private sector tools aimed at providing price transparency have also emerged. These tools typically provide personalized price information to consumers (Phillips & Labno, 2014). In particular, these tools often report prices for providers or facilities providing within a certain radius of the consumers' zip code or address. The reported prices reflect actual out-of-pocket costs for the consumer and take into account discounts off billed charges and health benefit design. Consumers can use these tools to search for procedures and providers before receiving care. The hope is that by providing information in a usable format, consumers will become more engaged in their health care choices and choose less expensive providers.

Despite the support for price transparency, little evidence exists on how consumers respond to price transparency. This paper helps fill this void by examining the effects of

[3]See http://nhhealthcost.nh.gov/

searching for services using an online price transparency platform on the prices for medical services received by consumers. This paper supplements an earlier paper, which found that active searchers of this platform had approximately 13% less expensive laboratory tests and advanced imaging (MRI and CT scans) and 1% less expensive physician office visit services than non-searchers (Whaley *et al.* , 2014). This paper finds approximately the same effects and finds an even larger effect in markets with higher levels of price dispersion. The smaller price effect for physician services is a natural result given the comparatively low level or price dispersion for physician services. To examine the overall effect of searching for physician services, I use a discrete choice model to examine the non-price attributes, such as provider gender and length of practice, that are displayed by the transparency platform. The primary contribution of this paper is the demonstration that active use of price transparency information leads to receiving less expensive medical care and provides other valuable information to consumers. While much of the economics literature has focused on search costs as a cause of price dispersion, this paper instead identifies how lowering search costs can in turn lead to lower prices for consumers. This contribution has substantial policy implications as the results from this paper demonstrate that healthcare consumerism can work if consumers are given and use price information.

1.2 Literature

Beginning with Arrow (1963), economists have long recognized the importance of information asymmetries in health care markets. In addition to little knowledge of diagnoses, recommended practice patterns, and other aspects of medical care, most individuals are covered by health insurance, which limits the incentive to search for less expensive providers. Stigler (1961) provides the first formalization of the costs associated with searching for new information. Since then, numerous papers have examined search costs, both in health care and other settings. Economic models of search posit that price variation in a given market is due to imperfect information and search costs associated with obtaining additional information. More recently, several studies have examined the effect of information, particularly information obtained through internet sources, that reduces search costs.

1.2.1 How the internet reduces search costs

Brown & Goolsbee (2002) provide the most prominent example of the internet leading to lower consumer prices for life insurance policies. They find that internet use reduces life insurance prices by 8-15%. However, they are not able to observe actual consumer searches for life insurance plans and instead create a predicted measure of internet access based on observable characteristics. In several papers, Florian Zettelmeyer, Fiona Scott Morton, and Jorge Xilva-Riso examine the effect of the internet on automobile prices. Unlike Brown & Goolsbee (2002), these studies have linked online use and automobile purchase

data, so individual-specific searches can be linked to future purchases. As discussed below, this feature is similar to the data construction I use to examine the effect of online information on health care prices and so this set of papers is an important analogue to my project. In their first paper, they compare prices for consumers who use an auto-referral service and those who do not (Morton *et al.* , 2001). They find a 2% reduction in prices but they are not able to identify if this decrease is due to a causal effect of internet searching or is due to selection. In a more detailed paper, they use several instrumental variable strategies and identify a causal 2.2% reduction in prices (Zettelmeyer *et al.* , 2001). Finally, Zettelmeyer *et al.* (2005) uses survey data to match consumers choices with auto purchases. They find that consumers who used the internet to search for car prices paid 1.5% less than those who did not.

1.2.2 Report cards

Several papers examine tools that provide information to consumers and effectively reduce search costs. Most notably, Jin & Leslie (2003) examine the effect of public restaurant hygiene report cards in Los Angeles. Their results suggest consumers face relatively high search costs for a basic service and reducing search costs can lead to substantial behavior changes and increases in consumer well-being. Starting with Chernew & Scanlon (1998), several studies have examined the effect of provider and insurer ratings on patient decision making. Nearly all provider report cards only include quality information so studies that include the effect of price information on provider choice are limited. Somewhat adversely, the strongest effect often comes from providers "gaming" report cards to improve their rankings. Dranove *et al.* (2003) examine the effect of publishing quality scores for New York cardiologists and find that cardiology report cards actually decrease patient welfare because providers adversely select patients and avoid patients who may potentially lower their reported scores. However, for healthy patients, there was an increase in patient match. Kolstad (2013) examines a similar setting-cardiologist report cards in Pennsylvania and finds the report cards lead to quality improvements beyond what can be explained by profit maximization. Instead, cardiologists appear to improve quality relative to their peers. The intrinsically motivated peer effect on patient quality is approximately four times as large as the profit effect.

Insurer report cards commonly include price information and several studies have examined the effect of price in addition to quality on plan choice. Scanlon *et al.* (2002) find insurance report cards lead consumers to choose plans with lower out-of-pocket costs and avoid plans with below average quality ratings. Strombom *et al.* (2002) document substantial price sensitivity but also find evidence of switching costs as new employees, who had to choose a plan, were more price sensitive than current employees, who could remain in their current plan. Finally, Dafny & Dranove (2008) note that in an efficient market, private agents, for example *U.S. News and World Reports*, may provide information that makes public report cards redundant. To test this hypothesis, they examine the enrollment in Medicare HMO plans following publicly reported plan information by

the Centers for Medicare & Medicaid Services (CMS). Prior to CMS providing publicly available report cards, they found increased migration to higher-quality plans in markets in which *U.S. News* provided plan information. However, there was still a response to the CMS report cards, even after accounting for market-based information.

1.2.3 Price Transparency

The literature surrounding healthcare price transparency is less robust than in other areas. Much of the literature has focused on the potential benefits of transparency rather than the effect of price transparency on outcomes (Sinaiko & Rosenthal, 2011). While the intended effect of price transparency information is for consumers to shift demand to less expensive providers, one potential fear is that price information may actually lead to an increase in use of expensive providers if consumers associate higher prices with higher quality (Mehrotra *et al.* , 2012). However, the initial evidence suggests that consumers are in fact behaving as expected. In a working paper, Lieber (2013) examines a similar setting and finds a small effect on prices. He also models the moral hazard effect on uptake of search behavior and finds a large effect. Similar to this study, a telephone-based price transparency program for MRI services in which price transparency was paired with a pre-authorization program shows that price transparency reduces MRI costs by 18.7 (Wu *et al.* , 2014). A previous study finds an association between searching for providers and lower prices for laboratory, advanced imaging, and physician services (Whaley *et al.* , 2014). Of the eligible population, price transparency searches proceeded approximately 7% of advanced imaging and laboratory claims and 27% of physician office visit claims. This paper examines consumer use of price transparency information for these same three services but adds in several extensions to look at heterogeneity in use.

In addition, while early evidence documents that consumers use price transparency information to obtain lower per-unit prices, consumers use of non-price information prices is not well known. Especially for a relatively price inelastic service, such as healthcare, prices may not be the most important provider attribute when choosing a provider. Information such as clinical quality, convenience, or patient satisfaction may be more valuable to consumers than price information. I use a discrete choice model to examine how consumers use non-price information and then estimate the willingness-to-pay for non-price information on physician services. This result provides the counterintuitive result that for physician services, the largest consumer benefit of price transparency is not for price but rather non-price attributes.

1.3 Theoretical Framework

As a motivating economic model of the effect of searching on consumer costs, I assume each individual consumes one unit of medical care. For each individual, let patient i's

indirect utility for receiving treatment from provider j be given by the linear expression

$$U_{ij} \quad = \quad quality_{ij} - p_{ij} - c_i n.$$

In this expression, $quality_{ij}$ encompasses both the effectiveness of treatment, p captures price, and c_i denotes the search costs required to obtain n price quotes. Prices are drawn from the distribution $F(p)$ with minimum and maximum prices $\underline{p}$ and $\bar{p}$, respectively. After n draws of $F(p)$, prices can be ordered such that $p^n_{\min} = \min\{p_1, \ldots, p_n\}$. With constant search costs, the expected cost of the provider visit after n draws can be written as

$$E[cost^n] \quad = \quad \underline{p} + \int_{\underline{p}}^{\bar{p}} [1 - F(p)]^n dp + cn. \tag{1.1}$$

Compared to the costless search environment, expected prices are higher both due to the costs of searching and the chances of paying above the lowest available price.

I assume that each consumer undergoes at least one search so that for a given search cost c, the optimal number of searches, $n^*(c)$, is given by

$$n^*(c) \quad = \quad \arg\min_{n>1} \underline{p} + \int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n(c)} dp + nc(n). \tag{1.2}$$

Following Stigler (1961), $[1-F(p)]^{n(c)}$ is decreasing at a decreasing rate in n, which implies that the marginal benefit of searching is decreasing. Thus, $n^*(c)$ is likewise decreasing at a decreasing rate. As is standard in search cost models, I assume that consumers search until the marginal benefits of searching are zero.

This formulation yields two simple and intuitive insights into the relationship between changing search costs and prices.

Proposition 1. *A reduction in search costs lowers expenditures.*

Proof. Fix search costs at $\bar{c}$ and take any level of search costs $c < \bar{c}$. Define the difference in expenditures between c and $\bar{c}$ as

$$\begin{aligned}
E[cost^{n^*(c)}] - E[cost^{n^*(\bar{c})}] \quad &= \Big(\quad \underline{p} + \int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n^*(c)} dp + cn^*(c) \Big) \\
&\quad - \Big(\underline{p} + \int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n^*(\bar{c})} dp + \bar{c}n^*(\bar{c}) \Big) \\
&= \quad \Big(\int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n^*(c)} dp - \int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n^*(\bar{c})} dp \Big) \\
&\quad + \Big(cn^*(c) - \bar{c}n^*(\bar{c}) \Big) \\
&< \quad 0
\end{aligned}$$

Because $n^*(c)$ is decreasing, the reduction in search costs leads to an increase in sample draws, which in turn increases the probability that a less expensive provider is found, and so the first part is negative. The second part is negative by the assumption that $n^*(c)$ is decreasing at a decreasing rate and so $\frac{c}{\bar{c}} < \frac{n^*(\bar{c})}{n^*(c)}$. □

Intuitively, the reduction in search costs is partially offset by the increase in the number of searches conducted but because the benefits of searching outweigh the costs, the overall effect is a reduction in both prices and the costs of searching.

Proposition 2. *A reduction in search costs has a larger effect when the distribution in prices is more dispersed.*

Proof. Let $F(p)$ and $G(p)$ be price distributions with the same means but let $G(p)$ have larger price dispersion and be a mean preserving spread of $F(p)$. More formally, let $\int_{\underline{p}}^{\bar{p}} F(p) = \int_{\underline{p}}^{\bar{p}} G(p)$ but for some $\alpha \in [\underline{p}, \overline{p}]$, $\int_{\underline{p}}^{\alpha} F(p) < \int_{\underline{p}}^{\alpha} G(p)$. Similar to Baye *et al.* (2006), define $\Delta^F_{c,\bar{c}} - \Delta^G_{c,\bar{c}}$ as the difference in transaction prices due to a reduction in search costs between the two price distributions:

$$\begin{aligned}
\Delta^F_{c,\bar{c}} - \Delta^G_{c,\bar{c}} &= \Big(E_F[cost_F^{n(c)}] - E[cost_F^{n(\bar{c})}]\Big) \\
&\quad -\Big(E[cost_G^{n(c)}] - E[cost_G^{n(\bar{c})}]\Big) \\
&= \Big(\int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n(c)} dp - \int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n(\bar{c})} dp\Big) \\
&\quad -\Big(\int_{\underline{p}}^{\bar{p}} [1 - G(p)]^{n(c)} dp - \int_{\underline{p}}^{\bar{p}} [1 - G(p)]^{n(\bar{c})} dp\Big) \\
&= \Big(\int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n(c)} dp - \int_{\underline{p}}^{\bar{p}} [1 - G(p)]^{n(c)} dp\Big) \\
&\quad -\Big(\int_{\underline{p}}^{\bar{p}} [1 - F(p)]^{n(\bar{c})} dp\Big) - \int_{\underline{p}}^{\bar{p}} [1 - G(p)]^{n(\bar{c})} dp\Big) \\
&= \Delta^{F,G}_{c} - \Delta^{F,G}_{\bar{c}}
\end{aligned}$$

As shown in Baye *et al.* (2006), for any c, $\Delta^{F,G}_c > 0$ due to the mean preserving spread property. Proposition 1 combined with the decreasing marginal rate of $E[cost^{n^*(c)}]$ in $n^*(c)$ implies that $\Delta^{F,G}_c > \Delta^{F,G}_{\bar{c}}$ and so the overall effect is positive. □

As shown in much of the previous search cost literature, searching has a larger effect in markets with more price dispersion because price searching is more likely to yield lower price quotes. Thus, decreasing search costs has a larger effect in markets with substantial price dispersion compared to markets with less price dispersion.

1.4 Data and Setting

The data used in this study are provided by a company that offers an online price transparency platform. The company's application uses proprietary algorithms to predict actual transaction costs for over 1,000 searchable services, procedures, and conditions. Self-insured employers purchase access to the platform but use of the platform is optional for eligible employees and their adult dependents. Employers that use the platform offer a variety of insurance plans, including high-deductible, limited network, and PPO plans. When registered individuals use the platform to search for a procedure, they see predicted total prices and consumer cost-sharing. Both amounts are personalized to the individual user and are based on the particular individual's insurance design, network, and benefit phase. Predicted rather than actual prices are used because both insurance companies and providers limit access to price schedules.

In addition to price information, patients also see provider location, quality measures, satisfaction ratings, and other non-price provider information (e.g. where the provider went to medical school). Hospital quality and safety information comes from a variety of sources, including CMS, AHRQ, and the Leapfrog Group. Users can also write and view provider reviews. Phillips & Labno (2014) provide a detailed discussion of the types of information conveyed by online price transparency platforms.

For this study, I use two key data components: search history of the online platform and medical claims. The first component includes data on what services were searched for, what providers were viewed, search dates, and other page view information. The search data are collected at an individual subscriber level. From the search data, I identify household-level searches and the search dates for three services-advanced imaging (CT scans and MRIs), laboratory tests, and physician office visits. I refine physician office into 4 specialist categories: primary care, pediatrics, dermatologist, and OBGYN. The study population used for this study consists of employees and dependents from several self-insured employers who had access to the platform for varying amounts of time beginning in 2010. Eligible employees and their adult family members could access the platform online (both internet and mobile) or via telephone but only web searches are included (99.4% of searches) in this study.

The second component consists of medical claims data. The claims data are provided by employers to the company and are used to predict future prices. Claims data are provided by employers for the two-year period prior to the employers providing access to the platform to their employee and all following periods that they provide the platform. Thus, the claims data covers the periods before and after each employer provided the platform to its employees. The claims data includes information of on patient demographics, the service date of the procedure, the provider who submitted the bill for the procedure, and the price of the procedure. The procedure's price is broken into the amount paid by the employer and the amount paid by the patient as cost-sharing. For this study, I use medical claims for the above three services. Within each of the service types, specific services

are identified by Current Procedural Terminology (CPT) procedure codes.[4] A complete list of the CPT codes included for this study is available in Appendix L of Whaley *et al.* (2014).

The search and claims data each contain unique household and patient identifiers. They also contain information on the date the search was performed and care was received, respectively. I use these fields to link the searches and medical claims at the household level. This linkage allows me to identify if a patient received a service that a household member searched for and if the procedure date follows a search. Searches and claims are linked at the household rather than the individual level because although there is no cost to employees and their dependents, family members may share a common account.[5] In addition, family members are likely to share information about searches and preferences for providers.

When linking the searches and claims, I do not separate imaging and lab searches by specific services (i.e. a search for a lipid panel can be mapped to a claim for a HbA1C test and a MRI search can be linked to a CT scan claim). For lab and imaging services, the same facility often performs multiple related services and so information from a search for one particular lab tests translates into usable information for a different lab test. For physician services, I require the physician's specialty in the claims data to match the specialty in the search data (i.e. cardiologist claims are mapped to cardiologist searches and not primary care searches).

Firms who provide access to their employees provide data for up to two years prior to access. The pre-access period data is used to develop the predicted pricing algorithms so that accurate prices are displayed at the beginning of each firm's access period. I use data from the pre and post-access periods to construct a longitudinal panel of each person's lab, imaging, and office visit claims. From this panel, I observe changes in provider choice and prices before and after a household-level search for a service. This longitudinal panel is key to my identification strategy, as discussed in the next section. This study and the use of this data was approved by The University of California, Berkeley IRB under protocol 2013-11-5834.

1.4.1 Descriptive Characteristics

Table 2.1 presents the descriptive characteristics of those who searched for each service. With the exception of pediatric physician services, searchers are evenly distributed throughout the 25-65 age range. Slightly more females than males are searchers. Table 2.1 also shows the mean cost-sharing level, the coefficient of variation, average prices across the service types. Patients have the lowest average cost-sharing for imaging services and the highest for dermatologist visits but the median for all services but dermatologist visits

[4]For example, within laboratory tests, a CPT code of 80061 identifies a lipid panel blood test. Within physician office visits, a CPT code of 99213 identifies a level-3 evaluation and management visit for an existing patient.

[5]Alternative specifications that linked at the individual level provided nearly identical results.

is 20%. There is a substantial difference in average prices between the three services. The prices reported represent the total negotiated price between the insurer and provider.Lab tests are the most common service type but also the least expensive. Prices for advanced imaging are the highest but the number of people receiving an imaging service and the number of imaging services per person are much lower than for the other services.

In addition, as suggested by Baker *et al.* (2013), price dispersion is substantial and the coefficient of variation ranges from 1.18 for lab tests, 0.85 for advanced imaging services, and around 0.25 for physician office visits. Figure 1.1 plots the metropolitan statistical area (MSA) specific weighted average coefficient of variation, which is discussed in greater detail in Section 1.5.3, by service. Figure 1.2 plots similar distributions at the county-level. These plots highlight the difference between the price distributions for lab and imaging compared with the price distributions for physician services. Consistent with the later regression results, this descriptive evidence also suggests that the potential gains from searching for physician services are much less than the potential cost-savings from lab or imaging searches. In addition, the density plots show the variation in price dispersion across the different services. I later use the variation in price dispersion to test if searching in markets with high levels of price dispersion has a larger effect than searching in markets with less price dispersion.

The levels of price dispersion in the data are much greater than that of other services. In Stigler's seminal work on price dispersion, the observed coefficients of variation for automobiles and anthracite coal were 0.02 and 0.07, respectively. Likewise, the average coefficient of variation from one study of price dispersion in online marketplaces was 0.09 (Baye *et al.* , 2004). Consistent with recent media and policy attention, this characteristic emphasizes that the degree of price variation faced by consumers for healthcare services far outpace other consumer goods and products.

1.5 Consumer Responses to Price Transparency

1.5.1 Effect of Searching on Consumer Prices

I first examine the effect of searching on prices by estimating the change in prices following searching:

$$\ln(p_{iktm}) = \alpha + \beta_1 search_{ikt} + \beta_2 oop_{ikt} + \zeta_k CPT_k + \tau_t year + \tau_{tm} year \times employer_m \quad (1.3)$$

$$+\boldsymbol{\delta} + \varepsilon_{ijt}. \quad (1.4)$$

In this expression, p_{ikt} measures the price of services delivered to individual i during time t for procedure k. Price is defined as the claim's allowed amount (i.e. the sum of employer and employee payments). I use two definitions for search behavior $search_{ikt}$. The first is an indicator variable equal to one if the individual has any search for a service before a claim for that service. The second categorizes the length of time between the search and the claim. I use intervals of 0-14, 15-30, and >30 days and define $searchcategory_{ikt}$ as

$$searchcategory_{ikt} = \begin{cases} 0 & \text{if household } i \text{ has not searched for service } k \text{ prior to time } t \\ 1 & \text{if household } i \text{ has searched for service } k > 30 \text{ days prior to time } t \\ 2 & \text{if household } i \text{ has searched for service } k \text{ 15-30 days prior to time } t \\ 3 & \text{if household } i \text{ has searched for service } k \text{ 0-14 days prior to time } t. \end{cases}$$

oop_{ikt} measures the share of the total price paid by the individual and CPT_k is a vector of procedure code fixed effects. I also include year and year interacted with employer fixed effects. The year-employer interactions control for other employer-specific changes that might influence prices, such as benefit design changes. Household fixed effects, δ, control for time-invariant factors that influence prices, such as preferences or access to other types of price information. I use household rather than patient fixed effects to match the link between household-level searching and medical service utilization. Robustness tests with patient fixed effects produce almost identical results. Because I include household fixed effects, I restrict the sample to the population with a claim for each service in the period before access. I estimate this regression using OLS and use robust standard errors clustered at the household level.

This model is similar to the one used in Whaley *et al.* (2014), which found similar results using a more flexible GLM regression with propensity score matching, but adds the household fixed effects and is further extended in the following specifications. The previous paper also shows that the results are robust to alternative search window definitions, excluding outliers, and controlling for specific insurance networks.

The household fixed effects remove potential bias from unobserved time-invariant differences that are also correlated with prices. The identification assumption for equation 1.3 is that preferences for providers or information about provider prices do not change over time. Patient fixed effects have been prominently used in two recent studies examining consumer behavior. In Finkelstein *et al.* (2014), patient fixed effects control for time-invariant health differences and preferences that influence utilization of medical services. More similarly to this study, Bronnenberg *et al.* (2014) use individual fixed effects to control for preferences in brand choices and consumer purchasing patterns.

Tables 1.2 and 1.3 present the results from equation 1.3. For these results, I restrict the sample to the population of searchers and thus the coefficients estimate the effect of searching on those who search. As robustness tests, I also estimate models that use a sample of non-searchers to compare both the within and between effects of searching. These tests provide nearly identical results, which supports the hypothesis that searchers and non-searchers are similar (Appendix Table 1.9).

The results in Table 1.3 use the first definition of $search_{ikt}$, a dummy variable equal to one following any search for service k before the service is received and so coefficients these result represent the average effect of performing any search on prices. This effect ranges from 10% for imaging services, 8% for lab tests, and about 1% for physician services. The next table, Table 1.3, uses the second definition of searching, $searchcategory_{ikt}$, the three

different search periods of 0-14, 15-30, and >30 days between the service-specific search and claim. Relative to the coefficients in Table 1.3, the effect of searching on services received within 14 days of a search for that service increases to 16% for lab tests and 13% for imaging services but remains approximately 1% for physician services. When applied to the mean prices, the percent price reductions represent dollar savings of $4.22 for lab tests and $129.05 for advanced imaging services.

In both search definitions, the effect of searching for imaging and lab services is large while the effect for physician office visits is much smaller. This effect may reflect the relative homogeneity of imaging and lab services when compared to physician office visits. Compared to the interpersonal relationships inherent to physician visits, imaging and lab tests are conducted by a machine. In addition, there is far greater price dispersion for imaging and lab services than there is for physician services. Consistent with the theoretical model, compared with the other services, the lower levels of price dispersion limits the potential for physician office visit price savings. The decreasing effect as the length of time between the search and claim increases also suggests a temporal dimension for the effectiveness of information on patient behavior. Provider information viewed over a month before receiving care has much less of an effect on prices then information viewed in the past two weeks. Several potential mechanisms can potentially explain this observation. Searchers may forget price information long after a search. Consumers may also search the platform at the time of selecting a new provider.

1.5.2 Endogeneity Concerns

Although δ controls for time-invariant unobservables, time varying unobservables beyond those controlled for by the firm-year controls that are correlated with searching may introduce bias to equation 1.3. One potential example is a employee-wellness program that directs individuals to low-cost providers and is used disproportionately by those who also search. Such a case would result in an overestimation of the price reductions found in this study. Bias from a contemporaneous event is pertinent as many employers launch several wellness and benefit designs concurrently at the beginning of the calendar year. To address this point, I first estimate placebo regressions where I replace the household-specific post-search variables with a firm-specific post-access variable, $postlaunch_{imt}$, which equals 0 in the t periods before firm m launches the platform and 1 afterwards. I remove each household's post-search period from $postlaunch_{imt}$ and thus estimates changes in prices strictly in the period following access but before searching. If these placebo tests show that simply having access to price transparency information but not actually viewing that information leads to lower prices, then the fixed effects identification assumption is not valid. As an extension of the placebo tests, I also calculate the length of time between the date each individual was provided access to the platform and the first household-level search. If wellness or other firm-wide programs induce individuals to search, then I may expect to see a large mass of individuals who search soon after gaining access.

The results from this placebo test show no consistent effect on prices for access but not

use of the platform (Table 1.4). These results support the belief that it is unlikely that the lower prices found following searching are actually due to a contemporaneous shock that occurs at the same time as the platform is offered by each employer. Additionally, the density of the length of time with access but before a search plotted in Figure 1.3 suggests that a uniform event did not lead to searches. Of course, there may be other time-varying events, such as an acute illness or medical event, that causes searching and also leads to lower prices. However, high-cost medical events that induce searching will typically move individuals out of their deductible, where they face partial cost-sharing, or into their out-of-pocket maximum, where they face no cost-sharing. As a result, these types of events will presumably make individuals *less* rather than more price sensitive.

While this test informally supports the identification of equation 1.3, potential endogeneity between prices and searching may still exist. As a more formal solution to potential endogeneity, I also instrument $search_{ikt}$ using the date which each employer first provided access to the platform as an instrument. These results (Table 1.5) are nearly identical to the OLS results presented in Table 1.2, which suggests the selection bias between searching and prices is small. Given the difficulty in obtaining accurate price information, this finding is not surprising. Even for unobservably price conscious individuals, there are few other means to easily obtain price information other than through price transparency providers.

1.5.3 Searching and Market-level Price Variation

The theoretical model hypothesizes that searching will have a larger effect in markets with increased price dispersion. To measure price dispersion, I use each market's coefficient of variation, which is the standard deviation divided by the mean price. I use two methods to classify each market's coefficient of variation. My primary results use MSAs as the definition of markets but I also use counties as a sensitivity test. The results are similar regardless of the market definition.

To assign measures of price dispersion to each market, I first calculate the coefficient of variation for each procedure code in that market. To calculate price dispersion in each market, I use the whole set of medical claims rather than claims from the subset of those who search. Within market g and for procedure k, as defined by unique CPT codes, I define the coefficient of variation as the standard deviation of prices divided by the mean price, $cv_{gk} = \frac{\sigma_{gk}}{\mu_{gk}}$. A coefficient of variation equal to 0 indicates no price dispersion while a large value indicates substantial price dispersion. From cv_{gk}, I create the weighted average coefficient of variation for each MSA as

$$\overline{cv_g} \quad = \quad \frac{cv_{gk} \times volume_{gk}}{\sum_{k=1}^{K} volume_{gk}}.$$

This weighted average measure of price variation captures the overall price level of price variation within a given market. Within each market, I calculate separate values of $\bar{cv}_g$ for each of the service categories-lab tests, advanced imaging, and the physician specialties.

To better compare price dispersion between markets, I also calculate a similar measure of price dispersion that relates the within-market price variation for a given procedure to other markets. For this measure, I calculate the median value of cv_{gk} across all markets for procedure k as $median_k$. Then, for each market, I identify the number of procedures with price dispersion above the median level for all markets for each procedure as

$$abovemedian_{gk} = \begin{cases} 1 & \text{if } cv_{gk} > median_k \\ 0 & \text{if } cv_{gk} \leq median_k. \end{cases}$$

I then calculate similar weighted average of the share of procedures with above the median price dispersion, $\overline{abovemedian_g}$. To test the role of price dispersion on the effect of searching, I then interact each measure of price dispersion with search behavior. Due to the temporal effect of searching on prices, I use the search window categorization rather than the average effect of searching.

Tables 1.6 and 1.7 present results that interact search behavior with the degree of price dispersion in each MSA. Results using counties as markets instead of MSAs show similar results. Table 1.6 presents results from the extension where the search behavior in equation 1.3 is interacted with the MSA-level of price variation, $\overline{cv_g}$. These results show a large effect for imaging services, albeit the result is not statistically significant. Table 1.7 presents the similar results that use the weighted share of procedures with above median price dispersion. The interaction terms for imaging services are again negative and sizable but not statistically significant. The price dispersion-search window interaction terms suggest that searching in MSAs with the highest degree of price dispersion leads to a 8.7% to 13.2% reduction in prices compared to searching in MSAs with the lowest levels of price dispersion. For all four physician office visit categories, there is little additive effect, which is not surprising given the much lower levels of price dispersion compared to imaging and laboratory services.

In Appendix 1.8, I examine similar specifications, including the effect of searching on the probability of having prices above the market-specific mean price, how consumers learn from initial searches, and how searching for physician office visits impacts the prices for downstream lab tests.

1.5.4 Physician Choice

The reduced form results show that searching has a sizable effect on costs for imaging and lab services but much less of an effect for physician office visits. This result is not surprising as lab and imaging services are much more commoditized. In contrast, patients establish relationships with their physicians and choose physicians based on quality, bedside manner, and other non-price attributes. Moreover, the lack of price variation for physician services, highlighted in Table 2.1 and Figures 1.1 and 1.2, limits the potential for choosing less expensive providers. Given the lack of meaningful price variation for physician services, finding large price effects due to searching would be surprising.

Nonetheless, many individuals still search for physician services. A natural question is what types of non-price information inform consumer choices for physician office visits. To address this question, I estimate a model of provider choices for physician office visits that includes price and non-price provider attributes. The estimation results are used to calculate the welfare implications of providing access to price and non-price provider information.

1.5.4.1 Model and estimation

I first assume additive and linearly separable utility for patient i choosing provider j, where j is an element of the set of available providers J of the form

$$\begin{aligned} U^j_{itk} &= \gamma_1 p^j_i + \gamma_2 distance^j_i + \gamma_3 provider^j + \\ &\quad \gamma_4 postsearch_{itk} \times p^i_j + \gamma_5 postsearch_{itk} \times distance^i_j \qquad (1.5) \\ &\quad + \gamma_6 postsearch_{itk} \times provider_j + \varepsilon^j_i \qquad (1.6) \end{aligned}$$

In this expression, p^j_{ikt} measures the price provider j charges to see patient i for service k at time t. $distance^j_i$ measures the distance between provider j and patient i while $provider^j$ captures provider-specific characteristics (e.g. quality, satisfaction ratings, length of practice). $postsearch_{itk}$ indicates that consumer i has searched for service k prior to receiving care.

I estimate equation 1.5 using a random coefficients mixed-logit regression Train (2009). The corresponding choice probabilities are

$$P_{ij} = \int \prod_{t=1}^{T} \frac{e^{U^j_{itk}}}{\sum_{l=1}^{L} e^{U^l_{itk}}} f(\gamma) d\gamma$$

where $f(\gamma)$ weights each attribute's importance.

In this model, prices may be correlated provider attributes, such as quality, that are unobserved to the econometrician but observed by the patient. In such a case, my estimated choice probabilities will be biased. Furthermore, because I use the price coefficients to calculate willingness to pay for provider information, my welfare calculations will also be biased. The direction could go in either direction as healthcare prices are often uncorrelated with quality. However, due to the richness of the data, I assume no unobserved provider attributes that are correlated with prices (Abaluck & Gruber, 2011).

In addition, the post-search interaction terms may be biased if consumers use other sources of information to learn about providers in addition to the transparency platform. This concern is especially relevant as other sources of non-price provider attributes may be more easily accessible than prices. To account for endogeneity between searching and provider choices, I also estimate models that interact provider attributes for post-access to the platform rather than post-searching.

1.5.4.2 Results

To test this model, I estimate random coefficients regressions for three physician specialties: primary care providers, OBGYNs, and pediatricians. For each, the outcome variable is the probability of choosing physician j from the set of J providers of that specialty in each market. I define the market as providers within 10 miles of the patient's zip code. I use a relatively small market definition to limit the number of choice options and increase computational efficiency. For the provider attributes, I first include the mean price of an office visit. The mean price is specific to each insurance company and new or preventative care visits. I also include the distance between the patient's home zip code and the physician's zip code, the year the physician graduated from medical school, the physician's gender, and whether or not the physician speaks a language in addition to English. I impose a log-normal distribution for physician prices. In the main results, I interact the provider characteristics with a dummy indicating that person i has searched for service l prior to receiving care. The post-access specifications similarly use a dummy indicating the employer has provided access to the platform.

Table 1.8 presents results for a specific MSA. These results suggest substantial consumer information gains about provider gender, board certification, and language. There is less of an effect for distance. The lack of an effect for distance is less surprising given the availability of other resources to learn about provider location (e.g. Google maps). However, fewer resources exist to learn about the other non-price physician attribute. The results from the sensitivity analysis that uses access to the platform rather than search behavior have the same sign but lower magnitudes from the main results.

These results suggest substantial differences in how consumers shop for different types of providers. For primary care providers, information on price, provider gender, provider age, and provider language all influence the choice probabilities. However, for OBGYNs, only information on price and provider gender matter. For pediatricians, price information does not influence choice probabilities but instead distance, which may be a proxy for convenience, provider age, provider gender, and provider language are all important.

From the estimated choice coefficients, the willingness-to-pay (WTP) for the information obtained by searching to can be calculated as the ratio between the price coefficients and the interaction term between searching and the specific provider attribute Train (2009). Table 1.10 presents the median willingness to pay estimates for each attribute and each physician specialty. The WTP results support the results from the reduced form model and the results presented in Whaley *et al.* (2014), which both find an approximately \$1 price effect for searching for physician services. However, the non-price information gained from physician searches still provides value to consumers. For primary care visits, the total WTP for physician information ranges between \$4.03 and \$4.31, approximately four times the price effect of the reduced form price regressions. The other services show much larger WTP estimates for the post-search models but have much less of an effect in the post-access models. Nonetheless, the post-search OBGYN and pediatrician results show that information on non-price attributes such as provider gender, age, and language

improves consumer welfare much more than price information alone.

1.6 Conclusion

This study combines detailed micro-data on search behavior of an online price transparency platform with medical claims information. Despite the promise that personalized price information will increase healthcare consumerism, the use of this type of information has not been rigorously studied in the existing literature. I find initial evidence that searching leads to lower prices for common medical services. The effect of searching is largest for lab and imaging services, which have substantial price variance and are more commoditized than physician services. The effect for physician services is still meaningful and largest for specialist services. Additionally, searching has a larger effect in markets with high price variation than in markets with less price variation.

The main results find that among searchers, searching leads to 13% lower prices for advanced imaging and has a 16% effect for laboratory tests. There is about a 1% price effect for physician services but the value of non-price information for physician services far outpaces the value of price information. When accounting for the non-price values, the effects of searching for physician services are comparable to the more commodity-based lab and imaging services.

These effect sizes are substantial. To place the results in context, a recent paper finds that online searching for books leads to a 2% reduction in prices (De Los Santos *et al.* , 2012). Similarly, the work by Zettelmeyer and Scott-Morton discussed above finds a similarly-sized effect for automobile purchases. Why is the effect of online searching so much larger in this study than in the existing studies? The large price variation for lab and imaging services is a substantial contributor to the larger effects found in this study relative to the previous literature on online search. Large price variation for common medical services, especially in the absence of appropriate information, harms consumers but it also leads to larger potential gains from reducing search costs.

This study is not without limitations. For one, my identification assumption rests on the assumption that there are no time-varying events that also influence prices. In a qualitative test and several robustness checks, I attempt to address this limitation but cannot rule out contemporaneous shocks. However, instrumenting for searching gives similar results as the main specification. Although I focus solely on the effect of searching among those who search, future work should examine the decision to search and further explore the heterogeneity in both searching behavior and the effect of searching on prices.

Finally, I do not examine the quantity of care consumed. Patients may go to lower cost providers but may use more services. However, the price reductions are not large enough to offset additional utilization and the low price elasticity typically observed for health care services makes this scenario unlikely. If anything, searching may reduce utilization by decreasing unnecessary utilization. At the same time, price transparency may help consumers navigate HDHPs and other benefit designs with differential cost-sharing (Sood

& Chernew, 2013; Robinson *et al.* , 2015).

While it is not clear that these results are generalizable to the population that chose to not search, Whaley *et al.* (2014) shows that searchers and non-searchers have similar characteristics. Presumably at least a portion of the benefits of searching would apply to the non-searching population. As such, policies that increase the availability of price transparency information are likely to benefit consumers. This paper implies that the benefits of increased price transparency information will be most important for homogeneous services like lab tests and imaging. Likewise, easily accessible information on physician and hospital quality, convenience, and other non-price attributes are likely to provide additional value to consumers. For highly differentiated services, the non-price information may provide even greater consumer value than price information. Despite its limitations, this study has important policy implications. It demonstrates that consumer-focused price information can lead to lower costs and supports the enthusiasm surrounding price transparency in health care. More importantly, this study shows that when the basic information frictions surrounding prices are reduced, health care consumers respond to market forces.

Bibliography

Abaluck, Jason, & Gruber, Jonathan. 2011. Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program. *American Economic Review*, **101**(4), 1180–1210. 00000.

Anderson, Gerard F., Reinhardt, Uwe E., Hussey, Peter S., & Petrosyan, Varduhi. 2003. It's The Prices, Stupid: Why The United States Is So Different From Other Countries. *Health Affairs*, **22**(3), 89–105.

Arrow, Kenneth J. 1963. Uncertainty and the Welfare Economics of Medical Care. *The American Economic Review*, **53**(5), 941–973.

Baker, Laurence, Bundorf, M. Kate, & Royalty, Anne. 2013. Private Insurers Payments For Routine Physician Office Visits Vary Substantially Across The United States. *Health Affairs*, **32**(9), 1583–1590. PMID: 24019363.

Baye, Michael, Morgan, John, & Scholten, Patrick. 2006. Information, Search, and Price Dispersion. *Pages 323–375 of: Economics and Information Systems*, 1 edn. Handbooks in Information Systems, vol. 1. London: Elsevier. 00238.

Baye, Michael R., Morgan, John, & Scholten, Patrick. 2004. Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site. *The Journal of Industrial Economics*, **52**(4), 463–496. 00394.

Bloche, M. Gregg. 2006. Consumer-Directed Health Care. *New England Journal of Medicine*, **355**(17), 1756–1759. PMID: 17065635.

Brill, Steven. 2013. Bitter Pill: Why Medical Bills Are Killing Us. *Time*, Mar.

Bronnenberg, Bart, Dube, Jean-Pierre, Gentzkow, Matthew, & Shapiro, Jessie. 2014. Do Pharmacists Buy Bayer? Informed Shoppers and the Brand Premium. *Working Paper*.

Brot-Goldberg, Zarek, Handel, Benjamin, Chandra, Amitabh, & Kolstad, Jonathan. 2015. What Does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics. *Working Paper*. 00000.

Brown, Jeffrey, & Goolsbee, Austan. 2002. Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry. *Journal of Political Economy*, **110**(3), 481–507. 00000.

Chernew, Michael, & Scanlon, Dennis P. 1998. Health Plan Report Cards and Insurance Choice. *Inquiry*, **35**(1), 9–22.

Claxton, Gary, Rae, Matthew, Panchal, Nirmita, Damico, Anthony, Bostick, Nathan, Kenward, Kevin, & Whitmore, Heidi. 2013 (Aug.). *2013 Employer Health Benefits Survey*. Tech. rept. Kaiser Family Foundation and Health Research & Educational Trust.

Cutler, David, & Dafny, Leemore. 2011a. Designing Transparency Systems for Medical Care Prices. *New England Journal of Medicine*, **364**(10), 894–895. PMID: 21388307.

Cutler, David, & Dafny, Leemore. 2011b. Designing Transparency Systems for Medical Care Prices. *New England Journal of Medicine*, **364**(10), 894–895.

Dafny, Leemore, & Dranove, David. 2008. Do report cards tell consumers anything they don't know already? The case of Medicare HMOs. *The RAND Journal of Economics*, **39**(3), 790–821.

De Los Santos, Babur, Hortacsu, Ali, & Wildenbeest, Matthijs R. 2012. Testing Models of Consumer Search Using Data on Web Browsing and Purchasing Behavior. *American Economic Review*, **102**(6), 2955–80.

Dranove, David, Kessler, Daniel, Mcclellan, Mark, & Satterthwaite, Mark. 2003. Is more information better? The effects of report cards on health care providers. *The Journal of Political Economy*.

Emanuel, Ezekiel, Tanden, Neera, Altman, Stuart, Armstrong, Scott, Berwick, Donald, de Brantes, Francois, Calsyn, Maura, Chernew, Michael, Colmers, John, Cutler, David, Daschle, Tom, Egerman, Paul, Kocher, Bob, Milstein, Arnold, Oshima Lee, Emily, Podesta, John D., Reinhardt, Uwe, Rosenthal, Meredith, Sharfstein, Joshua, Shortell, Stephen, Stern, Andrew, Orszag, Peter R., & Spiro, Topher. 2012. A Systemic Approach to Containing Health Care Spending. *New England Journal of Medicine*, **367**(10), 949–954. PMID: 22852883.

Finkelstein, Amy, Gentzkow, Matthew, & Williams, Heidi. 2014. Sources of Geographic Variation in Health Care: Evidence from Patient Migration. *Working Paper*.

Hsia, Renee Y., Antwi, Yaa Akosa, & Weber, Ellerie. 2014. Analysis of variation in charges and prices paid for vaginal and caesarean section births: a cross-sectional study. *BMJ Open*, **4**(1), e004017.

Huckfeldt, Peter J., Haviland, Amelia, Mehrotra, Ateev, Wagner, Zachary, & Sood, Neeraj. 2015 (Feb.). *Patient Responses to Incentives in Consumer-directed Health Plans: Evidence from Pharmaceuticals*. Working Paper 20927. National Bureau of Economic Research. 00000.

Hussey, Peter S., Wertheimer, Samuel, & Mehrotra, Ateev. 2013. The Association Between Health Care Quality and Cost: A Systematic Review. *Annals of Internal Medicine*, **158**(1), 27–34.

Jin, Ginger Zhe, & Leslie, Phillip. 2003. The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards. *The Quarterly Journal of Economics*, **118**(2), 409–451.

Kolstad, Jonathan T. 2013. Information and Quality When Motivation is Intrinsic: Evidence from Surgeon Report Cards. *American Economic Review*, **103**(7), 2875–2910.

Kullgren JT, Duey KA, & Werner RM. 2013. A Census of State Health Care Price Transparency Websites. *Journal of the American Medical Association*, **309**(23), 2437–2438.

Lieber, Ethan. 2013 (Sept.). *Does it Pay to Know the Prices in Health Care?* Working Paper. University of Notre Dame.

Mehrotra, Ateev, Hussey, Peter S., Milstein, Arnold, & Hibbard, Judith H. 2012. Consumers And Providers Responses To Public Cost Reports, And How To Raise The Likelihood Of Achieving Desired Results. *Health Affairs*, **31**(4), 843–851. PMID: 22459922.

Mehrotra, Ateev, Brannen, Tyler, & Sinaiko, Anna D. 2014. Use Patterns of a State Health Care Price Transparency Web Site What Do Patients Shop For? *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, **51**(Jan.), 0046958014561496. 00000.

Morton, Fiona Scott, Zettelmeyer, Florian, & Silva-Risso, Jorge. 2001. Internet Car Retailing. *The Journal of Industrial Economics*, **49**(4).

Phillips, Kathryn, & Labno, Anna. 2014 (Jan.). *A Trend: Private Companies Provide Health Care Price Data*.

Reinhardt, Uwe E. 2006. The Pricing Of U.S. Hospital Services: Chaos Behind A Veil Of Secrecy. *Health Affairs*, **25**(1), 57–69. PMID: 16403745.

Robinson, James C. 2011. Variation in Hospital Costs, Payments, and Profitability for Cardiac Valve Replacement Surgery. *Health Services Research*, **46**(6), 1928–1945. PMID: 21762141.

Robinson, James C., Brown, Timothy, & Whaley, Christopher. 2015. Reference-Based Benefit Design Changes Consumers' Choices And Employers' Payments For Ambulatory Surgery. *Health Affairs*, **34**(3), 415–422.

Rosenthal, Elisabeth. 2013. Colonoscopies Explain Why U.S. Leads the World in Health Expenditures. *The New York Times*, June.

Rosenthal, Jamie, Lu, Xin, & Cram, Peter. 2013. Availability of Consumer Prices From US Hospitals for a Common Surgical Procedure. *JAMA Internal Medicine*, **173**(6), 427–432.

Scanlon, Dennis P., Chernew, Michael, McLaughlin, Catherine, & Solon, Gary. 2002. The impact of health plan report cards on managed care enrollment. *Journal of Health Economics*, **21**(1), 19–41.

Sinaiko, Anna D., & Rosenthal, Meredith B. 2011. Increased Price Transparency in Health Care - Challenges and Potential Effects. *New England Journal of Medicine*, **364**(10), 891–894. PMID: 21388306.

Sood, Neeraj, & Chernew, Michael. 2013 (Sept.). *A Better Way to Encourage Price Shopping for Health Care*.

Sood, Neeraj, Wagner, Zachary, Huckfeldt, Peter, & Haviland, Amelia M. 2013. Price Shopping in Consumer-Directed Health Plans. *Forum for Health Economics and Policy*, **16**(1).

Stigler, George J. 1961. The Economics of Information. *Journal of Political Economy*, **69**(3), 213–225.

Stigler, George J. 1964. A Theory of Oligopoly. *Journal of Political Economy*, **72**(1), 44–61. 02293.

Strombom, Bruce A, Buchmueller, Thomas C, & Feldstein, Paul J. 2002. Switching costs, price sensitivity and health plan choice. *Journal of Health Economics*, **21**(1), 89–116.

Train, Kenneth. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press.

Tu, Ha T, & Lauer, Johanna R. 2009. Impact of Health Care Price Transparency on Price Variation: The New Hampshire Experience. *Issue brief (Center for Studying Health System Change)*, Nov., 1–4. PMID: 19908405.

Whaley, Christopher, Chafen Schneider, Jennifer, Pinkard, Sophie, Bravata, Dena, Kellerman, Gabriella, Kocher, Bob, & Sood, Neeraj. 2014. Association between availability of health service prices and payments for these services. *JAMA*, **312**(16), 1670–1676.

Wu, Sze-jung, Sylwestrzak, Gosia, Shah, Christiane, & DeVries, Andrea. 2014. Price Transparency For MRIs Increased Use Of Less Costly Providers And Triggered Provider Competition. *Health Affairs*, **33**(8), 1391–1398.

Zettelmeyer, Florian, Morton, Fiona Scott, & Silva-Risso, Jorge. 2001 (Dec.). *Cowboys or Cowards: Why are Internet Car Prices Lower?* Working Paper 8667. National Bureau of Economic Research.

Zettelmeyer, Florian, Morton, Fiona Scott, & Silva-Risso, Jorge. 2005 (Aug.). *How the Internet Lowers Prices: Evidence from Matched Survey and Auto Transaction Data.* Working Paper 11515. National Bureau of Economic Research.

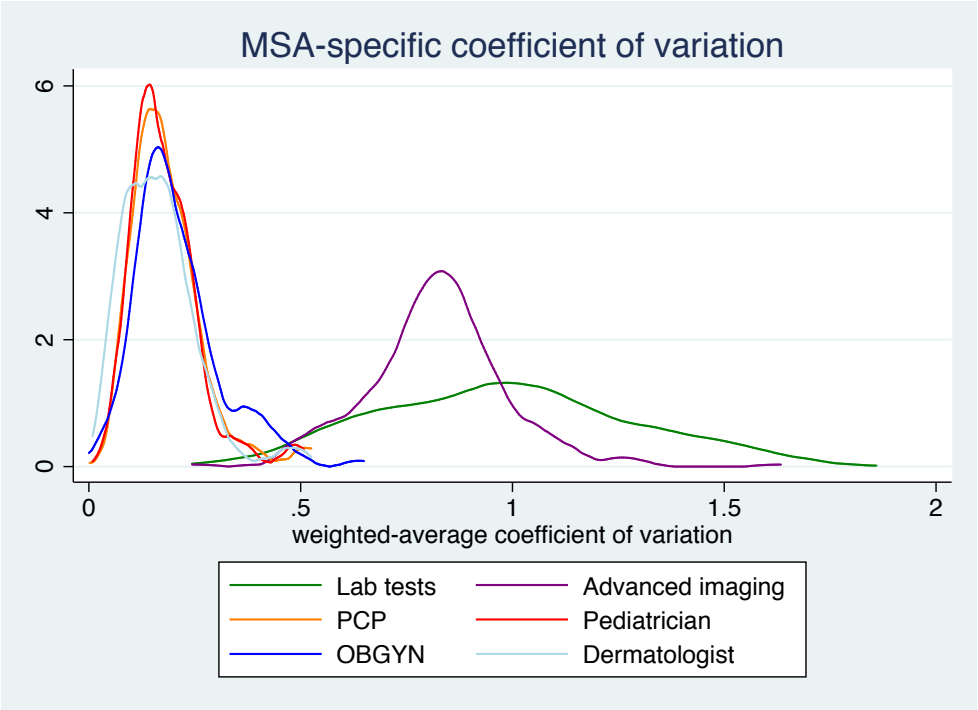
1.7 Figures and Tables

Table 1.1: Summary Statistics

	Lab		Imaging		PCP		Pediatrician		OBGYN		Dermatologist	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
Demographics												
age 0-19 (%)	0.19		0.09		0.11		0.54		0.06		0.15	
age 20-29 (%)	0.12		0.09		0.15		0.06		0.25		0.14	
age 30-39 (%)	0.13		0.15		0.20		0.19		0.32		0.16	
age 40-49 (%)	0.18		0.23		0.21		0.15		0.19		0.19	
age 50-59 (%)	0.26		0.30		0.23		0.05		0.15		0.24	
age 60+ (%)	0.11		0.13		0.10		0.01		0.04		0.11	
% male	0.45	0.50	0.45	0.50	0.47	0.50	0.48	0.50	0.06	0.24	0.42	0.49
Medical characteristics												
mean patient cost-sharing percent	0.41	0.45	0.36	0.39	0.44	0.43	0.38	0.43	0.31	0.41	0.57	0.41
median patient cost-sharing percent	0.20		0.20		0.20		0.20		0.10		0.58	
mean allowed amount ($)	$26.39	$40.04	$992.70	$778.01	$105.75	$46.87	$101.57	$41.22	$117.63	$60.10	$89.32	$44.84
median allowed amount ($)	$14.20		$731.00		$97.11		$94.57		$110.00		$78.31	
mean coefficient of variation	1.18	0.55	0.85	0.21	0.23	0.09	0.22	0.09	0.32	0.23	0.24	0.12
mean MSA weighted average coefficient of variation	1.16	0.23	0.91	0.12	0.23	0.08	0.22	0.08	0.32	0.12	0.24	0.11
median coefficient of variation	1.10		0.88		0.21		0.20		0.27		0.19	
median MSA weighted average coefficient of variation	1.15		0.91		0.22		0.20		0.33		0.18	
N individuals	29,434		7,381		58,516		14,562		20,666		13,732	
N claims	626,094		14,657		340,245		97,492		74,987		42,084	

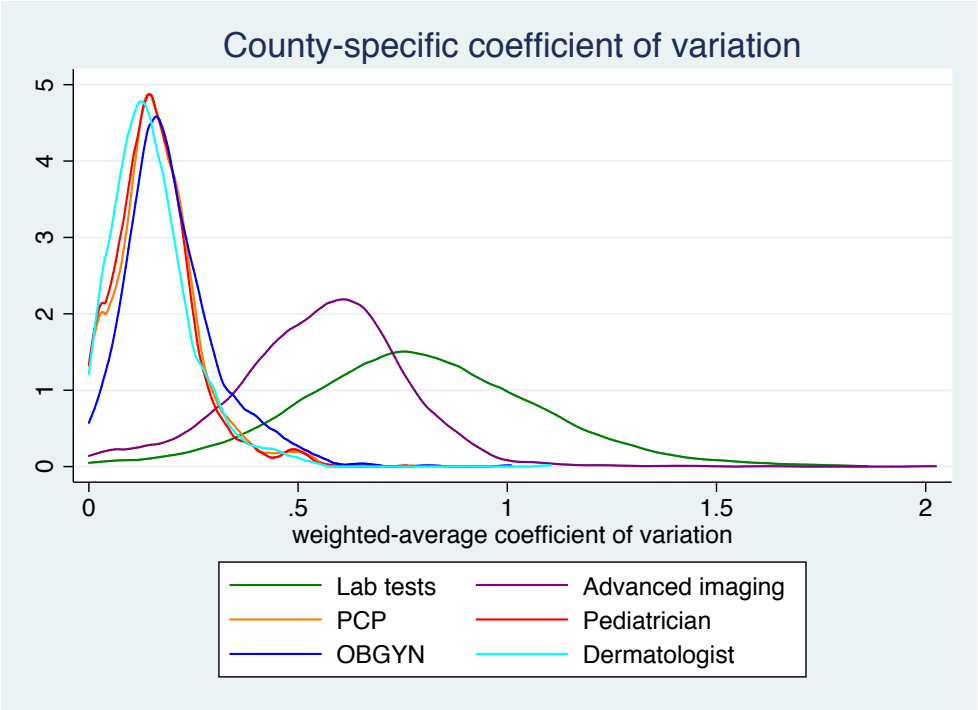
This table shows the descriptive statistics for individuals with a household-level search for the respective service.

Figure 1.1: Metropolitan Statistical Area (MSA) Price Variation Distribution



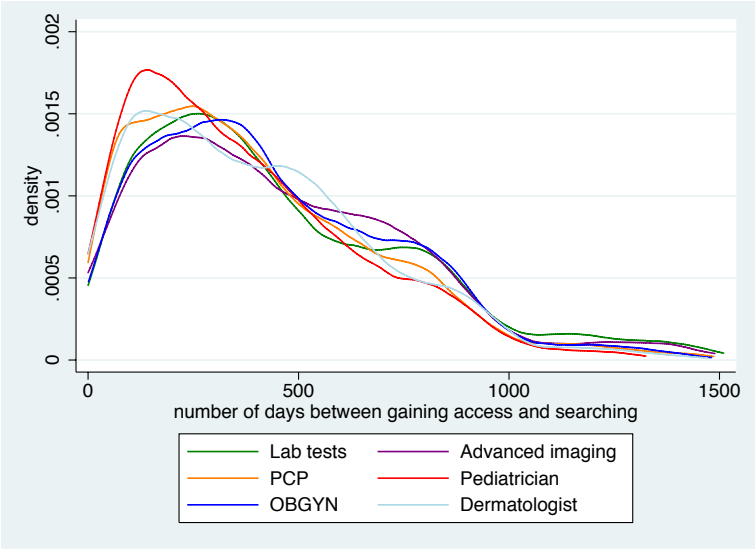
This figure plots the distribution of $\bar{cv}_g$ for each service by MSA.

Figure 1.2: County Price Variation Distribution



This figure plots the distribution of $\bar{cv}_g$ for each service by county.

Figure 1.3: Time between access and searching



This figure plots the distribution in the length of time between gaining access to the price transparency platform and the household-specific date of the first search.

Table 1.2: Main Effect: All claims following search

	(1)	(2)	(3)	(4)	(5)	(6)
Service	lab	imaging	PCP	Ped.	OBGYN	Derm.
all claims following search	-0.0838***	-0.108***	-0.00414***	-0.00308	0.00107	-0.00932**
	(0.00927)	(0.0227)	(0.00157)	(0.00307)	(0.00402)	(0.00419)
Observations	626,094	14,657	340,245	97,492	74,987	42,084
R-squared	0.512	0.295	0.793	0.763	0.791	0.795
Number of households	15,683	6,212	36,073	5,958	18,270	9,860

This table presents the regression results from equation 1.3 and examines the differences in prices for all claims following a search. The dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, month, procedure code, and household. Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.3: Main Effect: Length of time between searching and claim

	(1)	(2)	(3)	(4)	(5)	(6)
Service	lab	imaging	PCP	Ped.	OBGYN	Derm.
claim >30 days following search	-0.0607***	-0.0859***	-0.00319*	-0.00223	0.00330	-0.00773*
	(0.00983)	(0.0245)	(0.00164)	(0.00319)	(0.00439)	(0.00439)
claim 15-30 days following search	-0.0950***	-0.0725*	-0.00932***	-0.00716	0.00218	-0.00635
	(0.0143)	(0.0383)	(0.00262)	(0.00475)	(0.00576)	(0.00606)
claim 0-14 days following search	-0.175***	-0.143***	-0.00607**	-0.00637	-0.00800	-0.0181***
	(0.0130)	(0.0259)	(0.00248)	(0.00478)	(0.00571)	(0.00551)
Observations	626,094	14,657	340,245	97,492	74,987	42,084
R-squared	0.513	0.296	0.793	0.763	0.791	0.795
Number of households	15,683	6,212	36,073	5,958	18,270	9,860

This table presents the regression results from equation 1.3 but uses the search categories of 0-14 days, 15-30 days, and 31-365 days. The dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, month, procedure code, and household. Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.4: Placebo Test

	(1) lab	(2) imaging	(3) PCP	(4) Ped.	(5) OBGYN	(6) Derm.
claim after access but before search	-0.0416***	-0.0248	0.00279	-0.00842*	0.00610	0.0188**
	(0.0134)	(0.0392)	(0.00272)	(0.00506)	(0.00688)	(0.00802)
Observations	361,462	8,170	166,914	46,874	39,403	18,376
R-squared	0.525	0.351	0.832	0.805	0.810	0.830
Number of households	12,827	3,811	26,142	4,509	11,861	5,631

This table presents the regression results from the placebo test where the $search_{ikt}$ variable from equation 1.3 is replaced with the indicator for the period between the launch of the platform and searching. The dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, month, procedure code, and household. Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.5: Effect of Searching on Prices: Instrumental Variables Approach

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Searchers Only			
	lab	imaging	PCP	Ped.	OBGYN	Derm.
all claims following search	-0.181***	-0.101*	0.00438*	-1.65e-05	0.000224	0.00653
	(0.0117)	(0.0614)	(0.00229)	(0.00409)	(0.00876)	(0.00653)
Observations	626,094	14,657	340,245	97,492	74,987	42,084
Number of subscriber_id	15,683	6,212	36,073	5,958	18,270	9,860
First-stage F-statistic	2519.9	59.15	6708.89	2136.54	478.21	815.5
			Panel B: Searchers vs. Non-searchers			
	lab tests	advanced imaging	PCP	Ped.	OBGYN	Derm
all claims following search	-0.218***	-0.0946	-0.0186***	-0.0308**	0.00434	-0.00573
	(0.0194)	(0.150)	(0.00413)	(0.0126)	(0.0183)	(0.0144)
Observations	1,270,394	33,913	917,062	844,017	175,357	113,870
Number of subscriber_id	24,595	7,212	64,406	44,617	24,893	14,417
First-stage F-statistic	2,030.35	39.48	2,774.74	872.91	272.99	290.88

The top panel of Table 1.5 compares the within-searcher effect of searching using the post-access period as an instrument for searching while the bottom panel compares searchers to non-searchers.

Table 1.6: Price Variation: Weighted average share above mean cv_{gk}

	(1) lab	(2) imaging	(3) PCP	(4) Ped.	(5) OBGYN	(6) Derm.
Main effects						
claim >30 days following search	-0.0196	-0.000213	-0.0205***	-0.0272***	-0.0162*	-0.0252***
	(0.0304)	(0.132)	(0.00451)	(0.00837)	(0.00901)	(0.00797)
claim 15-30 days following search	-0.0470	0.0971	-0.0153*	-0.0295*	-0.0128	-0.00488
	(0.0641)	(0.252)	(0.00840)	(0.0152)	(0.0151)	(0.0131)
claim 0-14 days following search	-0.232***	0.0513	-0.0103	-0.0341**	-0.0133	-0.00893
	(0.0563)	(0.145)	(0.00741)	(0.0135)	(0.0151)	(0.0108)
$\overline{cv}_g$	-0.0104	0.537	0.0560	-0.254**	0.428	-0.0146
	(0.149)	(0.398)	(0.101)	(0.120)	(0.272)	(0.116)
Interaction terms						
claim >30 days following search $\times\overline{cv}_g$	-0.0353	-0.0945	0.0753***	0.113***	0.0620**	0.0726**
	(0.0249)	(0.146)	(0.0190)	(0.0374)	(0.0280)	(0.0292)
claim 15-30 days following search $\times\overline{cv}_g$	-0.0411	-0.187	0.0266	0.102	0.0472	-0.00827
	(0.0542)	(0.282)	(0.0360)	(0.0700)	(0.0500)	(0.0592)
claim 0-14 days following search $\times\overline{cv}_g$	0.0481	-0.213	0.0192	0.126**	0.0171	-0.0383
	(0.0457)	(0.160)	(0.0317)	(0.0600)	(0.0508)	(0.0468)
Observations	626,094	14,657	340,245	97,492	74,987	42,083
R-squared	0.513	0.297	0.793	0.763	0.792	0.795
Number of households	15,683	6,212	36,073	5,958	18,270	9,859

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, month, procedure code, and household.

Table 1.7: Price Variation: Weighted average share above median cv_{gk}

	(1) lab	(2) imaging	(3) PCP	(4) Ped.	(5) OBGYN	(6) Derm.
Main effects						
claim >30 days following search	0.0417**	-0.0453	-0.0130***	-0.000319	-0.00930	-0.0229***
	(0.0195)	(0.0504)	(0.00288)	(0.00506)	(0.00734)	(0.00680)
claim 15-30 days following search	-0.00913	-0.0481	-0.0184***	-0.00345	0.00984	-0.00330
	(0.0379)	(0.0924)	(0.00581)	(0.00897)	(0.0121)	(0.00878)
claim 0-14 days following search	-0.109***	-0.0616	-0.00642	-0.00794	0.00811	-0.0149*
	(0.0361)	(0.0596)	(0.00475)	(0.0103)	(0.0111)	(0.00796)
$\overline{abovemedian_g}$	-0.120	0.0842	0.0560*	-0.0337	0.142	-0.0195
	(0.151)	(0.218)	(0.0314)	(0.0299)	(0.101)	(0.0636)
Interaction terms						
claim >30 days following search $\times\overline{abovemedian_g}$	-0.142***	-0.0571	0.0131***	-0.00259	0.0174*	0.0207***
	(0.0250)	(0.0670)	(0.00339)	(0.00643)	(0.00906)	(0.00767)
claim 15-30 days following search $\times\overline{abovemedian_g}$	-0.119**	-0.0348	0.0121*	-0.00488	-0.0102	-0.00438
	(0.0508)	(0.127)	(0.00702)	(0.0118)	(0.0149)	(0.0129)
claim 0-14 days following search $\times\overline{abovemedian_g}$	-0.0911**	-0.114	0.000729	0.00205	-0.0211	-0.00405
	(0.0464)	(0.0780)	(0.00576)	(0.0133)	(0.0146)	(0.0110)
Observations	626,094	14,657	340,245	97,492	74,987	42,084
R-squared	0.513	0.297	0.793	0.763	0.792	0.795
Number of households	15,683	6,212	36,073	5,958	18,270	9,860

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, month, procedure code, and household.

Table 1.8: Choice Results: Post Search

	(1)	(2)	(3)	(4)	(5)	(6)
	PCP		OBGYN		Pediatrician	
	Mean	SD	Mean	SD	Mean	SD
Main Effects						
ln(price)	-0.912***	3.382***	0.101	-1.103***	-1.324***	-2.708***
	(0.116)	(0.121)	(0.311)	(0.376)	(0.295)	(0.288)
distance	-0.307***	0.424***	-0.315***	0.789***	-0.324***	0.510***
	(0.0122)	(0.0118)	(0.0705)	(0.0838)	(0.0325)	(0.0320)
male	0.450***	4.585***	-1.062**	5.831***	-0.0594	3.495***
	(0.101)	(0.175)	(0.453)	(0.944)	(0.253)	(0.296)
medschool after 1995	-1.290***	4.035***	-2.099***	5.189***	-0.858***	2.525***
	(0.124)	(0.175)	(0.577)	(0.669)	(0.254)	(0.250)
language other than english	0.859***	4.037***	1.655***	6.667***	2.157***	2.855***
	(0.0980)	(0.178)	(0.515)	(1.391)	(0.271)	(0.281)
Interactions						
post search X ln(price)	-0.337**	-0.246	-1.190**	1.884***	-0.0184	-0.215
	(0.140)	(0.179)	(0.501)	(0.500)	(0.393)	(0.371)
post search X distance	-0.0224	-0.00429	0.00963	0.108	-0.203***	0.0570**
	(0.0136)	(0.0173)	(0.0851)	(0.0843)	(0.0401)	(0.0250)
post search X male	0.236**	-0.168	-1.495***	-0.657	0.687**	0.603*
	(0.112)	(0.126)	(0.538)	(0.703)	(0.282)	(0.319)
post search X medschool after 1995	0.286**	0.299*	-0.705	0.0876	0.872***	1.747***
	(0.117)	(0.170)	(0.442)	(0.355)	(0.271)	(0.264)
post search X language other than english	0.385***	0.769***	-0.517	-5.117***	-1.113***	5.354***
	(0.119)	(0.153)	(0.711)	(0.935)	(0.316)	(0.580)
Observations	1,087,658	1,087,658	33,205	33,205	155,195	155,195

This table presents the physician choice results from Equation 1.5, which is estimated using a mixed-logit random coefficients regression. Each of the provider attributes is interacted with a dummy variable indicating that the claim follows a search for that provider. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.9: Choice Results: Post Access

	(1)	(2)	(3)	(4)	(5)	(6)
	PCP		OBGYN		Pediatrician	
	Mean	SD	Mean	SD	Mean	SD
Main Effects						
ln(price)	-0.941***	3.387***	0.187	-1.204***	-1.100***	-2.925***
	(0.117)	(0.124)	(0.349)	(0.395)	(0.320)	(0.329)
distance	-0.306***	0.423***	-0.343***	0.728***	-0.300***	0.487***
	(0.0125)	(0.0118)	(0.0627)	(0.0716)	(0.0301)	(0.0324)
male	0.434***	4.575***	-1.919***	5.496***	-0.807***	3.667***
	(0.101)	(0.177)	(0.489)	(0.821)	(0.249)	(0.307)
medschool after 1995	-1.350***	4.047***	-0.535	4.352***	-0.422**	2.375***
	(0.127)	(0.170)	(0.327)	(0.578)	(0.200)	(0.260)
language other than english	0.829***	4.009***	2.522***	5.701***	1.709***	5.416***
	(0.106)	(0.184)	(0.462)	(0.692)	(0.276)	(0.485)
Interactions						
post access X ln(price)	-0.267*	-0.196	-0.753	2.208***	-0.343	0.758**
	(0.139)	(0.186)	(0.519)	(0.587)	(0.408)	(0.360)
post access X distance	-0.0212	0.00259	0.0392	-0.171**	-0.152***	0.0755***
	(0.0133)	(0.0155)	(0.0764)	(0.0798)	(0.0370)	(0.0281)
post access X male	0.258**	-0.121	-0.865	1.579***	0.474*	-0.171
	(0.109)	(0.128)	(0.697)	(0.575)	(0.254)	(0.199)
post access X medschool after 1995	0.334***	0.291*	0.0382	3.231***	0.0248	1.485***
	(0.115)	(0.154)	(0.471)	(0.663)	(0.254)	(0.352)
post access X language other than english	0.324***	0.842***	-1.077**	-4.065***	-0.322	1.991***
	(0.116)	(0.163)	(0.537)	(0.640)	(0.322)	(0.300)
Observations	1,087,658	1,087,658	33,205	33,205	155,195	155,195

This table presents the physician choice results from Equation 1.5, which is estimated using a mixed-logit random coefficients regression. Each of the provider attributes is interacted with a dummy variable indicating that the claim follows gaining access to the price transparency platform. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.10: Willingness-to-pay estimates

Physician Attribute	PCP		OBGYN		Pediatrician	
	post-search	post-access	post-search	post-access	post-search	post-access
price	$1.78	$1.96	$0.92	NS	NS	NS
distance	NS	NS	NS	NS	$0.76	$0.46
gender	$0.59	$0.66	$4.50	NS	$2.58	$1.42
length of practice	$0.71	$0.86	$0.90	NS	$3.28	NS
language	$0.96	$0.83	$2.32	$0.89	$4.18	NS
Total	$4.03	$4.31	$8.64	$0.89	$10.81	$1.88

This table shows the willingness-to-pay for provider information estimates. The WTP estimates are calculated by dividing the post-search and post-access interaction terms by the price coefficients in the previous tables. Non-statistically significant results (NS) are not reported.

1.8 Appendix: Consumer Search Extensions

1.8.1 Relative Prices

As an additional test of the effect of searching on prices, I next look at provider selection to answer if searching decreases use of expensive providers. For each MSA, and procedure code, I calculate the mean prices and use a linear probability model to estimate the change in the probability that a patient's care is above the mean price for that MSA. I perform a similar test using mean prices at the county-level.

Table 1.11 shows the effect of searching on the relative prices in each MSA. For each service, the first set of results shows the probability that the claim's price is above the mean procedure-code, year, and MSA specific price. For imaging and lab services, searching in the 14 days prior to receiving care leads to a 8 and 4 percentage point decrease in the probability in having a claim above the mean price. Off of bases of 29% and 52%, these changes represent 26% and 7% effects, respectively. For physician services, the results are approximately a 2 percentage point decrease, which corresponds to a 7% effect. Using counties instead of MSAs results in nearly identical results (table 1.12).

Table 1.11: Relative Prices: Probability above mean price MSA price

	(1)	(2)	(3)	(4)	(5)	(6)
	lab	imaging	PCP	Ped.	OBGYN	Derm.
claim >30 days following search	-0.0289***	-0.0279	0.0162***	0.0311***	0.00563	0.0179**
	(0.00524)	(0.0208)	(0.00351)	(0.00698)	(0.00825)	(0.00896)
claim 15-30 days following search	-0.0512***	-0.0709**	0.0110**	0.000731	-0.00904	-0.00531
	(0.00746)	(0.0327)	(0.00530)	(0.0106)	(0.0103)	(0.0132)
claim 0-14 days following search	-0.0785***	-0.0579***	-0.00223	-0.00395	-0.0209**	-0.0243**
	(0.00657)	(0.0221)	(0.00496)	(0.0108)	(0.00967)	(0.0121)
Observations	626,094	14,657	340,245	97,492	74,987	42,084
R-squared	0.057	0.072	0.054	0.071	0.042	0.053
Number of households	15,683	6,212	36,073	5,958	18,270	9,860
Dep. variable mean	0.294	0.520	0.318	0.299	0.327	0.302

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is probability that price is above the mean procedure-specific price in the household's MSA. Covariates include patient cost-sharing and fixed effects for year, employer X year, procedure code, and household.

Table 1.12: Relative Prices: Probability above mean price county price

	(1)	(2)	(3)	(4)	(5)	(6)
	lab	imaging	PCP	Ped.	OBGYN	Derm.
claim >30 days following search	-0.0328***	-0.0217	0.0198***	0.0331***	0.0123	0.00904
	(0.00514)	(0.0234)	(0.00339)	(0.00661)	(0.00878)	(0.00918)
claim 15-30 days following search	-0.0514***	-0.0522	0.00756	-0.00615	-0.0238**	-0.0177
	(0.00735)	(0.0358)	(0.00533)	(0.0108)	(0.0114)	(0.0144)
claim 0-14 days following search	-0.0785***	-0.0840***	-0.00317	-0.00693	-0.00537	-0.0346**
	(0.00651)	(0.0241)	(0.00505)	(0.0106)	(0.0108)	(0.0138)
Observations	639,324	8,363	346,889	107,090	52,759	33,089
R-squared	0.052	0.089	0.058	0.062	0.051	0.067
Number of households	12,990	2,114	25,793	4,864	8,059	4,622
Dep. variable mean	0.316	0.433	0.318	0.305	0.334	0.316

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is probability that price is above the mean procedure-specific price in the household's county. Covariates include patient cost-sharing and fixed effects for year, employer X year, procedure code, and household.

1.8.2 Learning

One natural question is what happens to consumers once they have searched for and received an initial claim. Do they revert back to their initial state of knowledge or do they retain the information acquired from searching? Stigler (1961) points out that if provider prices remain relatively constant over time, then repeated searches may not necessarily. Consumers likely retain and learn from the information in initial searches. Thus, the results from the main results may not capture the entire effect of searching.

I examine the total effect of searching by defining a variable $maxsearch_{ikt}$ which I define as the maximum value of $searchcategory_{ikt}$. I allow $maxsearch_{jkt}$ to change based on changes in household searches. $maxsearch_{jkt}$ represents the maximum search categorization at each time period. In other words, if a household is ever linked to a search in the 0-14 day time period, this characterization allows the information from the original search to be retained rather than for the household's future claims to be categorized in the 15-30 or 31-365 day periods. I then use this categorical variable to estimate an analogue of equation 1.3.

The coefficients shown in Table 1.13 also show that this temporal relationship persists. Searchers who have ever received care in the 0-14 days continue to have lower prices for all subsequent services. For lab and imaging services, the magnitude of the effect remains a similar 8% for imaging, 11% for labs, and 1% for physician services. These results suggest that the information gained from an initial search remains retained for future medical care. In conjunction with the previous results, they also suggest that the benefits of searching

Table 1.13: Learning

	(1) lab	(2) imaging	(3) PCP	(4) Ped.	(5) OBGYN	(6) Derm.
maximum: >30 days	-0.0790***	-0.0556**	-0.00263	-0.00295	-0.00139	-0.00787*
	(0.0100)	(0.0261)	(0.00169)	(0.00328)	(0.00410)	(0.00454)
maximum: 14-30 days	-0.0551***	-0.0919**	-0.00250	-0.00692	0.00840	-0.0113
	(0.0165)	(0.0409)	(0.00286)	(0.00557)	(0.00768)	(0.00814)
maximum: 0-14 days	-0.102***	-0.162***	-0.00946***	-0.000996	0.00209	-0.0120*
	(0.0134)	(0.0295)	(0.00241)	(0.00449)	(0.00720)	(0.00618)
Observations	626,094	14,657	340,245	97,492	74,987	42,084
R-squared	0.512	0.297	0.793	0.763	0.791	0.795
Number of households	15,683	6,212	36,073	5,958	18,270	9,860

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, employer X year, procedure code, and household.

are largest for lab and imaging services but the relative persistent effect is visible for physician services. The lower magnitudes are expected due to attenuation searching's effect over time. In addition, these results potentially capture receiving different services than the one searched for, albeit within the same category.

1.8.3 Downstream Effects

As suggested by Figure 1.1, the effect of searching for physician office visits is modest. However, several studies have documented the correlation between provider prices and services for which providers refer patients. These "downstream" services reflect the referral patterns of a given provider. They also reflect the preferences and incomes of patients. Those who visit less expensive physicians also visit less expensive lab providers.

These services may also represent a more natural entry point for online searching. Searching for physicians is likely more natural for consumers, which may be especially important given the nascency of price transparency in healthcare. In addition, higher-quality physicians may be more likely to refer patients to less expensive providers. To test for downstream effects, I estimate the same model as equation 1.3 for lab tests but replace search behavior with searches for physician services. For example, I examine the effect of searching for primary care physicians on lab prices. If downstream effects are present, then this model will help capture the effect of searching for physicians on the entirety of medical costs.

At the same time, the downstream searching effect may instead reflect unobserved bias of searching on prices. If searches are spurred by another contemporaneous shock, which influences prices, then the estimates in equation 1.3 may be biased. If, despite

Table 1.14: Downstream effects

	(1) PCP	(2) Ped.	(3) OBGYN	(4) Derm.
Panel A: All downstream claims following search				
claim after search	-0.0129***	-0.0117	0.0137***	-0.0185***
	(0.00194)	(0.00758)	(0.00265)	(0.00308)
Observations	1,431,519	89,356	659,529	573,600
R-squared	0.551	0.578	0.543	0.557
Number of subscriber_id	29,774	2,036	16,222	11,894
Panel B: Downstream claims by length of time following search				
claim >30 days following search	-0.0112***	-0.0109	0.0226***	-0.0187***
	(0.00204)	(0.00796)	(0.00282)	(0.00321)
claim 15-30 days following search	-0.0288***	0.0597***	0.0120**	-0.0146**
	(0.00420)	(0.0169)	(0.00536)	(0.00710)
claim 0-14 days following search	-0.0119***	-0.0780***	-0.0317***	-0.0203***
	(0.00382)	(0.0159)	(0.00489)	(0.00702)
Observations	1,431,519	89,356	659,529	573,600
R-squared	0.551	0.578	0.543	0.557
Number of households	29,774	2,036	16,222	11,894

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log price for laboratory tests. Covariates include patient cost-sharing and fixed effects for year, employer X year, procedure code, and household.

the existing evidence, downstream physician effects do not exist then this estimate may instead reflect this bias. In the absence of downstream referral patterns, it is unlikely that the information conveyed by searching for physician office visits will influence a consumer's lab test or imaging service prices. Instead, a negative effect for searching for an unrelated service may reflect the influence of contemporaneous shocks.

Whaley *et al.* (2014) uses this motivation to test for unobserved differences between searchers and non-searchers and compare lab test prices for those who searched for imaging services (but not lab tests) and vice-versa. The previous analysis did not include physician visits due to the potential presence of referral patterns. This falsification test found no effect for searching for an unrelated service, which further supports the causal effect of searching. This test of downstream effects is similar to the previous falsification test but in this analysis, I expect an effect due to downstream referral patterns.

Table 1.14 presents the downstream results. Searching for each of the physician services leads to 1-3% lower prices for lab services. These results suggest potential spillovers from searching for physician services by benefiting from low-cost physician's lower total patterns of care costs.

1.9 Appendix: Searcher Non-searcher Comparisons

The main results estimate the effect of searching among the searchers. In this section, I estimate the effect of searching by using non-searchers as a control group. I use the same population of searchers but to reduce computational burden use a randomly selected 5% sample of non-searchers from each employer. Because the primary results are nearly identical to the within-searcher results, I do not estimate the same extensions.

Table 1.15: Searcher vs Non-Searcher Main Effect: All claims following search

	(1)	(2)	(3)	(4)	(5)	(6)
Service	lab	imaging	PCP	Ped.	OBGYN	Derm.
all claims following search	-0.0923***	-0.0660***	-0.00583***	-0.00366***	0.00466*	-0.00746***
	(0.00245)	(0.0163)	(0.000903)	(0.00132)	(0.00273)	(0.00277)
Observations	1,396,539	17,044	523,931	321,357	88,015	57,715
R-squared	0.490	0.282	0.784	0.765	0.768	0.760
Number of households	29,692	4,213	38,559	17,312	13,203	7,799
Mean dep. var	27.27	1020	105.0	102.9	117.9	91.47

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, employer X year, procedure code, and household.

Table 1.16: Searcher vs Non-Searcher Main Effect: Length of time between searching and claim

	(1)	(2)	(3)	(4)	(5)	(6)
Service	lab	imaging	PCP	Ped.	OBGYN	Derm.
claim >30 days following search	-0.0791***	-0.0383**	-0.00551***	-0.00328**	0.00580**	-0.00727**
	(0.00257)	(0.0188)	(0.000930)	(0.00135)	(0.00288)	(0.00288)
claim 15-30 days following search	-0.103***	-0.0258	-0.00759***	-0.00721*	-0.00280	-0.00136
	(0.00669)	(0.0355)	(0.00226)	(0.00423)	(0.00598)	(0.00648)
claim 0-14 days following search	-0.178***	-0.127***	-0.00785***	-0.00727*	0.00334	-0.0134**
	(0.00507)	(0.0225)	(0.00200)	(0.00384)	(0.00536)	(0.00576)
Observations	1,396,539	17,044	523,931	321,357	88,015	57,715
R-squared	0.490	0.283	0.784	0.765	0.768	0.760
Number of households	29,692	4,213	38,559	17,312	13,203	7,799
Mean dep. var	27.27	1020	105.0	102.9	117.9	91.47

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log-transformed price. Covariates include patient cost-sharing and fixed effects for year, employer X year, procedure code, and household.

Chapter 2

Provider Responses to Price Transparency

2.1 Introduction

Even without including publicly available price transparency websites, at least half of the commercially insured population now has access to some form of online healthcare price transparency (Phillips & Labno, 2014). Especially for the commercially insured population, the lack of price transparency is both a cause and an effect of high commercially insured prices. Price transparency advocates argue that the rapid growth in access to price information has the potential to substantially change the U.S. healthcare marketplace. The most obvious way for price transparency to lead to lower prices is by allowing consumers to shop for low-cost, high-quality providers. The results in the previous chapter and in Whaley *et al.* (2014) show how price transparency allows consumers to shop for low-price providers. For homogenous services like labs and imaging, the price effects of shopping are large. For differentiated services with little price variation, such as physician office visits, the price effects are smaller but there are larger effects on provider choice for non-price information.

Price transparency can also lead to lower healthcare prices by spurring provider price competition. If providers respond to price transparency by lowering their prices, the consumer benefits may be only a small portion of the overall benefits of price transparency. Evidence supporting a reduction in provider prices can be seen from the effect of the internet on firm prices for other goods. For example, Brynjolfsson & Smith (2000) find that book and CD prices are 9-16% lower 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. If healthcare providers are motivated by status and reputation more than other professions, then disclosing the most expensive providers may lead to a larger price reduction than a pure profit response would suggest.

At the same time, several economic concepts highlight the consumer benefits of price obfuscation. Most notably, price transparency may facilitate tacit collusion (Kyle & Ridley, 2007). In any market with negotiated prices, price disclosure provides firms with additional bargaining leverage. These problems are exacerbated in markets with a small number of firms and markets with inelastic consumer demand (Stigler, 1964; Mollgaard & Overgaard, 1999). Price transparency information increases the applicability of punishment strategies by allowing firms to know when one firm deviates from a collusive strategy. Within the economics literature, the most well-known case of adverse effects of price transparency occurred following the publishing of negotiated prices in the Danish cement industry. Following the introduction of price transparency, cement manufacturer prices increased by 15-20% (Albaek *et al.* , 1997).

This disconnect between the two potential effects of price transparency depends crucially on consumer price elasticities and product differentiation. If demand for healthcare 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 collusion. Similarly, if products are substantially differentiated, transparency may not lead to price competition. Schultz

(2009) uses a Hotelling model to show how price transparency leads to price competition in the cases of product homogeneity and sufficiently price sensitive consumers but can lead to provider collusion if either of these two conditions are not met.

If providers respond to price information in a collusive manner, by raising prices to match the most expensive providers, then the consumer benefits of transparency may be diminished or even counteracted. This type of phenomenon has led some economists to warn against potential pitfalls of price transparency for healthcare markets (Cutler & Dafny, 2011). A Federal Trade Commission (FTC) statement on healthcare 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). In particular, the presence of generous insurance coverage coupled with an already low price elasticity creates the potential for price collusion among providers. In fact, many of the price disclosure clauses in healthcare contracts are insisted upon by insurers to prevent price transparency among providers.

Perhaps to a greater extent than other markets, healthcare exhibits a substantial variety price sensitivities and degree of product differentiation. Emergency services are both price inelastic and highly differentiated while prescription drugs are much less differentiated and have much higher price elasticities. As a result, the responses to price transparency are unlikely to be uniform across different healthcare services. Healthcare markets also exhibit substantial variation in market power. Many insurance markets are concentrated and have become increasingly concentrated in recent years (Dafny, 2010; Robinson, 2004). Yet even in the face of monopsony insurers, hospitals and large health systems are able to more favorably negotiate than smaller providers (Ho, 2009). Physician markets also exhibit provider concentration but to a lesser extent than hospital and other healthcare provider markets (Baker *et al.* , 2014). Collusion concerns may be especially magnified in concentrated provider markets (Campbell, 2008).

Whether the competitive or collusive effect dominates in healthcare markets is not well understood. Anecdotal evidence suggests that when a large insurer ranked hospital prices, from "$" to "$$$$", low-cost hospitals used the information to push for higher reimbursements (Ginsburg, 2007). However, more recent empirical evidence suggests that price transparency leads providers to lower their prices. As an early test of healthcare provider responses to price transparency, Christensen *et al.* (2014) use a difference-in-differences approach to examine changes in charges for non-elective services following the introduction of the state online price transparency service. Instead of an increase in prices, they find a 3.1% decrease in within-hospital charges. One limitation of this study is that they report hospital "chargemaster" prices, rather than actual negotiated rates between hospitals and insurers. However, Wu *et al.* (2014) find that imaging providers lowered their negotiated prices by 13% ($175) when price transparency was combined with a telephone-based mandatory pre-authorization requirement.

In this chapter, I measure how lab and physician providers prices change in parallel with the diffusion of an online price transparency platform. Similar to Christensen *et al.*

(2014) and Wu *et al.* (2014), I find large effects for lab services but relatively mild effects for physician services. Moreover, the reduction in prices is driven by expensive providers lowering their prices. Contrary to the concerns that price transparency will exacerbate market power, I find larger effects in markets with concentrated provider markets. Finally, I measure the effects of price transparency on market-wide prices and price dispersion. Although not definitive, these results suggest that the concerns of provider price increases following price transparency for healthcare services are unlikely to materialize. Moreover, the provider price decreases for lab tests suggest substantial benefits to increasing price transparency.

2.2 Theoretical Motivation

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, healthcare 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 healthcare negotiations (Capps *et al.* , 2003; Ho, 2009; Grennan, 2013; Ho & Lee, 2013) but especially follows the insurer-hospital bargaining model in Gowrisankaran *et al.* (2015). As is standard, I start with consumer utility but unlike other insurer-provider bargaining models, I include consumer information about provider attributes. 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.

Similar to the previous chapter, assume each consumer purchases a single unit of medical care in period t from provider $j \in J$ and let patient utility be given by

$$\begin{aligned} U_{ijht} &= \beta_1 provider_{ij} - \beta_2 price_{jh} + \\ &\quad \gamma_1 search_t \times provider_{ij} - \gamma_2 search_t \times price_{jh}. \end{aligned} \tag{2.1}$$

In this expression, $price_{jh}$ represents provider j's price for consumer i's insurance plan, h and $provider_{ij}$ is a measure of product differentiation and measures the match between providers and individual consumers. The $search_t$ interaction terms measure changes in consumer utility following searching for providers. I assume that consumers become more price sensitive as their level of information increases:

$$\frac{\partial^2 U_{ijht}}{\partial search_t \partial price_{jh}} = -\gamma_2$$

This assumption was empirically demonstrated in the previous chapter. However, as the results from the previous chapter show, the increases in price sensitivity are not

uniform. Homogenous services like lab tests exhibit a much larger price response to price transparency information than differentiated physician office visits.

From equation 2.1 and assuming logit demand, provider market shares from a network of providers G are given by

$$s_{jht} = \frac{\exp(U_{ijht})}{\sum_{g \in G} \exp(U_{ight})}.$$

Following Capps *et al.* (2003), the consumer value of access to the network is

$$V_{ght} = \frac{1}{\beta_1} \ln \sum_{g \in G} \exp(U_{ight}). \tag{2.2}$$

By the logit demand assumption, the utility values, $\ln \sum_{g \in G} \exp(U_{ight})$, can be converted to monetary values by dividing by β_1. 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:

$$\Delta V_{jht} = \frac{1}{\beta_1} \frac{1}{1 - s_{jt}(U_{ijht})}. \tag{2.3}$$

Tying this expression back into the original consumer utility provides the intuitive result that the incremental gains in each provider's value to the network is decreasing in price following price transparency. Likewise, the incremental gain in each provider's value to the network is decreasing in price as the share of consumers searching increases:

$$\frac{\partial^2 \Delta V_{jht}}{\partial p_{jh} \partial search_t} < 0 \tag{2.4}$$

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.

2.2.1 Bargaining

I now model the bargaining process between providers and insurers. For a given provider, profits are a function of the negotiated prices and volume, which depend on negotiated prices:

$$\pi_{jht}(\vec{p_{ht}}) = \vec{p_{ht}} q(\vec{p_{ht}}).$$

In this expression, $\vec{p_{ht}}$ represents a vector or price offered by insurance plan h in each time period. For simplicity, I assume that all providers have the same costs.

The Nash bargaining problem solves

$$p^*_{hjt} \quad = \max_{p_{hjt}} \quad \Big(q_{hjt}(\vec{p_{ht}})p_{jht}\Big)^{b_{jt(h)}} \Big(\Delta V^*_{hjt}(\vec{p_{ht}})\Big)^{b_{ht(j)}}$$

where $\Big(\Delta V^*_{hjt}(N_{ht}, \vec{p_{ht}}\Big)^{b_{h(j)}} = \Big(V_{ht}(N_{ht}, \vec{p_{ht}}) - V_{ht}(N_{ht} \setminus J_s, \vec{p_{ht}})\Big)^{b_{h(j)}}$, each hospital's contribution to the equilibrium network's value. The terms $b_{h(j)}$ and $b_{j(h)}$ represent provider the bargaining abilities of providers with insurers and insurers with providers, respectively and 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

$$b_{jt}(h) \quad \frac{q_{hj} + \sum_{k \in J_s} \frac{\partial q_{hjt}}{\partial p_{hjt}}(p_{hjt})}{\sum_{k \in J_s} q_{hjt} p_{hjt}} = \quad -b_{ht(j)} \frac{\partial \Delta V_{ht} / \partial p_{hjt}}{\Delta V^*_{hjt}(\vec{p_{ht}})}$$

For a single provider, this translates into

$$p^*_{hjt} \quad = \quad -q_{hjt}\Big(\frac{\partial q_{hjt}}{\partial p_{hjt}} + q_{hjt} \frac{b_{ht}(j)}{b_{jt}(h)} \frac{\partial \Delta V^*_{ht}}{\partial p_{hjt}} \frac{q_{hjt}}{\Delta V^*_{htj}}\Big)^{-1}$$

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 equation 2.4, because the value added to the network is decreasing in price following consumer searching, the negotiated price is also decreasing following consumer searching:

$$\frac{\partial p^*_{jht}}{\partial search_t} \quad < \quad 0$$

Qualitatively, providing consumers with additional information, 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 physician 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, which would lead to higher prices, and making consumers more price sensitive, which leads to lower negotiated prices. Which effect dominates cannot be determined from this model but remains an empirical question to be estimated in the next section.

2.3 Data

To estimate provider responses to price transparency, I use data from two sources. The first consists of lab test and physician claims from employers who purchased access to the online price transparency provider. From this data, I create a 2010-2014 longitudinal panel of providers and restrict the population of providers to the 298,593 physician and 74,290 lab provider organizations that have claims in each year. For this analysis, I do not separately analyze physician specialties but rather pool all physicians. For each provider I calculate the procedure code and insurer-specific mean quarterly price for common office visits and lab tests. Each provider's mean price serves as the dependent variable for this analysis.[1]

The empirical strategy of this analysis is to measure how provider prices change in concordance with the diffusion of the price transparency platform. The second data source contains the share of the commercially insured population that has access to the platform in each quarter and county. 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. The commercially insured denominator population data comes from the 2009 Health Leaders InterStudy survey of insurers. The InterStudy data is collected through an annual survey of insurance companies about enrollment in each market and reports the total number of commercially insured enrollees in each county by specific insurance carrier and plan. For the purposes of this study, I exclude the number of individuals with Medicare or Medicaid coverage from a commercial insurer (e.g. Medicare Part C or Medicaid HMO) from the total commercially insured population denominator.

Each employer provided access at a different point in time and the employers and employee population are geographically dispersed throughout the country. As a result, the number of consumers who were provided access to the platform in each local market is plausibly quasi-randomly assigned. I use this variation in the share of individuals who were provided access to the platform in each local market to estimate the effects of having access on provider prices. However, one limitation of using claims data from employers who also 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 implemented the transparency platform did not make other benefit design changes that would lead to physicians changing their prices at the same time as they introduced price transparency. This identification strategy also assumes that there is no broader changes in physician prices that occurs concurrently with the platform's diffusion. The variation in the timing, intensity, and location of the platform's introduction alleviates these concerns.

Table 2.1 shows some basic descriptive statistics about the data. The mean provider price for physicians is about twice the mean price for lab test providers but price disper-

[1]For each of the two services, I use the 10 most frequently observed procedure codes. Physicians: 99213, 99214, 99212, 99203, 99396, 95117, 99204, 99202, 99395, and 99215. Lab test providers: 85025, 80061, 80053, 84443, 83036, 88305, 80050, 82306, 81001, 80048

sion is much greater for lab providers. The coefficient of variation in physician prices is 0.47 compared to 1.49 for lab providers. This dispersion is further seen in the differences between the above and below mean and 75th percentile providers. For physicians, the differences in prices are meaningful but much less substantial than the differences for lab providers. For both types of providers, the differences in baseline prices are much greater than the differences by market concentration. For all three measures of market concentration, the differences in provider prices are relatively small between the concentrated and non-concentrated markets.

2.3.1 Estimation

The estimation approach is to regress provider-level prices in market g at time t on the share of individuals in the market who have access to the platform in that quarter:

$$\begin{aligned} ln(price_{jthk}) &= \beta_0 + \beta_1 pctelig_{tg} + \boldsymbol{year}_t + \boldsymbol{quarter}_t + \boldsymbol{provider}_j \\ &\quad + \boldsymbol{insurance}_h + \boldsymbol{code}_k + \varepsilon_{tjhk}. \end{aligned} \tag{2.5}$$

In this expression, $price_{jthk}$ is the mean negotiated price between provider j and insurer h for procedure k in quarter t. This price represents the sum of consumer cost-sharing and insurer payments. $pctelig_{tg}$ captures the number of commercially insured individuals who have access to the platform in each market and time-period in each quarter. Year, quarter, and provider fixed effects control for unobserved temporal or provider differences. Insurance fixed effects control for payment differences between insurers. The identification of equation 2.5 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 & Brown (1999). To test for non-linear effects, I also categorize $pctelig_{tg}$ into both 1 and 2.5 percentage point increments: $\{0\%, (0-1\%], (1-2\%], (2-3\%], (3-4\%], > 4\%\}$ and $\{0\%, (0-2.5\%], (2.5-5\%], (7.5-10\%], > 10\%\}$.

In each specification, the primary dependent variable is the current level of diffusion in each time period. This diffusion measure may be appropriate if providers change prices in anticipation or in concordance of the presence of price transparency but not if they respond to the existence of price transparency. As such, I also the effect of 1, 2, 3, and 4 quarter lagged diffusion measures on prices.

Many papers have examined the appropriate market definition for healthcare services. I use counties rather than the more commonly used Hospital Referral Regions (HRR) because the commercially insured population data is at the county rather than the HRR level. In addition, the insurance, physician, and hospital concentration data, discussed in detail below is also at the county level. As sensitivity tests, I use three additional models of diffusion. The first simply uses zip codes as the market and defines transparency diffusion as the share of all individuals in the zip code who have access to the platform. I use the entire zip code population because zip code-level insurance coverage data is not readily available. In the second sensitivity test, I also perform the same analysis using HRRs.

In the third sensitivity test, I estimate a similar model where instead of using the share of individuals with access to the price transparency platform within a market, I use the share of a given provider's baseline volume as the variable of interest. I use 2010 as the baseline year because few consumers had access to the platform. This specification uses the within-provider variation in price transparency access to estimate provider responses. For each provider j, I calculate the share of patient visits from employer m as

$$share_{jm2010} = \frac{\sum_{m=1}^{M} visits_{jm2010}}{\sum visits_{j2010}}.$$

I estimate the same model as equation 2.5 but add employer fixed effects and replace $pctelig_{tg}$ with the baseline share of employers who have launched by time t, defined as the interaction term of $share_{jm2010} \times launch_{mt}$. I do not use this approach as the main specification because for each provider, I only observe patients from employers who have purchased the transparency platform. For a given provider, these patients are likely only a fraction of the provider's overall volume but a provider's response to transparency will depend on the overall share of consumers with access to price transparency information, which I do not observe.

2.3.1.1 Heterogeneous Provider Responses

To examine the heterogeneity in the effect of price transparency on provider prices, I next examine the market characteristics that differentially influence physician responses to transparency. The first test examines if providers with higher baseline prices exhibit larger responses to increased price transparency. For each market, I calculate the average price in the baseline year, 2010. I then calculate each provider's average 2010 prices and define $abovemean_{jg2010}$ to be equal to 1 if provider j's mean 2010 price is above the respective county-level baseline price and estimate

$$\begin{aligned} ln(price_{jthkg}) = {} & \beta_0 + \beta_1 pctelig_{tg} + \beta_2 abovemean_{jg2010} + \beta_3 pctelig_{tg} \times abovemean_{jg2010} + \\ & \boldsymbol{year_t} + \boldsymbol{quarter_t} + \boldsymbol{provider_j} + \\ & \boldsymbol{insurance_h} + \boldsymbol{code_k} + \varepsilon_{jthkg}. \end{aligned} \tag{2.6}$$

I also estimate an identical regression for using the 75th percentile baseline price instead of the mean.

The next tests incorporate the level of market concentration in the market. In particular, I examine if markets with concentrated hospital, physician, and insurance markets have different responses to the diffusion of the price transparency platform. To match the transparency diffusion measure, I use counties as the market-level for these tests. For each county, I calculate the baseline Herfindahl–Hirschman Index (HHI) for hospitals, physicians, and insurers. I use baseline rather than contemporaneous HHIs to avoid bias due to any possible effects of transparency on market structure. I then use the FTC guidelines and classify markets with an HHI above 0.25 as concentrated. Hospital and

insurance markets are quite concentrated but physician markets are overwhelmingly competitive. Of the counties in the sample, 79% have concentrated hospital markets, 66% have concentrated insurer markets, but only 7% have concentrated physician markets.

To construct hospital HHIs, I use data from the 2010 American Hospital Association's Annual Survey. I use hospital beds to measure market share but other definitions, such as revenue and number of admissions, are highly correlated. For physician HHIs, I use the 2011 IMS Physician Insights database. Finally, the insurance market share data comes from the previously discussed 2009 Health-Leaders-InterStudy survey. After constructing the three concentration measures, I estimate three similar equations to equation 2.5 but add the relevant HHI-based concentration dummy variable and interact $pctelig_{tg}$ with the concentration term:

$$\begin{aligned} ln(price_{jthkg}) &= \beta_0 + \beta_1 pctelig_{tg} + \beta_2 concentrated_g + \beta_3 pctelig_{tg} \times concentrated_g + \\ &\quad \boldsymbol{year}_t + \boldsymbol{quarter}_t + \boldsymbol{provider_j} + \\ &\quad \boldsymbol{insurance_h} + \boldsymbol{code}_k + \varepsilon_{tjg}. \end{aligned} \tag{2.7}$$

2.4 Results

2.4.1 Main Results

Figures 2.1 and 2.2 show the scale of the penetration over time. In accordance with my data use agreement, I have masked the penetration shares in the maps and instead present binary entry. The simple entry patterns highlight the variation in the diffusion patterns in access to the platform that are key to the identification strategy. The early entry patterns show clusters in the Western U.S. and around some metropolitan areas. By 2014, entry is much more widespread and all but a few counties have some presence. This rapid entry motivates this analysis as such widespread access to price information should influence pricing patterns among firms.

The provider price response regressions (Table 2.2) show how physicians respond to online price transparency. The preferred specifications, columns 3 and 6, suggest that full access to transparency has a small and non-statistically significant effect on physician office visit prices but leads to a 13.4% decrease in laboratory test provider prices. For physician office visits, including insurer fixed effects changes the sign and magnitude of the results while there is little effect for lab tests. At the mean penetration rate of 6.2% at the end of 2014, this result implies an approximately 1% reduction in lab provider prices due to the entry of the platform.

Tables 2.3 and 2.4 show similar results using the categorical diffusion definition. In both tables, the diffusion effect on physician office visits is negative but small in magnitude. However, for lab tests, both panels show an increasing relationship between the share of commercially insured individuals with access to the platform and within-provider

reductions in prices. In Table 2.3, a one percentage point increase in the share eligible leads to a slightly larger than one percentage point reduction in prices. In Table 2.4, the effect is most evident in the 2.5-5% and >10% categories. Evidence of a dose-response further supports the causal relationship between provider prices and the diffusion of price transparency. At the mean penetration rate, the results in Table 2.4 indicate a 4.7% reduction in lab test provider prices.

Table 2.5 presents similar results using the quarterly lagged diffusion measures. Most notably, the physician office visit effect increases by approximately one percentage point to a 1.8% reduction in prices. For lab tests prices, the magnitude of the provider price decrease remains consistent at around 10% regardless of the lag period. These results suggest an anticipatory effect to the entry price transparency by lab providers but a response to the existence of price transparency by physicians.

The results from the sensitivity test (Table 2.6), where I use each provider's baseline volume from each eligible employer, show small effects for physician office visits but a 2.4% effect for lab tests. For both services, the effect size is larger for providers who are above an employer's average price in the baseline year, 2010. At the end of 2014, the mean share launched for each provider was 59.2% for lab providers and 79.3% for physician services. Thus, the coefficients from this test imply that lab and physician prices were 1.4% and 0.3% lower than would have been the case in the absence of price transparency. These results are similar in magnitude to the main results. Using HRRs and zip codes as alternative market definitions yields similar results (Tables 2.7 and 2.8).

2.4.2 Heterogeneity Results

Table 2.9 reports the heterogeneity in the provider responses based on baseline provider prices. Consistent with the theoretical model, these results suggest that the overall provider price changes are driven by expensive providers lowering their prices. The regression coefficients imply that full transparency would lead to an additional 3.4% reduction in prices for physicians above the mean price at baseline and a 3.0% decrease for those above the 75th percentile. For lab tests, the corresponding effects are 8.0% and 11.8%. Adding in the main diffusion coefficient suggests a 20.4% decrease in lab test provider prices for providers above the 75th percentile at baseline.

The price transparency diffusion-market concentration interaction terms in Table 2.10 also suggest substantial differences in price responses to transparency based on market structure. On the provider side, the regression results suggest that full price transparency leads to additive decreases in physician prices of 8.5% in markets with concentrated hospital markets and 7.4% in markets with concentrated physician markets. For lab test prices, there is no additive change in markets with concentrated physician markets but a 21.7% additive effect in markets with concentrated hospital markets. These results show that the diffusion of price transparency has a larger effect on provider prices in markets with concentrated provider markets. This result makes sense as price transparency seeks to inform consumers of alternatives to expensive providers, who tend to be those with

market power.

Markets with concentrated insurance markets also show additional decreases in provider prices, 8.0% for physicians and 12.2% for lab test providers. The price reductions in counties with concentrated insurance markets may reflect insurers with bargaining power leveraging price transparency to negotiate even further reductions in prices. The larger reduction in lab test prices than physician prices in counties with competitive insurance markets may reflect the relative homogeneity of laboratory tests compared to physician visits. Dominant insurers may more easily use transparency in price negotiations for services that are easily substitutable. In addition, relative to other providers, physician markets are competitive. Even in the advent of price transparency, insurers have likely extracted stronger concessions from physicians than from lab providers, which are often extensions of physician groups, hospitals, or nationwide chains. Thus, if the use of transparency as a leveraging tool among insurers story is correct, then we should expect the smaller reduction in prices for physicians.

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 those with access, not all are actively shopping and so the engaged consumer share is even smaller. However, those consumers who are actively shopping and making provider decisions based on their shopping results likely constitute the marginal consumers upon whom providers in a competitive market set prices. Even if the marginal consumers constitute a small share of the overall market, their price shopping behavior should disproportionately influence provider pricing.

2.4.3 Provider Market Shares

The market-level effects are driven by both providers changing prices in response to price transparency and consumers shifting demand to less-expensive providers due to the reduction in search costs brought on by increased price transparency. The previous results suggest meaningful lab provider price responses to price transparency but limited evidence of physician price responses. However, if expensive physicians lose demand, then the overall effects may point to a reduction in total physician spending. To complete the provider analysis, I estimate the changes in market shares of expensive lab and physician providers relative to less expensive providers. Within each quarter, the market shares of each lab and physician provider are at the county, insurance company, and CPT-code level. Expensive providers are classified as those whose baseline (2010) mean prices are above the mean and 75th percentile price for the same county, insurance, and CPT code combination.

As shown in Table 2.11, I find no distinguishable changes in market shares for physicians. However, for lab providers, expensive providers actually gained market share. In combination with the provider price responses, these results highlight the differences in market dynamics for physicians and lab test providers. The physician results fit a capacity constrained environment with inelastic demand in which providers can simply shift

demand to non-shopping consumers without changing prices. On the other hand, lab providers can more easily accommodate increased demand because they do not face the same capacity constraints, the physician's time. Compared to the relatively constant marginal costs of physicians, the much lower marginal costs for lab providers, paired with more price elastic demand, allows expensive lab providers to maximize revenue in the presence of price transparency by lowering prices and accommodating a higher volume of patients.

2.4.4 Market-Level Effects

Given the results on both consumer and provider responses to price transparency, the combined market-level effects on both price levels and price dispersion are important. I start by examining changes in market level prices due to the diffusion of the price transparency platform. The market-level effects are driven by both providers changing prices in response to price transparency and consumer's shifting demand to less-expensive providers due to price transparency.

For each market, which I define as a county, procedure code, and insurance company combination, I calculate the mean quarterly price, which is based on each provider's mean price and volume in the market. I use the same cohort of providers as the previous analysis to prevent the introduction of bias to new providers entering the sample. Likewise, including insurance companies in the cell definition is important because changes in each county's insurance mix can change mean prices. For each county g, insurance company h, procedure code k, and quarter t, I estimate

$$\begin{aligned} ln(price_{ghkt}) &= pctelig_{gt} + \boldsymbol{county}_g + \boldsymbol{insurance}_h + \boldsymbol{code}_k \\ &\quad + \boldsymbol{year}_t + \boldsymbol{quarter}_t + \varepsilon_{ghkt}. \end{aligned} \tag{2.8}$$

Similar to the provider price analysis, I include heterogeneity tests that interact $pctelig_{gt}$ with each a dummy for counties above the mean and 75th percentile procedure code-specific price, and indicators for county-level hospital, physician, and commercial insurance market concentration.

Tables 2.12 and 2.13 show the county-level mean price results. Price transparency does not have an immediate effect on mean physician office prices but does have a 13.8% effect on lab test prices. As is the case with the provider price responses, the reductions are even larger for expensive markets and counties with concentrated hospital markets. The similarity between the market-level and provider-level price reductions suggests that most of the market-level reduction in lab test prices comes from provider price reductions rather than consumer switching.

I similarly calculate the standard deviation to obtain a longitudinal panel of each market's coefficient of variation. I use this coefficient of variation panel to estimate the same regression as Equation 2.8 as an empirical test of the classic attribution of price dispersion to a lack of price information (Stigler, 1961). If price transparency has the

intended effect of reducing search costs, then price dispersion should decrease. The results from the previous results provide the mechanisms; as price transparency information becomes more widespread, consumers shift demand and expensive providers lower their prices. As Tables 2.14 and 2.15 show, there is a reduction in price dispersion following diffusion of the platform. The reduction is largest in counties with high existing levels of price dispersion and counties with concentrated hospital markets. Consistent with the other results, there is a larger decrease in price dispersion for lab tests prices than there is for physician prices.

2.5 Conclusion

Recent years have seen a large increase in the availability of healthcare price information available to consumers. While consumer responses to price transparency are becoming well-understood, how providers respond to price transparency remains less developed. However, 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 healthcare expenditures than consumer responses alone. Using data from a particular online price transparency platform, I find substantial price reductions for lab test providers and small reductions for physicians. The differing results follow economic intuition as lab tests are much more homogenous than highly differentiated physicians. Moreover, these results mirror the approximate effect sizes found when consumers use the platform to shop for providers. In addition, the price effects are driven by expensive providers lowering their prices. I also find a larger effect in markets with concentrated hospital and insurance markets.

As expensive providers lower their prices, the reductions in provider prices lead to an overall reduction in the average cost per procedure and a reduction in price dispersion. The last finding is especially relevant to the work on search costs as a source of price dispersion. Beginning with Stigler (1961), economists have studied how search costs lead to price variation. In the economics literature, substantial evidence exists on how search costs for consumers leads providers to differentially price. However, especially for healthcare services, less evidence exists for the the opposite effect, how a reduction in search costs leads to a reduction in firm prices and decreases price dispersion. The results of this paper show how reducing search costs, by providing consumers with usable information on provider prices, can lead to a reduction in provider prices and this price variation.

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. There are multiple firms that provide price transparency 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 are captured in the control group markets. In this case, my results may actually be understated if there is a price decrease in the control groups due to other price transparency efforts. Finally, I only examine the responses of two types of providers, physicians and lab test providers. Providers for other services, such as hospitals or surgical centers, may respond differently.

Despite these limitation, 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 grows, these results suggest providers will respond competitively and the fears of provider collusion may not be warranted. In tandem with the consumer responses to price transparency information, these results show price transparency's potential to change the competitive landscape of healthcare markets.

Bibliography

Albaek, Svend, Mollgaard, Peter, & Overgaard, Per. 1997. Government-Assisted Oligopoly Coordination? A Concrete Case. *The Journal of Industrial Economics*, **45**(4), 429–443.

Baker, Laurence C. 1997. The effect of HMOs on fee-for-service health care expenditures: Evidence from Medicare. *Journal of Health Economics*, **16**(4), 453–481. 00197.

Baker, Laurence C., & Brown, Martin L. 1999. Managed Care, Consolidation among Health Care Providers, and Health Care: Evidence from Mammography. *The RAND Journal of Economics*, **30**(2), 351–374.

Baker, Laurence C., Bundorf, M. Kate, Royalty, Anne B., & Levin, Zachary. 2014. Physician practice competition and prices paid by private insurers for office visits. *JAMA*, **312**(16), 1653–1662.

Brynjolfsson, Erik, & Smith, Michael D. 2000. Frictionless commerce? A comparison of internet and conventional retailers. *Management Science*, **46**, 563–585.

Campbell, Sheila. 2008 (June). *Increasing Transparency in the Pricing of Health Care Services and Pharmaceuticals*. Tech. rept. Congressional Budget Office, Washington, DC.

Capps, Cory, Dranove, David, & Satterthwaite, Mark. 2003. Competition and Market Power in Option Demand Markets. *The RAND Journal of Economics*, **34**(4), 737–763.

Christensen, Hans Bonde, Floyd, Eric, & Maffett, Mark G. 2014 (Aug.). *The Effects of Price Transparency Regulation on Prices in the Healthcare Industry*. SSRN Scholarly Paper ID 2343367. Social Science Research Network, Rochester, NY.

Cutler, David, & Dafny, Leemore. 2011. Designing Transparency Systems for Medical Care Prices. *New England Journal of Medicine*, **364**(10), 894–895.

Dafny, Leemore S. 2010. Are Health Insurance Markets Competitive? *American Economic Review*, **100**(4), 1399–1431.

FTC. 1996 (Aug.). *Statements of Antitrust Enforcement Policy in Health Care*.

Ginsburg, Paul B. 2007. Shopping For Price In Medical Care. *Health Affairs*, **26**(2), 208–216.

Gowrisankaran, Gautam, Nevo, Aviv, & Town, Robert. 2015. Mergers When Prices Are Negotiated: Evidence from the Hospital Industry. *American Economic Review*, **105**(1), 172–203.

Grennan, Matthew. 2013. Price Discrimination and Bargaining: Empirical Evidence from Medical Devices. *American Economic Review*, **103**(1), 145–77.

Ho, Kate, & Lee, Robin S. 2013 (Sept.). *Insurer Competition and Negotiated Hospital Prices*. Working Paper 19401. National Bureau of Economic Research.

Ho, Katherine. 2009. Insurer-Provider Networks in the Medical Care Market. *American Economic Review*, **99**(1), 393–430.

Kolstad, Jonathan T. 2013. Information and Quality When Motivation is Intrinsic: Evidence from Surgeon Report Cards. *American Economic Review*, **103**(7), 2875–2910.

Kyle, Margaret K., & Ridley, David B. 2007. Would Greater Transparency And Uniformity Of Health Care Prices Benefit Poor Patients? *Health Affairs*, **26**(5), 1384–1391.

Mollgaard, H. Peter, & Overgaard, Per Baltzer. 1999. *Market Transparency: A Mixed Blessing?* CIE Discussion Paper 1999-15. University of Copenhagen. Department of Economics. Centre for Industrial Economics.

Phillips, Kathryn A., & Labno, Anna. 2014. Private Companies Providing Health Care Price Data: Who Are They and What Information do They Provide? *Journal of managed care medicine : JMCM*, **17**(4), 75–80.

Robinson, James C. 2004. Consolidation And The Transformation Of Competition In Health Insurance. *Health Affairs*, **23**(6), 11–24.

Schultz, Christian. 2009. *Collusion in markets with imperfect price information on both sides*. CIE Discussion Paper 2009-01. University of Copenhagen. Department of Economics. Centre for Industrial Economics.

Stahl, Dale. 1989. Oligopolistic Pricing with Sequential Consumer Search. *The American Economic Review*, **79**(4), 700–712.

Stigler, George J. 1961. The Economics of Information. *Journal of Political Economy*, **69**(3), 213–225. 07161.

Stigler, George J. 1964. A Theory of Oligopoly. *Journal of Political Economy*, **72**(1), 44–61.

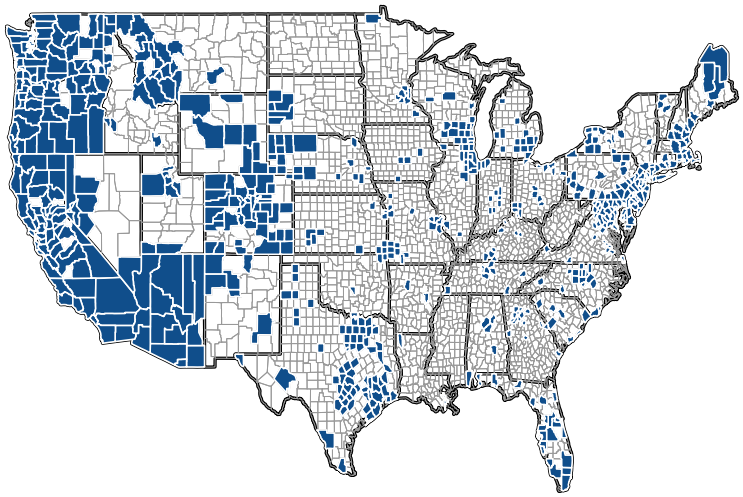
Varian, Hal R. 1980. A Model of Sales. *The American Economic Review*, **70**(4), 651–659.

Whaley, Christopher, Chafen Schneider, Jennifer, Pinkard, Sophie, Bravata, Dena, Kellerman, Gabriella, Kocher, Bob, & Sood, Neeraj. 2014. Association between availability of health service prices and payments for these services. *JAMA*, **312**(16), 1670–1676.

Wu, Sze-jung, Sylwestrzak, Gosia, Shah, Christiane, & DeVries, Andrea. 2014. Price Transparency For MRIs Increased Use Of Less Costly Providers And Triggered Provider Competition. *Health Affairs*, **33**(8), 1391–1398.

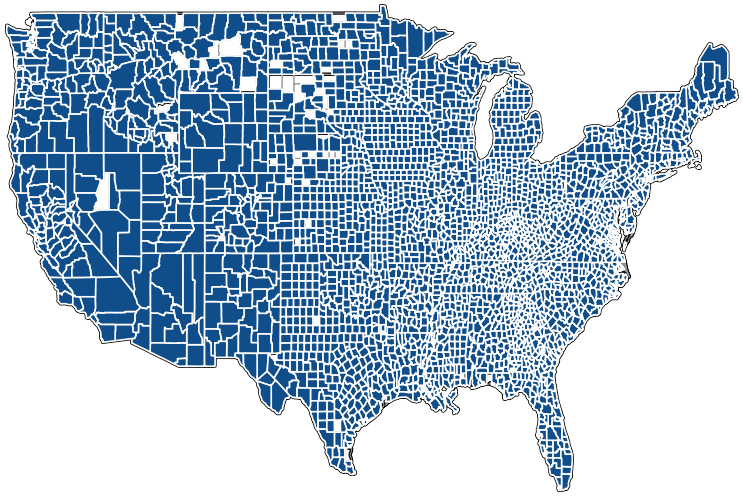
2.6 Tables and Figures

Figure 2.1: County Penetration: 2011



Shaded counties represent counties with any entry in the second quarter of 2011.

Figure 2.2: County Penetration: 2014



Shaded counties represent counties with any entry in the fourth quarter of 2014.

Table 2.1: Summary Statistics

	Physicians			Lab providers		
	mean	median	stdev	mean	median	stdev
	Prices[*]					
All providers	$103.01	$94.00	$48.52	$52.32	$23.77	$78.03
Provider price						
Below mean	$91.50	$84.45	$39.79	$35.77	$16.63	$57.56
Above mean	$116.81	$107.00	$54.13	$81.86	$50.63	$98.40
Below 75th percentile	$97.67	$90.00	$43.44	$41.30	$18.85	$63.29
Above 75th percentile	$123.94	$112.18	$60.29	$81.61	$47.63	$102.20
Market Characteristics						
Non-concentrated hospital market	$106.55	$96.08	$52.00	$53.81	$23.48	$82.64
Concentrated hospital market	$97.93	$90.37	$42.53	$50.44	$24.04	$71.75
Non-concentrated physician market	$103.11	$94.09	$48.58	$52.39	$23.80	$78.10
Concentrated physician market	$86.30	$78.31	$33.17	$40.81	$17.50	$66.19
Concentrated insurance market	$104.58	$94.50	$48.74	$54.00	$25.00	$80.21
Non-concentrated insurance market	$101.34	$93.20	$48.23	$50.87	$22.80	$76.08
	Provider Characteristics[&]					
Above mean	0.46	0.00	0.50	0.34	0.00	0.47
Above 75th percentile	0.20	0.00	0.40	0.23	0.00	0.42
Concentrated hospital market	0.41	0.00	0.49	0.46	0.00	0.50
Concentrated physician market	0.01	0.00	0.07	0.01	0.00	0.08
Concentrated insurance market	0.48	0.00	0.50	0.52	1.00	0.50

[*]Unit of observation is provider, CPT code, insurance company, and quarter.
[&]Unit of observation is provider and insurance company.

Table 2.2: Physician Price Responses to Price Transparency

	(1)	(2)	(3)	(4)	(5)	(6)
	Physician office visits			Laboratory tests		
$pctelig_{tg}$	0.0332***	0.0147***	-0.00509	-0.129***	-0.116***	-0.144***
	(0.00468)	(0.00451)	(0.00420)	(0.0212)	(0.0214)	(0.0206)
Observations	3,854,285	3,854,285	3,854,285	1,836,655	1,836,655	1,836,655
R-squared	0.653	0.654	0.688	0.479	0.479	0.542
Number of providers	298,593	298,593	298,593	74,290	74,290	74,290
Fixed effects	provider, CPT code, year	+ quarter	+ insurance company	provider, CPT code, year	+ quarter	+ insurance company

This table presents the continuous $pctelig_{tg}$ coefficients from equation 2.5, which is estimated using OLS. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 4 include provider, CPT code, and year fixed effects. Columns 2 and 5 add quarter fixed effects. The preferred specifications in columns 3 and 6 add insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.3: Physician Price Responses to Price Transparency: Diffusion Categories

	(1)	(2)	(3)	(4)	(5)	(6)
	Physician office visits			Laboratory tests		
(0-1%] percent eligible	-4.57e-05	-0.00736***	-0.00508***	-0.00280	0.000314	-0.00261
	(0.000612)	(0.000630)	(0.000612)	(0.00336)	(0.00346)	(0.00322)
(1-2%] percent eligible	0.00573***	-0.00903***	-0.00615***	-0.0132***	-0.00669	-0.0124***
	(0.000748)	(0.000797)	(0.000772)	(0.00408)	(0.00438)	(0.00411)
(2-3%] percent eligible	0.00835***	-0.0101***	-0.00760***	-0.0343***	-0.0265***	-0.0325***
	(0.000861)	(0.000935)	(0.000906)	(0.00512)	(0.00552)	(0.00521)
(3-4%] percent eligible	0.00745***	-0.0125***	-0.00966***	-0.0511***	-0.0429***	-0.0441***
	(0.00108)	(0.00116)	(0.00113)	(0.00574)	(0.00624)	(0.00590)
>4% percent eligible	0.0143***	-0.00448***	-0.00713***	-0.0603***	-0.0522***	-0.0681***
	(0.00102)	(0.00110)	(0.00106)	(0.00574)	(0.00622)	(0.00591)
Observations	3,854,285	3,854,285	3,854,285	1,836,655	1,836,655	1,836,655
R-squared	0.653	0.654	0.688	0.480	0.480	0.543
Number of providers	298,593	298,593	298,593	74,290	74,290	74,290
Fixed effects	provider, CPT code, year	+ quarter	+ insurance company	provider, CPT code, year	+ quarter	+ insurance company

This table presents the categorized $pctelig_{tg}$ coefficients from equation 2.5, which is estimated using OLS. In these results, $pctelig_{tg}$ is categorized in one percentage-point increments. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 4 include provider, CPT code, and year fixed effects. Columns 2 and 5 add quarter fixed effects. The preferred specifications in columns 3 and 6 add insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4: Physician Price Responses to Price Transparency: Alternative Diffusion Categories

	(1)	(2)	(3)	(4)	(5)	(6)
	Physician office visits			Laboratory tests		
(0-2.5%] percent eligible	0.000107	-0.00722***	-0.00500***	-0.00308	0.00114	-0.00158
	(0.000612)	(0.000630)	(0.000611)	(0.00337)	(0.00346)	(0.00323)
(2.5-5%] percent eligible	0.000199	-0.0124***	-0.0105***	-0.0350***	-0.0280***	-0.0276***
	(0.000863)	(0.000904)	(0.000874)	(0.00499)	(0.00525)	(0.00503)
(5-7.5%] percent eligible	0.00818***	-0.00336**	-0.00361***	-0.0418***	-0.0352***	-0.0485***
	(0.00129)	(0.00132)	(0.00128)	(0.00800)	(0.00813)	(0.00781)
(7.5-10%] percent eligible	0.00828***	0.000298	-0.00392***	-0.0265***	-0.0210**	-0.0290***
	(0.00157)	(0.00157)	(0.00152)	(0.00956)	(0.00965)	(0.00927)
>10% percent eligible	0.00961***	-0.00302**	-0.00729***	-0.0475***	-0.0406***	-0.0558***
	(0.00118)	(0.00122)	(0.00118)	(0.00697)	(0.00718)	(0.00688)
Observations	3,854,285	3,854,285	3,854,285	1,836,655	1,836,655	1,836,655
R-squared	0.653	0.654	0.688	0.480	0.480	0.542
Number of providers	298,593	298,593	298,593	74,290	74,290	74,290
Fixed effects	provider, CPT code, year	+ quarter	+ insurance company	provider, CPT code, year	+ quarter	+ insurance company

This table presents the categorized $pctelig_{tg}$ coefficients from equation 2.5, which is estimated using OLS. In these results, $pctelig_{tg}$ is categorized in 2.5 percentage-point increments. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 4 include provider, CPT code, and year fixed effects. Columns 2 and 5 add quarter fixed effects. The preferred specifications in columns 3 and 6 add insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: Provider Responses to Price Transparency: Lagged Diffusion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Physician office visits				Laboratory tests			
	1 quarter lag	2 quarter lag	3 quarter lag	4 quarter lag	1 quarter lag	2 quarter lag	3 quarter lag	4 quarter lag
percent eligible	-0.0149***	-0.0161***	-0.0176***	-0.0184***	-0.0834***	-0.0866***	-0.0922***	-0.103***
	(0.00189)	(0.00179)	(0.00182)	(0.00196)	(0.0132)	(0.0136)	(0.0141)	(0.0164)
Observations	3,854,285	3,854,285	3,854,285	3,854,285	1,836,655	1,836,655	1,836,655	1,836,655
R-squared	0.688	0.688	0.688	0.688	0.542	0.542	0.542	0.542
Number of provider_id	298,593	298,593	298,593	298,593	74,290	74,290	74,290	74,290

This table presents the continuous $pctelig_{tg}$ coefficients from equation 2.5, which is estimated using OLS. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 5 use a one quarter lag of $pctelig_{tg}$, columns 2 and 6 use a two quarter lag, columns 3 and 7 use a three quarter lag, and columns 4 and 8 use a one year lag. All columns include provider, CPT code, year, quarter, and insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6: Physician Price Responses to Price Transparency: Sensitivity Test

	(1)	(2)	(3)	(4)
	Physician office visits		Laboratory tests	
$share_{jm2010} \times launch_{mt}$	-0.00362***	0.00101	-0.0240***	-0.0127**
	(0.000694)	(0.000813)	(0.00584)	(0.00582)
$abovemean_{mk}$		0.0848***		0.453***
		(0.00249)		(0.0100)
$share_{jm2010} \times launch_{mt} \times abovemean_{mk}$		-0.0100***		-0.0365***
		(0.000823)		(0.00662)
Observations	1,766,027	1,766,027	967,067	967,067
R-squared	0.837	0.841	0.596	0.631
Number of provider_id	171,596	171,596	43,990	43,990

This table presents the $share_{jm2010} \times launch_{mt}$ coefficients from the sensitivity test that uses the share of each provider's baseline volume that has access to the platform and is estimated using OLS. The dependent variable is log-transformed mean quarterly provider price. Columns 2 and 4 interact this share-eligible measure with dummies indicating the provider is above the mean employer and procedure code-specific price in 2010. All columns include provider, CPT code, year, quarter, and employer fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7: Physician Price Responses to Price Transparency: Zip Code Sensitivity Test

	(1)	(2)	(3)	(4)	(5)	(6)
	Physician office visits			Laboratory tests		
$pctelig_{tg}$	0.0760***	0.0508***	0.0239***	-0.255***	-0.235***	-0.277***
	(0.00685)	(0.00682)	(0.00650)	(0.0417)	(0.0418)	(0.0401)
Observations	3,463,976	3,463,976	3,463,976	1,692,081	1,692,081	1,692,081
R-squared	0.651	0.651	0.685	0.477	0.477	0.537
Number of providers	250,501	250,501	250,501	63,952	63,952	63,952
Fixed effects	provider, CPT code, year	+ quarter	+ insurance company	provider, CPT code, year	+ quarter	+ insurance company

This table presents the results from a sensitivity test that uses zip codes as the market definition. $pctelig_{tg}$ is defined as the quarterly share of the total population eligible for the price transparency tool in each zip code. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 4 include provider, CPT code, and year fixed effects. Columns 2 and 5 add quarter fixed effects. The preferred specifications in columns 3 and 6 add insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8: Physician Price Responses to Price Transparency: Hospital Referral Region Sensitivity Test

	(1)	(2)	(3)	(4)	(5)	(6)
	Physician office visits			Laboratory tests		
$pctelig_{tg}$	0.0624***	0.0474***	0.0225***	-0.188***	-0.172***	-0.226***
	(0.00434)	(0.00438)	(0.00422)	(0.0266)	(0.0268)	(0.0246)
Observations	4,067,026	4,067,026	4,067,026	1,952,592	1,952,592	1,952,592
R-squared	0.657	0.658	0.692	0.477	0.477	0.539
Number of providers	324,903	324,903	324,903	82,443	82,443	82,443
Fixed effects	provider, CPT code, year	+ quarter	+ insurance company	provider, CPT code, year	+ quarter	+ insurance company

This table presents the results from a sensitivity test that uses hospital referral regions (HRR) as the market definition. $pctelig_{tg}$ is defined as the quarterly share of the total population eligible for the price transparency tool in each HRR. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 4 include provider, CPT code, and year fixed effects. Columns 2 and 5 add quarter fixed effects. The preferred specifications in columns 3 and 6 add insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9: Physician Price Responses to Price Transparency: Baseline Provider Prices

	(1)	(2)	(3)	(4)
	Physician office visits		Laboratory tests	
percent eligible	0.00928	0.00241	-0.112***	-0.102***
	(0.00566)	(0.00506)	(0.0231)	(0.0223)
above mean	0.0700***		0.314***	
	(0.00132)		(0.00649)	
percent eligible X above mean	-0.0344***		-0.0832**	
	(0.00731)		(0.0404)	
above 75th percentile		0.0727***		0.308***
		(0.00154)		(0.00696)
percent eligible X 75th percentile		-0.0302***		-0.126***
		(0.00830)		(0.0408)
Observations	3,854,285	3,854,285	1,836,655	1,836,655
R-squared	0.690	0.690	0.557	0.555
Number of providers	298,593	298,593	74,290	74,290

Table presents the $pctelig_{tg}$, provider baseline price, and $pctelig_{tg}$-baseline price interaction coefficients from equation 2.6, which is estimated using OLS. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 3 interact $pctelig_{tg}$ with a dummy variable indicating that the provider's price is above the CPT code, county, and insurance company-specific mean price in 2010. Columns 2 and 4 do the same for the 75th percentile price. All columns include provider, CPT code, year, quarter, and insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.10: Physician Price Responses to Price Transparency: Market Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
		Physician office visits			Laboratory tests	
% eligible	0.0180***	0.0236***	0.0691***	-0.0732***	-0.152***	-0.0261
	(0.00522)	(0.00504)	(0.00978)	(0.0218)	(0.0261)	(0.0465)
concentrated hospital market	-0.00504			0.177**		
	(0.0516)			(0.0758)		
% eligible X concentrated	-0.0892***			-0.244***		
hospital market	(0.00814)			(0.0434)		
concentrated physician market					0	
					(0)	
% eligible X concentrated		-0.0767***			0.0249	
physician market		(0.00776)			(0.0398)	
concentrated insurance market			0.162			0.153
			(0.128)			(0.246)
% eligible X concentrated			-0.0829***			-0.130***
insurance market			(0.0102)			(0.0493)
Observations	3,854,285	3,854,285	3,854,285	1,836,655	1,836,655	1,836,655
R-squared	0.688	0.688	0.688	0.542	0.542	0.542
Number of providers	298,593	298,593	298,593	74,290	74,290	74,290

This table presents the $pctelig_{tg}$, market concentration, and $pctelig_{tg}$-concentration interaction coefficients from equation 2.7, which is estimated using OLS. The dependent variable is log-transformed mean quarterly provider price. Columns 1 and 4 interact $pctelig_{tg}$ with a dummy indicating the county has a concentrated hospital market. Columns 2 and 4 include interactions for concentrated physician markets and columns 3 and 6 include interactions with concentrated insurance markets. Concentrated markets are defined as those with HHIs above 0.25. All columns include provider, CPT code, year, quarter, and insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.11: Market Share Changes

	(1)	(2)	(3)	(4)
	Physicians		*Lab test providers*	
	above mean	above p75	above mean	above p75
$pctelig_{tg}$	-0.00553	-0.00466	0.0245***	0.0245***
	(0.00360)	(0.00293)	(0.00870)	(0.00867)
above mean price	-0.00419***		-0.00655***	
	(0.00107)		(0.00128)	
$pctelig_{tg}$ X above mean price	0.00211		0.0271**	
	(0.00465)		(0.0136)	
above 75th percentile price		-0.00994***		-0.0137***
		(0.00119)		(0.00137)
$pctelig_{tg}$ X above 75th percentile price		0.000674		0.0377**
		(0.00509)		(0.0164)
Observations	3,854,285	3,854,285	1,836,655	1,836,655
R-squared	0.202	0.202	0.157	0.157
Number of providers	298,593	298,593	74,290	74,290
Mean market share	0.12	0.12	0.25	0.25

This table presents the $pctelig_{tg}$, provider baseline price, and $pctelig_{tg}$-baseline price interaction coefficients from the provider market share analysis. The dependent variable is each provider's market share in each of the county, insurance company, and procedure code markets. Columns 1 and 3 interact $pctelig_{tg}$ with a dummy variable indicating that the provider's price is above the CPT code, county, and insurance company-specific mean price in 2010. Columns 2 and 4 do the same for the 75th percentile price. All columns include provider, CPT code, year, quarter, and insurance company fixed effects. Robust standard errors clustered at provider level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.12: Market-level Average Price Changes:

	(1)	(2)	(3)	(4)	(5)	(6)
	mean price	mean price	mean price	mean price	mean price	mean price
			Physician office visits			
$pcteligi_{tg}$	0.0121	-0.0115	-0.00277	0.0378	0.0211	-0.0147
	(0.0208)	(0.0195)	(0.0191)	(0.0336)	(0.0292)	(0.0456)
above mean		0.107***				
		(0.00742)				
$pcteligi_{tg}$ X above mean		0.0630				
		(0.0576)				
above p75			0.132***			
			(0.0113)			
$pcteligi_{tg}$ X above p75			0.0593			
			(0.0547)			
$pcteligi_{tg}$ X concentrated				-0.0692		
hospital market				(0.0437)		
$pcteligi_{tg}$ X concentrated					-0.0245	
physician market					(0.0311)	
$pcteligi_{tg}$ X concentrated						0.0323
insurance market						(0.0496)
Observations	226,730	226,730	226,730	226,730	226,730	226,730
R-squared	0.870	0.875	0.874	0.870	0.870	0.870
Number of counties	1,696	1,696	1,696	1,696	1,696	1,696

This table presents the market-level price effects from equation 2.8. The dependent variable is the mean quarterly price in each county, insurance company, and procedure code market. Column 1 shows the overall price effect, columns 2 and 3 add interactions for providers above the mean and 75th percentile prices at baseline, and columns 4-6 add interactions for concentrated hospital, physician, and insurer markets. All columns include county, insurance company, procedure code, year, and quarter fixed effects. Robust standard errors clustered at the provider level in parentheses.

Table 2.13: Market-level Average Price Changes:

	(1)	(2)	(3)	(4)	(5)	(6)
	mean price	mean price	mean price	mean price	mean price	mean price
			Laboratory tests			
$pcteligtg$	-0.148**	-0.124*	-0.140**	-0.126	-0.152*	-0.184
	(0.0674)	(0.0660)	(0.0615)	(0.0841)	(0.0829)	(0.142)
above mean		0.348***				
		(0.0152)				
$pcteligtg$ X above mean		-0.0558				
		(0.121)				
above p75			0.369***			
			(0.0142)			
$pcteligtg$ X above p75			-0.0309			
			(0.105)			
$pcteligtg$ X concentrated				-0.0590		
hospital market				(0.121)		
$pcteligtg$ X concentrated					0.0156	
physician market					(0.107)	
$pcteligtg$ X concentrated						0.0409
insurance market						(0.155)
Observations	295,731	295,731	295,731	295,731	295,731	295,731
R-squared	0.607	0.624	0.622	0.607	0.607	0.607
Number of counties	1,494	1,494	1,494	1,494	1,494	1,494

This table presents the market-level price effects from equation 2.8. The dependent variable is the mean quarterly price in each county, insurance company, and procedure code market. Column 1 shows the overall price effect, columns 2 and 3 add interactions for providers above the mean and 75th percentile prices at baseline, and columns 4-6 add interactions for concentrated hospital, physician, and insurer markets. All columns include county, insurance company, procedure code, year, and quarter fixed effects. Robust standard errors clustered at the provider level in parentheses.

Table 2.14: Market-level Price Dispersion Changes:

	(1)	(2)	(3)	(4)	(5)	(6)
	cv	cv	cv	cv	cv	cv
	Physician office visits					
$pcteligtg$	-0.0104	0.0115*	0.00351	0.000960	-0.0210*	0.00698
	(0.0107)	(0.00622)	(0.00732)	(0.00910)	(0.0118)	(0.0153)
above mean		0.0364***				
		(0.00173)				
$pcteligtg$ X above mean		-0.0590***				
		(0.0163)				
above p75			0.0438***			
			(0.00224)			
$pcteligtg$ X above p75			-0.0609***			
			(0.0226)			
$pcteligtg$ X concentrated hospital market				-0.0306*		
				(0.0169)		
$pcteligtg$ X concentrated physician market					0.0288**	
					(0.0121)	
$pcteligtg$ X concentrated insurance market						-0.0209
						(0.0184)
Observations	226,730	226,730	226,730	226,730	226,730	226,730
R-squared	0.086	0.100	0.105	0.086	0.086	0.086
Number of counties	1,696	1,696	1,696	1,696	1,696	1,696

This table presents the market-level price effects from equation 2.8. The dependent variable is the quarterly coefficient of variation in each county, insurance company, and procedure code market. Column 1 shows the overall price effect, columns 2 and 3 add interactions for providers above the mean and 75th percentile prices at baseline, and columns 4-6 add interactions for concentrated hospital, physician, and insurer markets. All columns include county, insurance company, procedure code, year, and quarter fixed effects. Robust standard errors clustered at the provider level in parentheses.

Table 2.15: Market-level Price Dispersion Changes:

	(1)	(2)	(3)	(4)	(5)	(6)
	cv	cv	cv	cv	cv	cv
			Laboratory tests			
$pcteligtg$	-0.0508*	-0.0206	-0.0183	-0.00713	-0.0703***	-0.0567
	(0.0290)	(0.0343)	(0.0255)	(0.0287)	(0.0264)	(0.0541)
above mean		0.0847***				
		(0.00427)				
$pcteligtg$ X above mean		-0.0466				
		(0.0456)				
above p75			0.0944***			
			(0.00504)			
$pcteligtg$ X above p75			-0.0753*			
			(0.0442)			
$pcteligtg$ X concentrated hospital market				-0.116***		
				(0.0389)		
$pcteligtg$ X concentrated physician market					0.0855**	
					(0.0425)	
$pcteligtg$ X concentrated insurance market						0.00684
						(0.0569)
Observations	295,731	295,731	295,731	295,731	295,731	295,731
R-squared	0.097	0.107	0.110	0.097	0.097	0.097
Number of counties	1,494	1,494	1,494	1,494	1,494	1,494

This table presents the market-level price effects from equation 2.8. The dependent variable is the quarterly coefficient of variation in each county, insurance company, and procedure code market. Column 1 shows the overall price effect, columns 2 and 3 add interactions for providers above the mean and 75th percentile prices at baseline, and columns 4-6 add interactions for concentrated hospital, physician, and insurer markets. All columns include county, insurance company, procedure code, year, and quarter fixed effects. Robust standard errors clustered at the provider level in parentheses.

Chapter 3

Provider Responses to Consumer Incentives: Evidence from Reference Based Benefits

3.1 Introduction

In recent years, many employers and insurers have introduced substantial changes in their insurance benefit designs as a means to restrain healthcare spending. These new benefit designs incentivize patients to receive care from less expensive providers or simply reduce their volume of care. While a large volume of evidence describes financial savings and consumer responses to benefit design changes, how these benefit designs influences provider prices is not well understood (Parente *et al.* , 2004; Beeuwkes Buntin *et al.* , 2011; Buntin *et al.* , 2006; Sood *et al.* , 2013; Haviland *et al.* , 2015). This paper measures how providers respond to a particular insurance benefit innovation, Reference Based Benefits (RBB), and finds that provider price reductions in responses to RBB for three common outpatient services leads to a $3.1 million reduction in medical spending over two years. Importantly, the majority of this savings spills over to consumers beyond the plan that implemented the RBB program.

While the growth of high deductible health plans (HDHPs) has received the most attention, many employers and insurers are continuing to innovate their benefit designs beyond HDHPs. This innovation is often spurred by a desire to lessen the blunt effects of HDHPs while still providing financial incentives to receive care from low-cost providers. In particular, several employers have implemented RBB programs. Under typical RBB programs, the payer establishes a maximum reimbursable amount for a given service, often referred to as a reference price. If the price for a patient's care is above this amount, the patient pays the difference. In this sense, RBB serves as a "negative deductible" for care. Rather than front-loading cost-sharing, as is the case in HDHP plans, RBB plans incentivize patients to receive care at less expensive providers. RBB programs borrow from several European nations' pharmaceutical pricing strategies. These countries establish a reference price for many pharmaceuticals and patients who purchase more expensive drugs must pay the difference in prices.

Early evidence from several California studies shows that RBB plans shift volume from expensive to low-price providers. In the same setting examined in this paper, the introduction of RBB led to a 20% reduction in knee and hip replacement procedure spending for the California Public Employees Retirement System (CalPERS) (Robinson and Brown 2013). A more recent study finds an 18% reduction in procedure spending for cataract surgery (Robinson, Brown, and Whaley 2015). On an aggregate basis, the procedure spending reductions translate into financial savings to CalPERS of $3.1 million for knee and hip replacements, and $1.3 million for cataract surgeries. The previously measured financial savings for both procedures occurs through patients switching from expensive providers to providers priced below the reference price. For joint replacements and cataract replace surgery, RBB led to shifts in patient volume from high-cost to fully covered providers of 15.0 percentage points and 8.6 percentage points, respectively.

However, if providers respond to the RBB program by lowering prices, the financial savings may be much greater. In addition, the financial savings will apply to all consumers, not just those covered by RBB. The literature on how providers respond to

stringent consumer cost-sharing plans in general remains thin. In the European setting, reference pricing has been linked to substantial reductions in prices for pharmaceuticals as manufacturers lower their prices to the reference price (Brekke *et al.* , 2011). In the U.S., one paper that studies a particular firm's transition from a generous fee-for-service plan to a HDHP finds a small increase in provider prices (Brot-Goldberg *et al.* , 2015). Like the setting studied in that paper, the firm studied in this paper is geographically concentrated. On a related spectrum, recent studies show how consumer information leads to provider price changes. In one setting, the combination of price transparency information with a telephone-based prior authorization program led providers to lower prices by 12% (Wu *et al.* , 2014). In a similar study, the diffusion of online price transparency information is associated with an approximately 3% decreases in provider prices for lab tests (Whaley, 2015).

The most similar paper to this one examines the effect of CalPERS' RBB program for knee and hip replacements on California hospital prices (Brown & Robinson, 2015). Following the RBB program, prices for both and low-price hospitals decreased but over time, the low-cost hospitals increased prices. This paper follows a similar approach but focuses on how the variation in provider exposure to RBB influences provider responses. Unlike the previous paper, this paper focuses specifically on how RBB changes the negotiated rate between providers and insurers.

3.2 Institutional Background

CalPERS provides health insurance coverage to 1.4 million California state, municipal, and county employees and their dependents, making it the third largest purchaser of health services in the United States.[1] Nearly all State of California employees and their dependents receive health insurance through CalPERS. California municipalities and counties can choose to provide coverage through CalPERS or to provide their own coverage. Nearly all CalPERS health insurance enrollment is split between three plans; a Kaiser Permanente fully integrated plan, a health maintenance organization (HMO) administered by Blue Shield of California, and a preferred provider organization (PPO) plan administered by Anthem Blue Cross.

CalPERS added RBB to its Anthem PPO insurance plan in 2011 for knee and hip replacement surgery and expanded it to colonoscopy, cataract surgery, and joint arthroscopy in 2012. The decision to implement RBB was motivated by the substantial variation in provider prices that was not accompanied by discernable differences in procedural quality or complication rates. Figure 1 shows the variation in colonoscopy, cataract surgery, knee arthroscopy, and shoulder arthroscopy provider prices for hospital outpatient departments (HOPDs) and ambulatory surgical centers (ASCs), in 2011, the year before implementation. For colonoscopies, the 75th percentile price for hospital outpatient facilities was

[1]Source: CalPERS at a Glance: http://www.calpers.ca.gov/eip-docs/about/facts/calpers-at-a-glance.pdf

$3,119 while the 25th percentile price was $1,575. The range is much narrower for ASCs, $1,392 to $651, respectively. Unlike HOPDs, ASCs are freestanding units that do not deliver emergency care or accept uninsured patients. As a result, they typically have lower fixed costs than HOPDs. ASCs also tend to specialize in a few surgical procedures.

In light of this variation, CalPERS established reimbursement limits of $1,500 for colonoscopy, $2,000 for cataract replacement surgery, and $6,000 for arthroscopy. Using a reference price to cap insurer payments is the key mechanism for RBB insurance programs. As shown in Table 1, these reimbursement limits represent approximately the 80th percentile of ASC prices and the 35th percentile of HOPD prices. CalPERS enrollees who receive care at a HOPD priced at or under these thresholds are responsible for the standard cost-sharing, deductible payments, copayments, and coinsurance, but patients who receive care from HOPDs priced above the reference prices are responsible for the entirety of the difference in the facility price and the reference price, in addition to standard cost sharing. CalPERS enrollees receiving care at any ASC, regardless of the price, are only responsible for the standard cost-sharing. Nearly all ASCs prices are below the reference price and so this design makes the RBB program easier to understand for enrollees without substantially increasing costs. Additional exemptions from the RBB program are in place for enrollees without an ASC or HOPD under the reference price within 30 miles of their home zip code and enrollees with special care considerations.

3.3 Data and Methods

To model provider responses to RBB, we use colonoscopy, cataract surgery, knee arthroscopy, and shoulder arthroscopy medical claims data from two California populations that receive insurance coverage through an Anthem PPO. The first population consists of CalPERS enrollees, who are subject to RBB starting in 2012. For a control group, we use non-CalPERS Anthem PPO enrollees. With the exception of RBB, the insurance networks between the two populations are the same. Moreover, Anthem as a whole negotiates provider rates and so each population faces the same price at a given provider.

However, due to the nature of CalPERS, the two populations differ in their geographic distribution. The CalPERS population is highly clustered around the Sacramento region while the non-CalPERS Anthem population is more evenly distributed throughout the state. Table 2 shows the geographic distribution of the two populations by Hospital Referral Region (HRR). This geographic variation in the two populations is key to our identification strategy. The regions with a small share of CalPERS members collectively serve as a control group for the Northern California regions with a larger share. Due primarily to the geographic distribution, California HOPDs and ASCs vary substantially in their exposure to CalPERS RBB program. Providers in markets with a smaller share of CalPERS enrollees are relatively unaffected by the RBB program while providers for whom CalPERS enrollees constitute a large share of their patient population are more

affected.

To exploit the variation in provider exposure to the RBB program, for each provider and service, we compute the baseline share of procedures received by CalPERS and non-CalPERS enrollees in 2011, the year before CalPERS implemented RBB. We define $CalPERS_{jk}$ as the mean share of procedure k received by CalPERS enrollees by provider j in the pre-RBB period of 2009-2011. Our primary specifications use the distribution in each provider's baseline share of CalPERS patients as a source of exogenous variation but we also use the geographic distribution of CalPERS enrollment in each Hospital Service Area (HSA) as a sensitivity test. We also create $above_{jk}$ as a dummy variable indicating that the provider's baseline, 2011, average price is above the reference price for service k.

We then estimate a triple differences regression of

$$\begin{aligned} \ln(price_{ijtk}) &= \alpha + \beta_1 CalPERS_{jk} + \beta_2 post + \beta_3 above_{jk} + \\ &\quad \beta_4 CalPERS_{jk} \times post_t + \\ &\quad \beta_5 CalPERS_{jk} \times above_{jk} + \beta_6 post_t \times above_{jk} + \\ &\quad \beta_7 CalPERS_{jk} \times post_t \times above_{jk} + \Gamma_j + X_i + \varepsilon_{ijtk}. \end{aligned} \tag{3.1}$$

where $price_{ijtk}$ represents provider j's negotiated price with Anthem in year t for procedure k. The dummy $post_t$ indexes the post RBB period. We include provider fixed effects, $\Gamma_j$to control for unobserved time-invariant pricing practices. The provider fixed effects allow us to estimate the within-provider change in prices. To control for patient differences, X_i includes patient age, sex, Charlson comorbidity score, and patient HRR fixed effects. In this regression, providers with a low share of CalPERS patients at baseline serve as a control group for providers with a high share. The β_7 coefficient estimates the change in provider prices along the continuum of a provider's exposure to CalPERS for providers at risk of losing volume due to RBB compared to those not at risk.

We estimate this equation separately for HOPDs and ASCs. RBB only applies to HOPDs and so the first specification provides the effect of RBB while the ASC specification serves as a placebo test. We estimate each equation for all procedures combined and for each separate procedure. All regressions are estimated using OLS and with bootstrapped robust standard errors clustered at the provider level. Because they are not covered by RBB, the ASC providers can serve as an additional control group for the HOPDs. To incorporate ASCs as a control group for HOPDs, in our preferred specification, we estimate the quadruple differences equation of

$$\begin{aligned} \ln(price_{ijtk}) &= \alpha + \beta_1 CalPERS_{jk} + \beta_2 post_t + \beta_3 above_{jk} + \beta_4 HOPD_j + \\ &\quad \beta_5 CalPERS_{jk} \times post_t + \beta_6 CalPERS_{jk} \times above_{jk} + \beta_7 post_t \times above_{jk} + \\ &\quad \beta_8 CalPERS_{jk} \times HOPD_j + \beta_9 post_t \times HOPD_j + \beta_{10} above_{jk} \times HOPD_j + \\ &\quad \beta_{11} CalPERS_{jk} \times post_t \times above_{jk} + \beta_{12} post_t \times above_{jk} \times HOPD_j + \\ &\quad \beta_{13} CalPERS_{jk} \times post_t \times HOPD_j + \beta_{14} CalPERS_{jk} \times above_{jk} \times HOPD_j + \\ &\quad \beta_{15} CalPERS_{jk} \times post_t \times above_{jk} \times HOPD_j + \Gamma_j + X_i + \varepsilon_{ijjk} \end{aligned} \tag{3.2}$$

In this expression, the quadruple interaction term, β_{15} captures the effect of RBB among the providers targeted by RBB, expensive HOPDs in markets with a large share of CalPERS patients.

3.4 Results

Figure 2 shows graphical evidence that HOPDs with at least 10% exposure to CalPERS patients in 2011 lowered their prices relative to HOPDs with less than 10% exposure. The bivariate trends are most clear for colonoscopy and knee arthroscopy. There does not appear to be the same type of relationship for ASCs. Price trends are parallel for ASCs regardless of their exposure to CalPERS.

Table 3 presents the triple differences results that use both the provider's exposure to RBB and the provider's baseline price as sources of identifying variation. As shown in the first two columns, HOPDs above the reference price at baseline lowered their prices by 1% for every 10 percentage point increase in their exposure to CalPERS compared to the 1.3% increase for HOPDs above the reference price. The full triple differences coefficient in column 3 implies 1.9% effect for the treatment group of HOPDs above the reference price. This effect is driven largely by the 3.7% price reduction for colonoscopies. This finding is intuitive, as the expensive HOPDs have the largest to incentive to lower their prices or face decreased patient volume. As shown in Table 4, the same results for ASCs alone show a much smaller differential change in provider prices. ASCs above the reference price at baseline and lowered their prices by 1% but there was no change in prices for ASCs above the reference price at baseline.

Finally, when we also include ASCs as a control group in the quadruple differences regression, we find large decreases in HOPD provider prices. Column 1 of Table 5 implies RBB leads to a 0.9% reduction in prices for every 10 percentage point increase in the baseline share of CalPERS enrollees for HOPDs that are above the reference price at baseline. The results are much larger for colonoscopies and cataract replacement surgeries, 4.0% and 2.1%, respectively.

3.4.1 Heterogeneity in Effect

We next examine the distributional effects of two features that influence the magnitude of provider responses to RBB. First, we categorize $CalPERS_{jk}$ into increments of <5%, 5-9.9%, 10-19.9%, and >20% to show the distributional price changes based on CalPERS patient concentration. We similarly categorize the difference between the baseline price and the reference price into 4 categories: <-\$500, \$-500-\$0, \$0-\$500, and >\$500. For each categorization, we then estimate the respective analogues of specification 2. The interaction terms give the provider responses to RBB within each of the baseline CalPERS exposure and price categories. For both heterogeneity tests, we restrict the population to services received at an HOPD.

As shown in Table 6, we find a large change in prices due to the distribution of the share of CalPERS enrollees. For all procedures combined, we find no effect for providers with fewer than 10% CalPERS volume at baseline. For HOPDs with 10-20% CalPERS baseline volume, we find an 8.8% reduction in prices and a 15.3% reduction for providers with more than 20% CalPERS baseline volume. These results suggest a dose-response effect to the share of baseline CalPERS patients. Providers who are minimally impacted by the RBB program, those with only a small share of CalPERS patients, do not change their prices following the introduction of RBB. However, the degree of provider price reduction is increasing in the share of the provider's volume covered by RBB.

The differences based on baseline HOPD provider price also show heterogeneous provider responses to the RBB program (Table 7). HOPDs with baseline prices below the reference price at baseline actually raised their prices, most notably for colonoscopies. However, HOPDs with prices just above the reference price lowered their prices by 0.6% for every 10-percentage point increase in their exposure to CalPERS. Providers with baseline prices at least $500 above the reference price lowered prices even more, by 1.4% on average. This result suggests that providers with a large volume of CalPERS patients at baseline respond by either raising or lowering their prices towards the reference price. The increased effect for providers well above the reference price suggests that providers are most concerned about the RBB program's impact on quantity. Rather than trade off high prices for lower volume, the most expensive providers greatly reduced their prices.

3.5 Financial Savings

To illustrate the magnitude of these results, we use colonoscopies as a particular example. Of the 214 HOPDs that provide colonoscopy services, 163 had 2011 CalPERS volumes of at least 10%. Of these 163 HOPDs, 128 had baseline prices above the reference price. Thus, the primary regression results in Table 6 imply a 4% reduction in prices for 60% of the HOPDs in the data. The mean 2011 colonoscopy price for these HOPDs was $2,968 and so the coefficients imply a $119 reduction in prices. These facilities performed 14,039 colonoscopies for Anthem PPO-covered patients in 2012 and 2013 and so the estimated reduction in total medical spending due to this price decrease is $1.67 million. Of the 14,039 colonoscopies in the post-period, 1,723 (12.2%) were in the treatment group of CalPERS enrollees. As a result, 87.8% of the spending reduction, $1.46 million, was captured by the non-CalPERS Anthem population.

Similar calculations for cataract surgery show a $122 reduction in per-procedure prices, which translates to a $1.80 million reduction in total medical spending with $1.51 million captured by non-CalPERS patients. For knee arthroscopy, there is a $99 reduction in per-procedure prices, an $88,000 decrease in total medical spending, and a $77,000 reduction in non-CalPERS Anthem spending.

3.6 Discussion

In an effort to reduce healthcare costs, many employers and payers have moved towards innovative benefit designs. For "shoppable" services, insurance benefit designs such as RBB exploit the large variation in healthcare prices to incentivize receiving care from less expensive providers. While previous research has shown that the CalPERS RBB program does in fact lead patients to select less expensive providers, little evidence exists on how providers, in particular those at risk for losing volume, respond to RBB. This paper shows that expensive HOPD providers with substantial exposure to CalPERS lower their prices following the introduction of RBB. To highlight the importance of the provider responses to RBB, for cataract surgeries, the $1.8 reduction in medical expenditures attributable to RBB is $0.5 million more than the previously estimated $1.1 million reduction in spending due to consumers switching providers. The financial savings are relatively large because they apply to the much broader non-CalPERS Anthem population in addition to the CalPERS population. Including these broader savings are important when evaluating the impact of RBB and other insurance benefit programs. These results support the expansion of RBB as one means to reduce healthcare spending. Based on the increasing effect of exposure to RBB and the magnitude of the price reductions, if other California employers were to simultaneously implement similar RBB programs, the provider price reductions would increase. As the most expensive providers lower their prices, the extreme price variation found in Figure 1, which underlies the motivation behind RBB, may be reduced. At the same time, few payers have the purchasing power of CalPERS. As a result, RBB programs for individual employers will likely have less of an effect or no effect on provider pricing behaviors.

Bibliography

Beeuwkes Buntin, Melinda, Haviland, Amelia M., McDevitt, Roland, & Sood, Neeraj. 2011. Healthcare spending and preventive care in high-deductible and consumer-directed health plans. *The American Journal of Managed Care*, **17**(3), 222–230.

Brekke, Kurt R., Holmas, Tor Helge, & Straume, Odd Rune. 2011. Reference pricing, competition, and pharmaceutical expenditures: Theory and evidence from a natural experiment. *Journal of Public Economics*, **95**(7–8), 624–638.

Brot-Goldberg, Zarek, Handel, Benjamin, Chandra, Amitabh, & Kolstad, Jonathan. 2015. What Does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics. *Working Paper*.

Brown, Timoth, & Robinson, James. 2015. Reference Pricing with Endogenous or Exogenous Payment Limits: Impacts on Insurer and Consumer Spending. *Health Economics*. 00000.

Buntin, Melinda Beeuwkes, Damberg, Cheryl, Haviland, Amelia, Kapur, Kanika, Lurie, Nicole, McDevitt, Roland, & Marquis, M. Susan. 2006. Consumer-Directed Health Care: Early Evidence About Effects On Cost And Quality. *Health Affairs*, **25**(6), w516–w530.

Haviland, Amelia M., Eisenberg, Matthew D., Mehrotra, Ateev, Huckfeldt, Peter J., & Sood, Neeraj. 2015 (Mar.). *Do "Consumer-Directed" Health Plans Bend the Cost Curve Over Time?* Working Paper 21031. National Bureau of Economic Research.

Parente, Stephen T., Feldman, Roger, & Christianson, Jon B. 2004. Evaluation of the Effect of a Consumer-Driven Health Plan on Medical Care Expenditures and Utilization. *Health Services Research*, **39**(4p2), 1189–1210.

Sood, Neeraj, Wagner, Zachary, Huckfeldt, Peter, & Haviland, Amelia M. 2013. Price Shopping in Consumer-Directed Health Plans. *Forum for Health Economics and Policy*, **16**(1).

Whaley, Christopher. 2015. Provider Responses to Online Price Transparency. *Working Paper*.

Wu, Sze-jung, Sylwestrzak, Gosia, Shah, Christiane, & DeVries, Andrea. 2014. Price Transparency For MRIs Increased Use Of Less Costly Providers And Triggered Provider Competition. *Health Affairs*, **33**(8), 1391–1398.

3.7 Figures and Tables

Figure 3.1: Distribution of Provider Prices

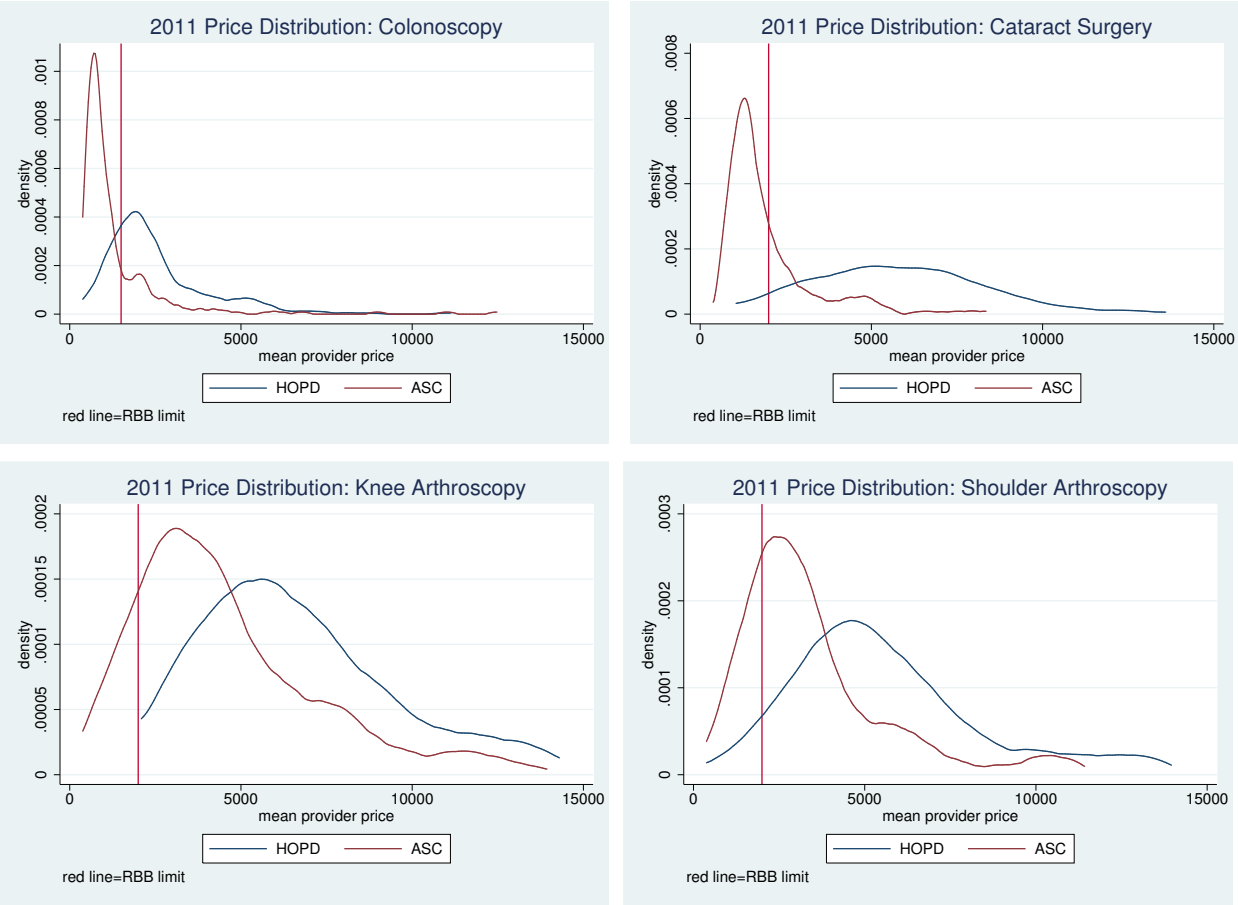


Figure 3.2: Provider Price Trends

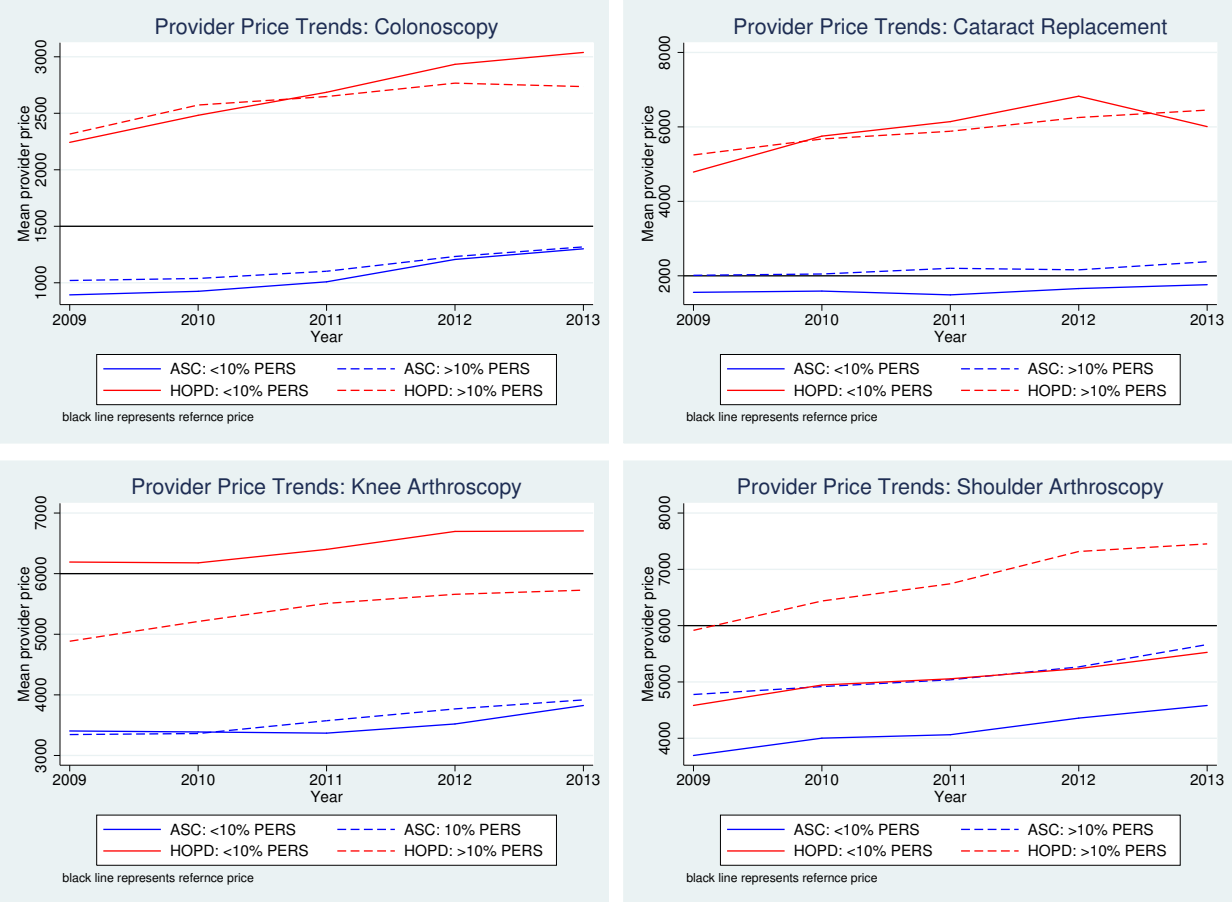


Table 3.1: Summary Statistics

Procedure	Colonoscopy		Cataract replacement		Knee arthroscopy		Shoulder arthroscopy	
Facility	HOPD	ASC	HOPD	ASC	HOPD	ASC	HOPD	ASC
Number of procedures (all years)	75,807	207,450	4,967	15,603	12,426	26,407	5,198	9,211
Percent CalPERS (provider)	16.6%	12.9%	35.8%	28.0%	30.1%	21.6%	32.2%	30.0%
Percent CalPERS (HRR)	11.9%	11.9%	13.4%	15.1%	10.1%	9.9%	10.5%	11.2%
Mean procedure price	$2,630	$1,041	$5,981	$1,983	$5,758	$3,560	$6,166	$4,789
Percentile of reference price	19	85	8	72	70	88	59	76

Table 3.2: Concentration of CalPERS Enrollees by Hospital Referral Region

HRR	colonoscopy	cataract replacement	knee arthropscopy	shoulder arthroscopy
Alameda County	10.6%	5.3%	6.1%	5.7%
Bakersfield	7.2%	8.3%	6.3%	6.1%
Chico	18.4%	23.0%	12.5%	0.0%
Contra Costa County	9.2%	10.3%	11.6%	14.6%
Fresno	9.3%	11.9%	8.8%	4.8%
Los Angeles	9.8%	10.4%	9.0%	8.2%
Modesto	13.8%	11.6%	10.6%	9.2%
Napa	18.7%	26.4%	15.3%	10.7%
Orange County	10.5%	12.5%	8.7%	8.2%
Palm Springs	13.1%	18.4%	11.5%	20.6%
Redding	34.7%	39.2%	29.5%	24.5%
Sacramento	26.7%	32.7%	22.5%	22.7%
Salinas	34.4%	35.7%	38.5%	27.5%
San Bernardino	15.4%	18.8%	14.6%	14.6%
San Diego	7.4%	9.7%	6.4%	6.6%
San Francisco	7.6%	9.3%	6.4%	7.2%
San Jose	8.6%	10.7%	11.0%	10.0%
San Luis Obispo	23.8%	31.0%	18.2%	18.6%
San Mateo County	8.6%	8.1%	7.3%	5.3%
Santa Barbara	3.6%	0.0%	3.8%	4.0%
Santa Cruz	11.3%	17.4%	12.0%	11.7%
Santa Rosa	9.4%	5.1%	11.3%	13.4%
Stockton	12.5%	13.3%	10.8%	3.8%
Ventura	9.7%	9.9%	7.7%	6.3%

Table 3.3: Provider Responses to RBB

	(1) all procedures	(2) colonoscopy	(3) cataract	(4) knee arthroscopy	(5) shoulder arthroscopy
$post_t$	0.0870***	0.100***	0.0333***	0.119***	0.102***
	(0.00330)	(0.00363)	(0.0111)	(0.0115)	(0.0225)
$CalPERS_{jk}$	-0.181***				
	(0.0154)				
$CalPERS_{jk}$Œ$post_t$	-0.00343	-0.105***	-0.00167	0.0828**	0.122*
	(0.0149)	(0.0234)	(0.0297)	(0.0324)	(0.0635)
$post_t \times HOPD_j$	-0.0486***	-0.113***	-0.0997***	-0.0241*	-0.0475**
	(0.00644)	(0.00715)	(0.0142)	(0.0126)	(0.0204)
$HOPD_j \times CalPERS_{jk}$	0.192***				
	(0.0196)				
$post_t \times HOPD_j \times CalPERS_{jk}$	0.112***	0.389***	0.163*	-0.0151	-0.0840
	(0.0228)	(0.0319)	(0.0925)	(0.0336)	(0.0673)
$above_{jk}$	0.134***				
	(0.0128)				
$post_t \times above_{jk}$	0.0595***	0.0730***	-0.0252*	-0.195***	-0.0898**
	(0.0110)	(0.0133)	(0.0131)	(0.0207)	(0.0356)
$above_{jk} \times CalPERS_{jk}$	0.0548*				
	(0.0287)				
$post_t \times above_{jk} \times CalPERS_{jk}$	-0.111***	0.0581	0.0715*	-0.00822	-0.158
	(0.0395)	(0.0607)	(0.0418)	(0.0539)	(0.129)
$HOPD_j \times above_{jk}$	0.00242				
	(0.0117)				
$post_t \times HOPD_j \times above_{jk}$	0.0260**	0.0859***	0.169***	0.157***	0.122***
	(0.0122)	(0.0138)	(0.0177)	(0.0220)	(0.0423)
$HOPD_j \times above_{jk} \times CalPERS_{jk}$	0.0667**				
	(0.0301)				
$post_t \times HOPD_j \times above_{jk} \times CalPERS_{jk}$	-0.0941**	-0.515***	-0.239**	-0.125*	0.0783
	(0.0421)	(0.0551)	(0.100)	(0.0674)	(0.128)
Observations	357,066	283,256	20,570	38,831	14,409
R-squared	0.292	0.048	0.037	0.042	0.050
Number of providers	670	480	233	343	227

This table presents the quadruple differences results from equation 3. The dependent variable is the log-transformed procedure price. Column 1 includes procedure fixed effects and all columns include demographic controls (age, Charlson comorbidity score, gender, patient HRR fixed effects), year fixed effects, and provider fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: HOPD Responses to RBB

	(1) all procedures above RP	(2) all procedures below RP	(3) all procedures	(4) colonoscopy	(5) cataract	(6) knee arthroscopy	(7) shoulder arthroscopy
$post_t$	0.129***	0.0291***	0.0419***	-0.0170**	-0.0911***	0.0689***	0.0921***
	(0.00302)	(0.00740)	(0.00466)	(0.00794)	(0.0283)	(0.00719)	(0.0114)
$CalPERS_{jk}$	0.120***	-0.0215*	-0.000124				
	(0.0100)	(0.0119)	(0.01000)				
$CalPERS_{jk}$Œ$post_t$	-0.103***	0.118***	0.102***	0.277***	0.151	0.0671***	0.0360*
	(0.0106)	(0.0170)	(0.0141)	(0.0269)	(0.306)	(0.0153)	(0.0207)
$above_{jk}$			0.135***				
			(0.00706)				
$post_t \times above_{jk}$			0.0861***	0.158***	0.136***	-0.0345***	0.0330*
			(0.00481)	(0.00663)	(0.0257)	(0.0127)	(0.0169)
$above_{jk} \times CalPERS_{jk}$			0.112***				
			(0.0143)				
$post_t \times above_{jk} \times CalPERS_{jk}$			-0.207***	-0.454***	-0.155	-0.137***	-0.0751**
			(0.0186)	(0.0276)	(0.303)	(0.0269)	(0.0370)
Observations	72,784	25,614	98,398	75,807	4,967	12,426	5,198
R-squared	0.576	0.454	0.649	0.135	0.177	0.130	0.147
Number of providers	195	136	237	214	94	157	105

This table presents the triple differences results from equation 2 and restricts the population to HOPDs. The dependent variable is the log-transformed procedure price. Columns 1 and 2 include procedure fixed effects and all columns include demographic controls (age, Charlson comorbidity score, gender, patient HRR fixed effects), year fixed effects, and provider fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: ASC Responses to RBB

	(1) all procedures above RP	(2) all procedures below RP	(3) all procedures	(4) colonoscopy	(5) cataract	(6) knee arthroscopy	(7) shoulder arthroscopy
$post_t$	0.136***	0.132***	0.0951***	0.110***	0.106***	0.118***	0.133***
	(0.00988)	(0.00290)	(0.00312)	(0.00293)	(0.0136)	(0.0153)	(0.0200)
$CalPERS_{jk}$	-0.0588**	-0.0882***	-0.176***				
	(0.0273)	(0.0191)	(0.0226)				
$CalPERS_{jk}$Œ$post_t$	-0.109***	0.00954	-0.00114	-0.105***	0.000459	0.0845***	0.121**
	(0.0336)	(0.0156)	(0.0156)	(0.0209)	(0.0280)	(0.0295)	(0.0541)
$above_{jk}$			0.117***				
			(0.0158)				
$post_t \times above_{jk}$			0.0564***	0.0700***	-0.0229*	-0.194***	-0.0908***
			(0.00967)	(0.0133)	(0.0129)	(0.0304)	(0.0254)
$above_{jk} \times CalPERS_{jk}$			0.113***				
			(0.0258)				
$post_t \times above_{jk} \times CalPERS_{jk}$			-0.0999***	0.0654	0.0674	-0.0127	-0.157
			(0.0356)	(0.0729)	(0.0508)	(0.0850)	(0.122)
Observations	42,830	215,838	258,668	207,449	15,603	26,405	9,211
R-squared	0.238	0.145	0.179	0.037	0.027	0.037	0.046
Number of providers	100	381	433	266	139	186	122

This table presents the triple differences results from equation 2 and restricts the population to ASCs. The dependent variable is the log-transformed procedure price. Columns 1 and 2 include procedure fixed effects and all columns include demographic controls (age, Charlson comorbidity score, gender, patient HRR fixed effects), year fixed effects, and provider fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6: Heterogeneity: CalPERS share

	(1) all procedures	(2) colonoscopy	(3) cataract	(4) knee arthroscopy	(5) shoulder arthroscopy
$post_t \times above_{jx} \times$ 5-10%$CalPERS_{jk}$	0.00468	0.00259	0.206**	0.197***	
	(0.0122)	(0.0201)	(0.104)	(0.0425)	
$post_t \times above_{jx} \times$ 10-20% $CalPERS_{jk}$	-0.0925***	-0.153***	0.0550	0.118***	-0.148***
	(0.0136)	(0.0169)	(0.0952)	(0.0438)	(0.0451)
$post_t \times above_{jx} \times$ >20% $CalPERS_{jk}$	-0.166***	-0.219***		0.0632	-0.151***
	(0.0152)	(0.0167)		(0.0476)	(0.0455)
Observations	98,398	75,807	4,967	12,426	5,198
R-squared	0.650	0.137	0.183	0.133	0.151
Number of providers	237	214	94	157	105

This table presents the triple differences results from equation 2 and restricts the population to HOPDs. This specification categorizes $CalPERS_{jk}$ into <5% (reference group), 5-10%, 10-20%, and >20% categories. The dependent variable is the log-transformed procedure price. Column 1 includes procedure fixed effects and all columns include demographic controls (age, Charlson comorbidity score, gender, patient HRR fixed effects), year fixed effects, and provider fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.7: Heterogeneity: Baseline Price

	(1) all procedures	(2) colonoscopy	(3) cataract	(4) knee arthroscopy	(5) shoulder arthroscopy
$post_t \times CalPERS_{jk} \times above_{jk} - \$500 - \$0$	0.248***	0.531***		0.0384	0.0419
	(0.0329)	(0.0938)		(0.0509)	(0.0793)
$post_t \times CalPERS_{jk} \times above_{jk}$ \$0-\$500	-0.0645**	-0.0894*	-1.210*	-0.273*	-0.0550
	(0.0310)	(0.0496)	(0.682)	(0.159)	(0.0499)
$post_t \times CalPERS_{jk} \times above_{jk} > \$500$	-0.147***	-0.303***	-1.192*	-0.113***	-0.0350
	(0.0209)	(0.0426)	(0.642)	(0.0383)	(0.0498)
Observations	98,398	75,807	4,967	12,426	5,198
R-squared	0.656	0.139	0.178	0.132	0.150
Number of providers	237	214	94	157	105

This table presents the triple differences results from equation 2 and restricts the population to HOPDs. This specification categorizes $above_{jk}$ into categories of less than \$500 under the reference price (reference group), \$500-\$0 below the reference price, 0-\$500 above the reference price, and greater than \$500 above the reference price. The dependent variable is the log-transformed procedure price. Column 1 includes procedure fixed effects and all columns include demographic controls (age, Charlson comorbidity score, gender, patient HRR fixed effects), year fixed effects, and provider fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.