Eye-opening products: Uncertainty and surprise in cataract surgery outcomes*

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Abstract

For experience goods, benefits from consumption are ex-ante unknown but revealed after repeated interactions. This uncertainty might lead to under-consumption. We use data from a large cataract surgery provider in Mexico City to estimate demand, given uncertainty in surgical outcomes. We consider forward-looking consumers with a surgery demand per eye and information revealed after the first surgery. We exploit data from sales agents to identify structural demand parameters; namely, price elasticities and the value of the uncertain shock. We simulate counterfactual policies, showing that budget-neutral price changes are more effective at increasing welfare than persuasive advertising.

Keywords: uncertainty; experience goods; treatment choices; cataract surgery.
JEL: I11, L15, D83, C73.

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1 Introduction

For many products, often called experience goods, consumers are unable to ex-ante evaluate their characteristics, such as quality (Nelson, 1970). Thus, the benefits from their consumption are revealed ex-post, and although consumers may form a prior, information or quality shocks are only revealed with consumption. This is often the case with durable goods, such as electric vehicles, refrigerators, or housing. In many of these instances, the ex-ante uncertainty is particularly salient because individuals or households only tend to consume one of these products at a time, and often consider purchases to be long-lasting.

These features are particularly relevant for healthcare treatments. First, patients face uncertainty about their own benefits from taking a prescription drug or undergoing an elective procedure. Second, in many cases, negative health shocks and their subsequent treatment choices are often a one-time event (e.g., elective surgeries like hernia repair, bariatric surgery or tonsillectomy). Hence, uncertainty may lead to lower take-up than in a world with perfect information, particularly because the information will not be revealed through repeated interactions.

However, there are some healthcare goods for which there are (potentially) repeated interactions, such as antidepressants, joint replacement surgery or angioplasty. In such a setup, the patient's decision for initial take-up may consider not only the inherent uncertainty, but the fact that information about the idiosyncratic benefits of treatment will be revealed before having to make subsequent choices. Hence, treatment take-up may be higher or lower depending on the degree of uncertainty and the option value of the first interaction. Potential uncertainty about the number of repeated interactions may also factor into decision-making.[1]

This paper focuses on the case of cataract surgeries, which is an important experience good market, because forgoing treatment implies a lower quality of life or, even potentially, worse health outcomes (Keel et al., 2021; Ehrlich et al., 2021). We estimate a structural model of demand for cataract surgeries, exploiting patient-level data from a large provider in Mexico City. We explicitly incorporate the fact that undertaking surgery for the first eye reveals idiosyncratic information about the benefits from surgery, allowing forward-looking patients

[1] For example, patients with vascular disease may have varying numbers of affected arteries at varying degrees of deterioration, which may or may not worsen with age. Therefore, patients might need anywhere from one to many angioplasties in a relatively short time span to manage this condition.

to have full information before having to decide on getting surgery on their second eye. We recover estimates of patients' price elasticity for each surgery (first vs second) as well as individual-specific uncertainty parameters. We then use our estimates to evaluate counterfactuals that consider policies proposed in the medical literature as a means for increasing take-up of cataract surgeries.

Cataracts occur when the eye's natural (and normally clear) lens becomes cloudy, due to a breakdown of its proteins. This leads to vision problems, ranging from blurry eyesight to complete loss of vision. Age is the leading risk factor, although co-morbidities and risky behaviors (such as smoking) may also increase their likelihood (Miller et al., 2022). The majority of patients develop cataracts in both eyes, although there may be differences in severity. Surgery to replace the clouded lens with an artificial intra-ocular lens is the only available treatment. Physicians tend to recommend surgery on both eyes, but perform the surgeries in a sequential manner to minimize complications and inconveniences during post-operative care. While cataracts are a common condition, a majority of patients—particularly, in low- and middle-income countries—do not undergo treatment (Lansingh et al., 2010; Congdon and Thomas, 2014). Some commonly identified barriers to treatment in the medical literature include prices, access, and fear (Lewallen and Courtright, 2000; Syed et al., 2013).

Cataract surgeries are an ideal setting for studying how uncertainty and revealed information affect initial and consequent product take-up of experience goods with repeated interactions. First, as mentioned above, most patients develop cataracts in both eyes, meaning that the number of potential repeated interactions is ex-ante known to the patient. Second, it is very uncommon for patients to undergo surgery in both eyes simultaneously (in our data, there are zero patients with same-day operations). Lastly, in our setting, patients are not given the option of scheduling surgery for both eyes; instead, they must schedule and pay for each surgery sequentially, guaranteeing that the first surgery's benefits are fully realized before the patient must decide on the second surgery. Taken together, these features allow us to effectively model this decision-making process as a sequential game in two stages, with information fully revealed before the second stage (conditional on having chosen the surgery in the first stage).

We focus on patients at a low-cost private provider in Mexico City specializing in cataract surgery. We obtain patient-level records that allow us to observe cataract diagnoses, subsequent price quotes, and whether the patient purchases a particular surgical product. Our data contain all patients whose first contact with this provider occurred during 2018, and whom we observe over multiple visits to the clinics during 2018 and 2019. Aside from the features outlined above, we leverage the fact that prices are not homogeneous across patients. After the diagnosis, patients are assigned to a sales agent based on availability, who then proposes a price quote from a menu of options.

We present a model in which a patient must choose—sequentially—whether or not to get surgery in each eye, conditional on her current information set. From her point of view, there is an uncertain component in the outcome of the first operation, which is fully revealed after the first surgery, conditional on making that choice. Then, all information is known to the patient before having to decide on the second surgery. This setup implies that there is an option value from the first surgery, due to the uncertainty parameter that is revealed. In our estimation, we deal with endogenous prices with a control function that uses daily sales targets as an instrument, and we identify the magnitude of the uncertainty shocks from discrepancies in estimated coefficients between the first and second surgery. We deal with potential selection into going back after the first surgery by simulating announced prices for the second surgery for patients who did not come back for a quote. Throughout we allow for diminishing returns for the second surgery, and control for patients' health and demographic characteristics.

Our estimates show that demand elasticities for the first operation are larger in absolute value than those for the second surgery. We also find that heterogeneity matters for our estimation of the uncertainty parameters, and we obtain a distribution of estimated values, suggesting an important role in this decision-making process for the option value of the first surgery. We also back out a money metric of consumer surplus indicating quite a bit of variation across patients.

With our estimated parameters, we proceed to simulate counterfactual policies that may increase take-up of cataract surgeries. First, we consider interventions related to the uncertainty parameter in the form of persuasive advertising. Experimental studies that attempt to fully eliminate uncertainty have found mixed results (Liu et al., 2012), while awareness campaigns in which a "champion" (i.e., someone with a positive result) informs about potential outcomes have been more favorable (Mailu et al., 2020). In our exercise, we consider that the champion reveals a particular value for the uncertainty parameter in an attempt to persuade patients about potential outcomes. Our simulations show that this intervention may be welfare-improving, as long as the size of the revealed information shock is large enough (i.e., the champion must reveal a sizable shock and consumers must believe her). However, for small values (including removing uncertainty altogether), consumer surplus declines. These results suggest that the uncertainty shocks are actually valuable for patients, and that welfare improvements are possible through persuasion only if it leads to very positive beliefs.

Our second set of counterfactual exercises consider revenue-neutral price changes, subsidizing the price of the first surgery but taxing the price of the second, all while leaving the firm indifferent. Across a range of symmetric and asymmetric price changes, we consistently find large welfare gains: consumer surplus increases, because lowering the price of the first surgery leads both to an increase in the first and second surgeries (recall that patients are more inelastic on the second surgery and that, trivially, second surgery demand is increasing in the first surgery demand). We also find that for large enough percentage changes in the price, our counterfactual is better than budget-neutral: albeit slightly, revenues for the firm also increase.

Overall, our counterfactual exercises suggest that persuasive advertising that reduces uncertainty will not be as effective, unless the firm is able to convince potential patients that their outcome will be very positive. Instead, implementing revenue-neutral price changes will allow for a larger take-up of surgeries for both the first and second eyes. By explicitly considering the dynamic link and the option value due to uncertainty that is revealed, we show how—at least in this setting—welfare-improving price changes can be implemented due to the size and heterogeneity of the uncertainty.

Our paper speaks to various strands of literature. First, we add to a long-standing literature in industrial organization analyzing dynamics in experience goods markets (Bergemann and Välimäki, 2006; Gowrisankaran and Rysman, 2012; Jing, 2011; Yu, Debo and Kapuscinski, 2016). However, unlike many of these settings, ours is one with a limited and small number of repeated interactions, which may limit firms' capacity to adapt and customers to react to these dynamics. This feature may be relevant in other settings as well, such as durable goods markets.

Related work on the role that uncertainty plays in demand has also focused on how providing additional external information—for instance, in the form of expert advise or customer reviews—might affect product demand. Studies in this area have analyzed, among others, negative book reviews (Berger, Sorensen and Rasmussen, 2010), movie critics (Reinstein and Snyder, 2005), and expert opinion labels for wine (Hilger, Rafert and Villas-Boas, 2011). Moreover, a related literature has further explored the effects of free trials before purchasing on consumption decisions (Foubert and Gijsbrechts, 2016; Sunada, 2020).

Second, our paper is related to the health economics literature attempting to understand dynamic treatment choices under uncertainty. In particular, it has been shown that in low- and middle-income countries, demand for pharmaceutical treatments is inelastic while demand for diagnoses is more elastic (Dupas and Miguel, 2017). Our results echo this finding: once patients are aware of the benefits, they respond more inelastically. Our findings on the importance of the learning effect is also consistent with evidence on the adoption of health products in these developing country settings (Dupas, 2014; Oster and Thornton, 2012).

Other work in this area has focused on search and learning costs for pharmaceutical products, for instance, in the context of generic prescription drugs (Ching, 2010), anti-ulcer drugs (Crawford and Shum, 2005), antidepressants (Dickstein, 2021), and flu shots (Maurer and Harris, 2016). Our paper adds to this literature by identifying the option value of the first round of consumption in a context where the number of repeated interactions is fixed. Indeed, in a setup with only two interactions, it is not obvious that subsidizing initial take-up is an efficient use of resources, although here, with this level of uncertainty, it actually improves welfare.

Lastly, we contribute to the (mostly) medical literature exploring why take-up rates of cataract surgeries are low. Although cataracts are an important cause of blindness in advanced age worldwide, many patients do not undergo surgery. Experimental studies have shown that prices are an important barrier (Zhang et al., 2013), but there is little consensus on the impact of other factors such as information, uncertainty, and peer effects, among others (Mailu et al., 2020; Adhvaryu et al., 2020). Our paper innovates on these experiments by focusing on the dynamic problem inherent to cataract surgeries and the fact that previously unknown information is revealed after the first surgery. Furthermore, our counterfactual exercises show important ways in which take-up may be increased across settings.

2 Context

The healthcare system in Mexico is a mix between private and public providers (OECD, 2016). The government supplies healthcare coverage to individuals through its own network of providers. This public system is mostly free of charge, but is plagued by long waiting times and heterogenous quality. Alternatively, patients may visit private providers. However, low insurance rates imply that most private services are paid for out-of-pocket. Traditionally, large segments of the population do not have access to private care given their high prices and the lack of health insurance.

Cataracts are a condition where the lens of the eye becomes clouded, leading to important declines in eyesight. Age is the biggest risk factor. According to the National Eye Institute, around 45% of Americans ages 75-79 are affected, as well as over 60% of those ages 80 and over.[2] Other important risk factors include obesity, high blood pressure, and diabetes. While early symptoms may improve with glasses, advanced cataracts require surgery to replace the lens with an artificial one. The main product characteristic of these surgeries is the method used, which is either phacoemulsification or small incision surgery.[3] Surgery products are also differentiated by the type of artificial lens introduced in the eye.

Estimates suggest that 30-40% of individuals in Mexico have cataracts, with 350,000 new cases per year.[4] With diabetes cases on the rise, cataract rates in non-elderly populations are increasing as well.[5] Although cataract surgery is covered by the public healthcare system, long waiting times hamper timely access to treatment.[6] Furthermore, clinical guidelines in the public sector only allow cataract surgery once the patient's eyesight is severely deteriorated, at a much higher threshold of vision loss than the standard of care in developed nations, like the US.[7] In the private market, recommendations for surgery follow

[2]See `nei.nih.gov`, last accessed Sep. 1, 2020. In this paper, urls are truncated, but their hyperlinks are not.

[3]Most surgeries nowadays use phacoemulsification, whereby the eye's internal lens is emulsified and vacuumed out of the eye. Alternatively, the doctor may make a series of small incisions to remove the lens. An artificial lens, made of various materials, is then placed in the eye.

[4]See `excelsior.com.mx`, last accessed Sep. 2, 2020.

[5]Recent estimates from public providers suggest that 15 to 20% of young adults are affected by cataracts in Mexico. See `imss.gob.mx`, last accessed Jan. 11, 2021.

[6]According to information from our partner firm, patients in the public system wait ten months on average for cataract surgery after diagnosis.

[7]Clinical guidelines from the largest public provider in Mexico (IMSS) state that surgery is required once a patient "has difficulty performing daily activities such as recognizing familiar faces, has

international standards, but surgical treatment costs on average between 1,300 and 1,500 USD per eye, equivalent to 64-77% of the median monthly household income in the Mexico City metropolitan area (ENIGH 2018).[8]

Our partner firm is a large private provider of ocular healthcare based in the Mexico City metropolitan area that opened to the public in 2011. The firm provides various eye care servicies such as regular check-ups, eye exams, lab analyses, surgery, and an optical store. Eye care clinics are spread out over 20 locations, with a main clinic in downtown Mexico City, where a majority of surgical interventions are carried out. The firm specializes in diagnosing and operating cataracts, with a target population made up of mostly lower-income patients.

Patients at our partner firm are diagnosed with cataracts by ophthalmologists based on eye exams and lab analyses, some of which are conducted by optometrists.[9] Each eye is assigned a cataract score ranging from zero (no cataracts) to six (severe cataracts). Surgery is generally recommended for patients with a score of three or higher, signifying blurry eyesight. Once a patient has been diagnosed by the physician and surgery has been chosen as the recommended treatment, patients are referred to a sales agent at the clinic. Agents are assigned based on availability, although it is likely that a returning patient is assigned the same agent as before. The sales agent then generates a price quote for the patient based on various factors, such as patient and surgery characteristics, available discounts, and a certain degree of discretion.[10] If the patient chooses to go forward with the surgery, payment plans are discussed and a date is set.[11] Impor-

reduced mobility, and/or is unable to work and live independently". These guidelines also recognize that this standard is very different from others, such as the UK's NHS (which considers surgery once the patient's vision is blurry or opaque), and that the private market in Mexico may fill this void for patients whose eyesight is not as deteriorated, conditional on their payment capabilities. See imss.gob.mx, last accessed Jan. 11, 2021.

[8]These quotes are based on posted prices on websites of the most common eye care clinics in Mexico City. Since surgeries are paid mostly out-of-pocket, we were unable to find any systematic statistics on the price of cataract surgeries. However, conversations with our partner firm suggest that these estimates are correct.

[9]For clarity, throughout the paper we use the term "physician" or "doctor" to refer to the ophthalmologist. The diagnosing physician may or may not coincide with the doctor performing the surgery.

[10]Sales agents may offer discounts based on a menu of options that changes over time. However, agents' commission is based on the sale price, creating an incentive to avoid using the discounts if possible. Ophthalmologists do not have discretion over prices. At most, they may make a note on whether the patient is ineligible for certain options or characteristics of the surgery.

[11]Patients may be required to make a small down payment in order to schedule the surgery. The firm may also provide interest-free credit by allowing patients to pay over various installments, although the full cost must be covered by the day of the surgery.

tantly, surgeries are sold as a single-eye product, requiring patients to schedule each surgery independently. Price quotes also correspond only to surgery on one eye, and patients only schedule and pay for surgeries consecutively. On average, patients who undergo both surgeries do so within three months of each other.

3 Data

We obtained anonymized patient-level data directly from our partner firm spanning all patient visits from 2018 and 2019. We restrict our attention to new patients in 2018, allowing us to observe repeated interactions with the firm over a span of at least one year. The data contain some observable patient characteristics (namely, age, gender, health insurance status, and zip code) as well as details from all patient visits. For each visit, we observe the service provided by our partner firm, any diagnoses made, and all price quotes generated by sales agents for different services. Physician and sales agent identifiers are included throughout. This effectively allows us to observe what patients are doing at the firm in each visit and which products were offered to them, at what price, and whether a purchase was made. Observations are therefore at the patient-visit-product level, regardless of whether the product was actually bought.

We focus our attention on patient-visit-product observations related to cataract diagnoses and surgery products with non-missing or duplicated information. We exclude a small number of patients that had three cataract surgeries over this period, cataract surgeries that were not catalogued as either phacoemulsification or small incision surgery, and pro-bono surgeries for which patients were not billed. Overall, we are left with a sample of 4,077 patients and a total of 4,911 patient-quote observations. Table 1 shows summary statistics of ocular health measures for patients in our sample and those not included. As expected, eyesight measures—particularly, those related to cataracts—are worse among patients in our sample. These patients are also older, less likely to be privately insured, more likely to have access to public healthcare, and more likely to lack access to any type of healthcare. Table 2 breaks down the sample by whether the quote corresponds to the first or second surgery, as well as by total number of surgeries observed for the patient during the sample period.

In our data, cataracts in each eye are measured by ophthalmologists on a zero to six scale, where zero denotes no cataracts and six is the highest level of cataract risk. If cataracts were not reevaluated on a particular visit, we assign the

TABLE 1: Patient summary statistics

	Cataract patients	Non-cataract patients	Difference
Has a surgery	0.807	0	-
	(.395)	(0)	
Age	69.194	45.215	-23.979***
	(12.257)	(19.836)	(0.318)
Female	0.608	0.606	-0.002
	(0.488)	(0.489)	(0.008)
Has private insurance	0.073	0.174	0.101***
	(0.260)	(0.379)	(0.006)
Has access to public healthcare	0.216	0.165	-0.051***
	(0.412)	(0.371)	(0.006)
Lacks access to any healthcare	0.720	0.684	-0.036***
	(0.449)	(0.465)	(0.008)
RE cataract score	2.669	0.329	-2.340***
	(1.605)	(0.895)	(0.015)
LE cataract score	2.628	0.332	-2.297***
	(1.612)	(0.901)	(0.016)
RE max. cataract score	3.048	0.395	-2.653***
	(1.585)	(0.987)	(0.017)
LE max. cataract score	3.008	0.397	-2.611***
	(1.593)	(0.996)	(0.017)
RE far visual acuity	254.731	106.094	-148.637***
	(710.901)	(382.128)	(7.742)
LE far visual acuity	250.026	105.552	-144.474***
	(808.543)	(392.828)	(7.946)
RE near visual acuity	0.416	0.433	0.018
	(0.761)	(0.680)	(0.011)
LE near visual acuity	0.418	0.432	0.014
	(0.763)	(0.680)	(0.011)
RE amblyopia	0.034	0.010	-0.024***
	(0.182)	(0.099)	(0.002)
LE amblyopia	0.031	0.010	-0.021***
	(0.173)	(0.098)	(0.002)
RE anisometropia	0.012	0.002	-0.009***
	(0.107)	(0.048)	(0.001)
LE anisometropia	0.011	0.002	-0.009***
	(0.104)	(0.049)	(0.001)
RE astigmatism	0.617	0.516	-0.101***
	(0.486)	(0.500)	(0.008)
LE astigmatism	0.609	0.516	-0.093***
	(0.488)	(0.500)	(0.008)
RE myopia	0.382	0.311	-0.072***
	(0.486)	(0.463)	(0.008)
LE myopia	0.370	0.308	-0.062***
	(0.483)	(0.462)	(0.007)
RE presbyopia	0.345	0.196	-0.148***
	(0.475)	(0.397)	(0.007)
LE presbyopia	0.339	0.196	-0.143***
	(0.473)	(0.397)	(0.007)
RE hypermetropia	0.229	0.180	-0.049***
	(0.420)	(0.384)	(0.006)
LE hypermetropia	0.249	0.180	-0.069***
	(0.432)	(0.384)	(0.006)
RE emmetropia	0.007	0.022	0.015***
	(0.084)	(0.146)	(0.002)
LE emmetropia	0.006	0.022	0.016***
	(0.077)	(0.145)	(0.002)
Observations	4,077	60,121	64,198

Notes: This table shows patient characteristics for those within our sample (having at least one cataract-related visit) and those not in our sample. Means shown with standard errors in parentheses. Stars in the last column report a difference in means test. RE and LE denote "right eye" and "left eye". The cataract score is based on a 0-6 classification. The maximum score is the largest value observed during the study period. In some patients with severe problems, visual acuity may not be measurable under the standard methods. In those cases, alternative methods (not reported) are used. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 2: Price quotes by number of surgery and patient outcomes

	Number of surgery 1st	2nd	Total
Patients with zero surgeries	1,480	-	1,480
Patients with one surgery	1,981	93	2,074
Patients with two surgeries	679	678	1,357
Total	4,140	771	4,911

Notes: This table shows number of observations by whether the quote corresponds to the first or second surgery, and by type of patient based on the number of surgeries eventually purchased in the sample period.

cataract score from the patient's previous visit. For each price quote, we observe whether the surgery method is phacoemulsification or small incision cataract surgery. Phacoemulsification is more expensive and also more common (67% of surgery quotes in our sample). However, patient outcomes and complication rates are similar across both methods (Gogate et al., 2005; Riaz, de Silva and Evans, 2013). We also observe another quality-related characteristic referring to the type of lens.[12] The firm also offers a three-tier service based on additional services (e.g., lab work) and amenities provided.[13] Lastly, we observe whether the patient bought the surgery offered by the sales agent in the price quote. We assume that all patients that are candidates for a cataract surgery receive at least a first price quote from the sales agent.

Table 3 shows summary statistics at the patient-quote level. The first panel distinguishes between phacoemulsification and small incision quotes. As noted above, phacoemulsification is about 70% more expensive than small incision. It is also associated with slightly less severe cataract scores, younger patients, and more likely to be privately insured (which in turn may signal a higher socioeconomic status). The remaining panels in Table 3 further break down statistics by type of lens and amenities for each surgery.

4 Model

As an overview, we model a forward-looking consumer who has to decide whether to undergo surgery in each of her eyes, conditional on her current

[12]Our partner firm has three main lens products (Aurofold, Aurolab, Aurovue) as well as a standard option. Patients with small incision surgeries are only fitted with the standard lens, while all four options are available for phacoemulsification.

[13]These categories are basic, standard, and platinum. Patients with small incision surgeries are not eligible for platinum service, while all three tiers are available for phacoemulsification.

TABLE 3: Summary statistics by type of surgical product

	SICS	Phaco.	Diff.
Age	70.997	68.414	-2.584***
	(11.022)	(12.659)	(0.373)
Female	0.611	0.610	-0.001
	(0.488)	(0.488)	(0.015)
Has private insurance	0.055	0.080	0.024***
	(0.229)	(0.271)	(0.008)
Has access to public healthcare	0.249	0.200	-0.049***
	(0.433)	(0.400)	(0.012)
Lacks access to any healthcare	0.707	0.728	0.021
	(0.455)	(0.445)	(0.014)
RE cataract score	2.709	2.383	-0.326***
	(1.677)	(1.703)	(0.051)
LE cataract score	2.770	2.400	-0.371***
	(1.676)	(1.655)	(0.050)
Price (MXN)	8,996.588	15,405.345	6,408.757***
	(2,928.356)	(5,468.127)	(144.953)
Observations	1,625	3,286	4,911

	Phacoemulsification				SICS
	Aurofold	Aurolab	Aurovue	Standard	Standard
Age	69.421	70.084	68.347	65.648	70.997
	(11.958)	(11.902)	(12.982)	(13.360)	(11.022)
Female	0.645	0.603	0.616	0.574	0.611
	(0.479)	(0.490)	(0.487)	(0.495)	(0.488)
Has private insurance	0.055	0.077	0.058	0.130	0.055
	(0.228)	(0.267)	(0.234)	(0.336)	(0.229)
Has access to public healthcare	0.310	0.165	0.166	0.161	0.249
	(0.463)	(0.371)	(0.372)	(0.368)	(0.433)
Lacks access to any healthcare	0.642	0.762	0.783	0.723	0.707
	(0.480)	(0.426)	(0.412)	(0.448)	(0.455)
RE cataract score	2.429	2.408	2.409	2.282	2.709
	(1.760)	(1.638)	(1.692)	(1.723)	(1.677)
LE cataract score	2.408	2.482	2.404	2.297	2.770
	(1.648)	(1.666)	(1.665)	(1.636)	(1.676)
Price (MXN)	13,523.421	12,122.091	16,206.829	20,108.133	8,996.588
	(3,853.602)	(2,289.257)	(3,514.546)	(7,209.785)	(2,928.356)
Observations	816	868	807	795	1,625

	Phacoemulsification			SICS	
	Basic	Platinum	Standard	Basic	Standard
Age	67.837	68.691	68.520	71.319	70.873
	(12.921)	(12.467)	(12.707)	(10.422)	(11.248)
Female	0.637	0.591	0.613	0.587	0.620
	(0.481)	(0.492)	(0.487)	(0.493)	(0.486)
Has private insurance	0.057	0.083	0.096	0.051	0.057
	(0.232)	(0.276)	(0.294)	(0.220)	(0.232)
Has access to public healthcare	0.307	0.145	0.187	0.329	0.219
	(0.461)	(0.353)	(0.390)	(0.470)	(0.414)
Lacks access to any healthcare	0.649	0.777	0.724	0.644	0.731
	(0.478)	(0.416)	(0.447)	(0.479)	(0.444)
RE cataract score	2.120	2.401	2.598	2.551	2.769
	(1.772)	(1.661)	(1.672)	(1.767)	(1.639)
LE cataract score	2.235	2.429	2.507	2.627	2.826
	(1.723)	(1.654)	(1.579)	(1.789)	(1.628)
Price (MXN)	13,564.293	14,755.570	18,134.650	8,401.870	9,224.353
	(4,167.958)	(4,826.679)	(6,378.340)	(1,731.428)	(3,244.716)
Observations	874	1,472	940	450	1,175

Notes: This table shows summary statistics by type of product offered in each quote. Observations are at the patient-quote level. Phacoemulsification and SICS (small incision cataract surgery) refer to the method used by the surgeon. The third column in the first panel shows a difference in means test; *** p<0.01, ** p<0.05, * p<0.1 The second panel shows different types of artificial lenses. The last panel shows different levels of service (amenities) offered by our partner firm. During this period, 1 USD = 19.22 MXN.

information set. For the first eye, the outcome of the surgery has an uncertain component, from the consumer's point of view. We assume the consumer has perfect foresight about prices and the rest of the characteristics of the surgery. The first eye is always chosen by nature as the eye with the worst cataract score. After the consumer has had a surgery for the first eye, the outcome is no longer uncertain, because the consumer learns from the experience. Moreover, the consumer knows that information is revealed after the first surgery, which implies an option value from it.

4.1 Forward-looking consumer

A forward-looking consumer takes into account that the first surgery reveals information about the second one. Let i index consumers. We represent the uncertain outcome of a surgery with α_i, an iid random shock. In particular, the variance of α_i is a measure of the size of uncertainty that consumer i is facing. We allow for consumer heterogeneity in such measure.

Let $\boldsymbol{x}_{i1}$ and $\boldsymbol{x}_{i2}$ be patient and surgery characteristics, which are known in advance, and let shocks $\varepsilon_{i1}, \varepsilon_{i2}$ be iid standard normal. Let $y_{it} = \mathbb{1}\{i \text{ operates eye } t\}$, for surgeries $t = 1, 2$.

The timing is as follows:

1. Consumer i observes ε_{i1}.
2. i decides to operate eye 1 or not.
   (a) If $y_{i1} = 0$, utility is 0. Game ends.
   (b) If $y_{i1} = 1$, nature draws α_i from a distribution G_i and ε_{i2}.
3. i observes α_i and ε_{i2}.
4. i decides to operate 2 or not.
   (a) If $y_{i2} = 0$, utility is $\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1}$. Game ends.
   (b) If $y_{i2} = 1$, utility is $\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} + \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2}$. Game ends.

Define $u_{it} \equiv \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{it} + \varepsilon_{it}$, for $t = 1, 2$. An implicit outside option is valued at zero.

We proceed by backward induction. The consumer decides to get the second surgery if and only if

$$u_{i2} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2} > 0.$$

Then, the expected utility of the second surgery is

$$\begin{aligned}\mathbb{E}\left[u_{i2}|u_{i2}>0\right] &= \mathbb{E}[\alpha_i+\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\varepsilon_{i2}|\alpha_i+\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\varepsilon_{i2}>0] \\ &= \boldsymbol{\beta}'\boldsymbol{x}_{i2}+\mathbb{E}[\alpha_i+\varepsilon_{i2}|\alpha_i+\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\varepsilon_{i2}>0],\end{aligned}$$

where the expectations are with respect to $\alpha_i+\varepsilon_{i2}$.

Therefore, before the first surgery, after ε_{i1} is known, but before α_i is known, the expected utility of the consumer from the first surgery is

$$\mathbb{E}_{\alpha_i}[u_{i1}+\mathbb{E}\left[u_{i2}|u_{i2}>0\right]] = \int \alpha_i+\boldsymbol{\beta}'\boldsymbol{x}_{i1}+\varepsilon_{i1}+\mathbb{E}\left[u_{i2}|u_{i2}>0\right] dG_i(\alpha_i)$$

where the integration is over the support of α_i.

The consumer chooses the first surgery if and only if

$$\mathbb{E}_{\alpha_i}[u_{i1}+\mathbb{E}\left[u_{i2}|u_{i2}>0\right]]>0.$$

Therefore, the demand for the first surgery is

$$P\left[y_{i1}=1\right]=P\left[\mathbb{E}_{\alpha_i}[u_{i1}+\mathbb{E}\left[u_{i2}|u_{i2}>0\right]]>0\right].$$

In order to solve analytically for the equilibrium of the model, we make the following simplifying assumption.

Assumption 1. α_i iid $\mathcal{N}(\mu_{\alpha,i},\sigma_{\alpha,i})$.

Under assumption 1, we can simplify,

$$\begin{aligned}&\mathbb{E}\left[u_{i2}|u_{i2}>0\right] \\ &= \boldsymbol{\beta}'\boldsymbol{x}_{i2}+\mu_{\alpha,i}+\sqrt{1+\sigma^2_{\alpha,i}}\,\mathbb{E}\left[\frac{\alpha_i+\varepsilon_{i2}-\mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\middle|\frac{\alpha_i+\varepsilon_{i2}-\mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}>-\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right], \\ &= \boldsymbol{\beta}'\boldsymbol{x}_{i2}+\mu_{\alpha,i}+\sqrt{1+\sigma^2_{\alpha,i}}\,\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right), \qquad (1)\end{aligned}$$

where λ is the inverse Mills ratio: $\lambda(z)\equiv\phi(z)/\Phi(z)$, with ϕ and Φ the pdf and cdf of a standard normal.

Then,

$$\begin{aligned}
&\mathbb{E}_{\alpha_i}\left[u_{i1} + \mathbb{E}\left[u_{i2}|u_{i2} > 0\right]\right] \\
&= \int \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right) dG_i(\alpha_i) \\
&= \mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right), \qquad (2)
\end{aligned}$$

and,

$$\begin{aligned}
P\left[y_{i1} = 1\right] &= P\left[\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right) > 0\right] \\
&= P\left[\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right) > -\varepsilon_{i1}\right] \\
&= \Phi\left[\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)\right]. \qquad (3)
\end{aligned}$$

Also, once α_i is known to the consumer, the demand for the second surgery is

$$\begin{aligned}
P\left[y_{i2} = 1\right] &= P\left[y_{i2} = 1, y_{i1} = 1\right] + P\left[y_{i2} = 1, y_{i1} = 0\right], \\
&= P\left[y_{i2} = 1|y_{i1} = 1\right] P\left[y_{i1} = 1\right] + 0,
\end{aligned}$$

and

$$\begin{aligned}
P\left[y_{i2} = 1|y_{i1} = 1\right] &= P\left[\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2} > 0|y_{i1} = 1\right] \\
&= \Phi\left(\frac{\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i2}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right). \qquad (4)
\end{aligned}$$

From (3) and (4), we can see that if we assume $\mu_{\alpha,i} = \mu_\alpha\ \forall i$, then, μ_α is not separately identified from the constant. Therefore, we assume:

Assumption 2. $\forall i,\ \mu_{\alpha,i} = 0$.

Note assumption 2 is consistent with rational expectations.

We further parameterize $\sigma_{\alpha,i} \equiv \exp(\boldsymbol{\theta}' w_i)$, where w_i are some time-invariant patient characteristics, and $\boldsymbol{\theta}$ is a vector of parameters to be estimated.

Finally, the probability mass function of both operations (y_{i1}, y_{i2}) is

$$P\left[y_{i1} = y, y_{i2} = y'\right] = P\left[y_{i2} = y' | y_{i1} = y\right] P\left[y_{i1} = y\right],$$

where $y, y' = 0$ or 1.

Let $s_{i1} \equiv P\left[y_{i1} = 1\right]$ and $s_{i2} \equiv P\left[y_{i2} = 1 | y_{i1} = 1\right]$.

Then, for each i the likelihood of observing (y_{i1}, y_{i2}) is

$$\begin{aligned}
P\left[y_{i1} = 0, y_{i2} = 1\right] &= P\left[y_{i2} = 1 | y_{i1} = 0\right] P\left[y_{i1} = 0\right] = 0 \\
P\left[y_{i1} = 0, y_{i2} = 0\right] &= P\left[y_{i2} = 0 | y_{i1} = 0\right] P\left[y_{i1} = 0\right] = 1 - s_{i1} \\
P\left[y_{i1} = 1, y_{i2} = 0\right] &= P\left[y_{i2} = 0 | y_{i1} = 1\right] P\left[y_{i1} = 1\right] = s_{i1}(1 - s_{i2}) \\
P\left[y_{i1} = 1, y_{i2} = 1\right] &= P\left[y_{i2} = 1 | y_{i1} = 1\right] P\left[y_{i1} = 1\right] = s_{i1} s_{i2}.
\end{aligned}$$

Or, equivalently,

$$s_{i1}^{y_{i1}} (1 - s_{i1})^{1 - y_{i1}} \left[s_{i2}^{y_{i2}} (1 - s_{i2})^{1 - y_{i2}} \right]^{y_{i1}}.$$

Therefore, the log-likelihood becomes

$$\ell = \sum_{i=1}^{N} y_{i1} \log s_{i1} + (1 - y_{i1}) \log(1 - s_{i1}) + y_{i1} y_{i2} \log s_{i2} + y_{i1}(1 - y_{i2}) \log(1 - s_{i2}).$$

which is maximized for $(\boldsymbol{\beta}, \boldsymbol{\theta})$.

4.2 Price endogeneity and control function

To deal with endogenous prices, we use a control function. We assume:

Assumption 3. Shocks can be decomposed as $\varepsilon = \gamma\rho + \widetilde{\varepsilon}$, where prices $p \perp \widetilde{\varepsilon}$, and ρ is correlated with prices, with $\mathbb{V}\left[\rho\right] = 1$.

Then,

$$\mathbb{V}\left[\varepsilon\right] = 1 = \gamma^2 + \mathbb{V}\left[\widetilde{\varepsilon}\right] \Rightarrow \mathbb{V}\left[\widetilde{\varepsilon}\right] = 1 - \gamma^2.$$

Define

$$\sigma_{\widetilde{\varepsilon}} \equiv \sqrt{1 - \gamma^2}.$$

Therefore, by decomposing ε in the preceding derivations, we have

$$\begin{aligned}\mathbb{E}\left[u_{i2}|\alpha_i, u_{i2}>0\right] &= \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2} + \mathbb{E}_{\widetilde{\varepsilon}_{i2}|\alpha_i}[\widetilde{\varepsilon}_{i2}|\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2} + \widetilde{\varepsilon}_{i2} > 0] \\ &= \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2} + \sigma_{\widetilde{\varepsilon}}\lambda\left(\frac{\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2}}{\sigma_{\widetilde{\varepsilon}}}\right).\end{aligned}$$

Then,

$$\begin{aligned}P\left[y_{i1}=1\right] &= P\left[\int \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \gamma\rho_{i1} + \widetilde{\varepsilon}_{i1} + \mathbb{E}\left[u_{i2}|\alpha_i, u_{i2}>0\right] dG_i(\alpha_i) > 0\right], \\ &= \Phi\left[\frac{1}{\sigma_{\widetilde{\varepsilon}}}\int \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \gamma\rho_{i1} + \mathbb{E}\left[u_{i2}|\alpha_i, u_{i2}>0\right] dG_i(\alpha_i)\right].\end{aligned}$$

Also,

$$\begin{aligned}P\left[y_{i2}=1|y_{i1}=1\right] &= P\left[\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2} + \widetilde{\varepsilon}_{i2} > 0|y_{i1}=1\right] \\ &= \Phi\left(\frac{\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2}}{\sqrt{\sigma^2_{\widetilde{\varepsilon}} + \sigma^2_{\alpha,i}}}\right), \\ &= \Phi\left(\frac{\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \gamma\rho_{i2}}{\sigma_{\widetilde{\varepsilon}}\sqrt{1 + \frac{\sigma^2_{\alpha,i}}{\sigma^2_{\widetilde{\varepsilon}}}}}\right),\end{aligned}$$

where we see every parameter of the model is rescaled by $1/\sigma_{\widetilde{\varepsilon}}$, which needs to be accounted for to report the parameters in the original scale. Indeed, from an estimate of $\widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}$, we can back out

$$\widehat{\gamma} = \frac{\widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}}{\sqrt{1 + \widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}^2}} \Rightarrow \widehat{\sigma_{\widetilde{\varepsilon}}} = \sqrt{\frac{1}{1 + \widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}^2}}.$$

4.3 Identification and estimation

To identify the price coefficient, we use sales targets variables as instruments in the control function strategy described above. Specifically, we use the daily percentage of operations sold up to the moment the sales agent was talking with the consumer. Intuitively, on a slow day, the agent might decrease offered prices to close a sale, and on a good day, the agent might raise prices. However, how slow a day is for the agents should not directly affect the consumer. Moreover, we include agent fixed effects in our estimation to control for agent-specific price biases or persuasion techniques. To alleviate the incidental parameter problem due to agent fixed effects, we keep only those agents with 10 or more quotes in the data (Greene, 2004). Other patient controls include: log age, gender, type of insurance, cataract scores, type of surgery, type of intra-ocular lens, and type of amenities.[14]

Intuitively, the magnitude of shocks, $\sigma_{\alpha,i}$, is identified from the discrepancies between the covariates' effects from the first operation and the second one. The coefficients $\boldsymbol{\theta}$ are identified from the correlations between the magnitudes of $\sigma_{\alpha,i}$ and covariates w_i.

The outstanding issue is one of selection into our sample of second surgeries. Consumers who return for a consultation about the second surgery presumably had a positive shock from it. Consumers who never return are not in the data and the counterfactual prices of a second surgery are unobservable to us. If we ignore this fact, we might overestimate the benefit from the surgery.

Therefore, when missing, we predict the (log) price that a consumer would have had if she came back for a second consultation, as a function of characteristics of patients, surgeries, and sales agents. We use a simple machine learning technique, LASSO, to predict prices; we found LASSO outperforms a linear regression in this setting, as measured by the mean prediction error, and achieves an R^2 of .72. We further shock predicted prices to match the empirical distribution of non-missing prices, in order to estimate meaningful standard errors.

Estimation is performed in two steps. We first construct a control function, as described in 4.2. Then, we add the control function as an extra regressor, and we perform a maximum likelihood estimation as in 4.1. We perform 500 (panel) bootstraps of the whole process to calculate standard errors clustered at the patient level.

5 Results

The estimation is carried out on our sample of patients whose initial contact with our partner firm occurred in 2018 and had at least one cataract-related visit. We follow the estimating procedure described above for imputing unobservable price quotes and estimating parameters via maximum likelihood over 500

[14] Results are similar if we use an alternative instrument: the difference between the day's percentage of operations sold and the month's percentage.

bootstrap repetitions.

Table 4 shows our estimated elasticities and associated standard errors clustered at the patient level. The top panel shows estimates for the indicator variable for whether the patient takes up the surgery, and the bottom panel corresponds to our uncertainty shock parameter σ_i. We present exponentiated coefficients for the latter. Different columns add control variables to specifications and a control function to address the endogeneity of prices based on the daily percentage of operations sold up to the moment of the quote as an instrument. Importantly, one of such controls corresponds to sales agent fixed effects, which addresses any unobservable heterogeneity in sales tactics, such as persuasion or announcing ad hoc prices.

Our results are qualitatively similar across columns, with much smaller estimates in column 1, where we do not include any controls nor address the endogeneity of prices. Effect sizes tend to grow with these controls. Our preferred specification includes both the control variables and control function approach (column 6). Intuitively, patient heterogeneity matters for both the decision to get the surgery and the uncertainty parameter. As expected, we estimate a negative and significant effect of prices on surgery take up. For our patient characteristics, we find insignificant effects that are also very close to zero.[15] As for the information shock, we consistently find that older people, women, and patients with worse scores experience lower uncertainty from the first surgery.[16] We also find that a model that allows for heterogeneity in $\sigma_{\alpha,i}$ fits the data slightly better than one without heterogeneity, as measured by the mean prediction error and a pseudo-R^2.[17]

We report our estimated elasticities across all operations as well as by first vs second surgery. Our elasticities are in line with what one might expect (with the exception of column 1 where our overall estimate is less than one in absolute value). We also find that elasticities are consistently larger for the first operation compared to the second (on average, about twice as large). In our preferred specification, we find that a 10% increase in the price leads to an overall decline of

[15] Estimates for log age are not as small, but are all insignificant. These point estimates seem to suggest that perhaps older people are more likely to take up surgery.

[16] The medical literature has documented that take-up of cataract surgery in low- and middle-income countries is consistently lower for women than men, but has been unable to provide a convincing explanation for this differential (Mercer, Lyons and Bassett, 2019; Briesen et al., 2010). In our setting, gender differences seem to be driven entirely by the lower uncertainty parameter.

[17] In this paper, R_p^2 is constructed as (number of correct predictions - number of most frequent outcome) / (number of outcomes - number of most frequent outcome).

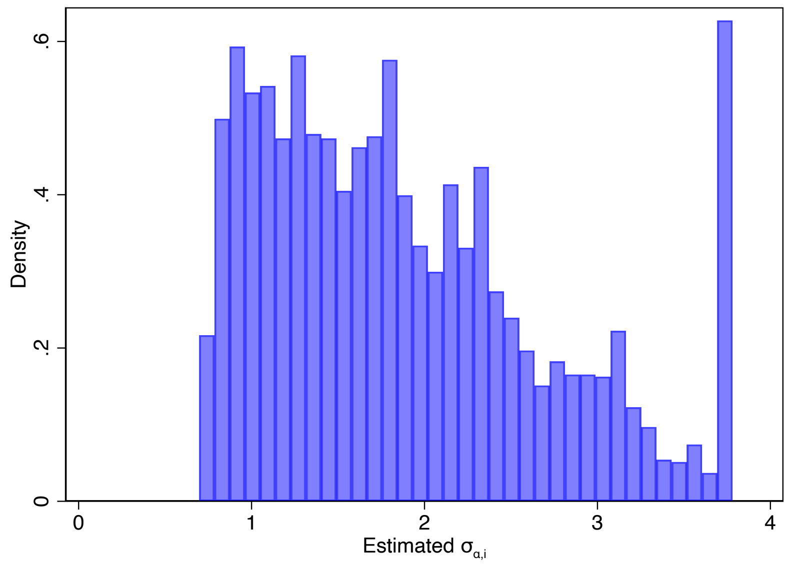


FIGURE 1: Distribution of $\widehat{\sigma}_{\alpha,i}$

Note: Distribution winsorised at 95th percentile.

25.6% in the probability of getting cataract surgery. However, for a 10% increase in the price of the first surgery, take-up goes down by 31.4%, while the same percentage change for the second surgery only leads to a decline of 19.6% in the probability of take-up.

Figure 1 plots the distribution of our estimated uncertainty shock parameter. We find considerable heterogeneity, with a relatively long right tail (although for clarity, the plot winsorizes the distribution at the 95th percentile). To put it in perspective, the standard deviation of the demand shocks, ε, is equal to 1. We predict that, on average, the surprise component of the surgery is 1.9 times as large as the unobservable shocks, ε. This suggests that the option value from revealed information after the first surgery might be quite large.

Lastly, we measure consumer surplus with the (ex ante) expected utility from getting the first surgery, which is,

$$CS_i \equiv \mathbb{E}\left[u_{i1} + \mathbb{E}\left[u_{i2}|u_{i2} > 0\right] \middle| u_{i1} + \mathbb{E}\left[u_{i2}|u_{i2} > 0\right] > 0\right],$$

and where the outer expectation is with respect to both α_i and ε_{i1}. In other words, the consumer surplus includes the benefit from the first surgery and the option value from the second surgery.

As an element of $\boldsymbol{x}_{it}$, $t = 1, 2$, we include log prices, $\log p_{it}$. Let β_p be its

TABLE 4: DEMAND ESTIMATIONS

DEP VAR: Operates$_{it}$	(1)	(2)	(3)	(4)	(5)	(6)
log price	-0.49^{***}	-1.36^{***}	-2.05^{***}	-3.95^{***}	-2.04^{***}	-3.95^{***}
	(0.038)	(0.099)	(0.038)	(0.069)	(0.037)	(0.078)
log Age		0.14^{*}		0.05		0.11
		(0.075)		(0.073)		(0.104)
Female		-0.10^{***}		-0.03		0.01^{*}
		(0.034)		(0.026)		(0.041)
Min cataract score		-0.09^{***}		0.02^{**}		-0.04^{***}
		(0.013)		(0.010)		(0.017)
Max cataract score		0.18^{***}		-0.01		0.00
		(0.015)		(0.011)		(0.014)
DEP VAR: $\sigma_{\alpha,i}$						
log Age					0.15^{***}	0.12^{***}
					(0.020)	(0.039)
Female					0.13^{***}	0.13^{***}
					(0.018)	(0.034)
Min cataract score					0.14^{***}	0.23^{***}
					(0.018)	(0.048)
Max cataract score					0.17^{***}	0.16^{***}
					(0.021)	(0.034)
cons	10.61^{**}	5.53^{***}	2.33^{**}	2.23^{**}	1.56	6.37
	(4.893)	(1.628)	(0.663)	(0.519)	(0.668)	(8.243)
ELASTICITIES						
ALL OPS	-0.76	-1.50	-1.28	-2.39	-1.28	-2.56
FIRST OPS	-1.47	-2.76	-1.84	-3.32	-1.80	-3.14
SECOND OPS	-0.04	-0.23	-0.72	-1.44	-0.75	-1.96
CONTROLS	NO	YES	NO	YES	NO	YES
CONTROL FUNCTIONS	NO	NO	YES	YES	YES	YES
MPE	0.41	0.40	0.34	0.33	0.33	0.33
R^2_p	0.00	0.01	0.17	0.20	0.17	0.20
PATIENTS	3,979	3,979	3,979	3,979	3,979	3,979
QUOTES	8,003	8,003	8,003	8,003	8,003	8,003

Notes: Bootstrapped standard errors clustered at individual level with 500 repetitions. Control functions for prices are constructed with daily percentage of operations sold up to the moment as an instrument (Petrin and Train, 2010). Controls include: sales agents fixed effects, surgery characteristics, age, gender, type of insurance, and cataract scores. MPE stands for mean prediction error. Coefficients for σ_i equation are exponentiated, which implies their relevant significance test is $H_0: \exp(\text{coef}) - 1 = 0$.

coefficient. Then, the model implies the marginal utility of income, $\frac{\partial u_{it}}{\partial p_{it}} = \beta_p / p_{it}$. Therefore, we transform consumer surplus into dollar terms by considering $p_{it} CS_i / \beta_p$.

Figure 2 presents the distribution of the estimated consumer surplus in US dollars, which is on average 215 USD.[18] About 15% of patients have an estimated surplus that is very close to zero (below 15 USD), but the distribution presents a high dispersion. Given the long right tail, we also winsorize this plot at the 95th percentile, which is around 550 USD. As a reminder, the average price of cataract surgery at this provider is around 13,000 pesos or 700 USD (Table 3).

[18] During this period, 1 USD = 19.22 MXN.

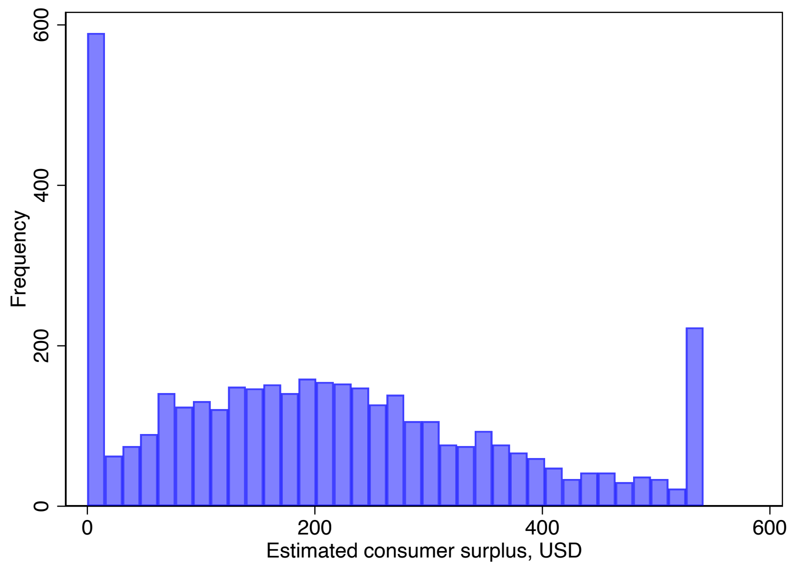


FIGURE 2: Distribution of estimated consumer surplus
Note: Distribution winsorised at 95th percentile.

6 Counterfactuals

An important question is how efficient the equilibrium amount of surgeries is, given the uncertain outcomes. A priori, we can have undersupply or oversupply. If surprises are relatively important, the option value of the first surgery increases, which would lead to oversupply of the first surgery. On the other hand, undersupply would be likely if prices are relatively high and consumers are not surprised.

With estimated preferences we can simulate counterfactual policies. We first quantify the welfare costs (or gains) from surprises by setting surprises to zero in a counterfactual resolution of uncertainty.

We also ask if we can increase surgeries, while leaving the firm indifferent. To that end, we consider a budget-neutral subsidy to first operation and tax to second operation.

Throughout we analyze the heterogeneous effects of these policies.

6.1 Quantifying uncertainty and persuasion

In this section, we consider a counterfactual unveiling of α_i. This scenario could be interpreted as a hypothetical persuasion or educational campaign, where "champion" patients inform potential consumers about their successful results. For instance, a champion c might reveal their outcome $\alpha_c = 2\sigma_i$ to a potential consumer i. The potential consumer i might believe totally or partially in this information. We offer a range of possible outcomes based on the level of α_i that potential consumers might believe, including $\alpha_i = 0$, a natural α_i of interest, which would quantify the value of uncertainty.

That is, given a *revealed* α, we compute

$$CS_i^{\alpha} \equiv \mathbb{E}\left[u_{i1} + \mathbb{E}\left[u_{i2}|u_{i2} > 0\right] \middle| u_{i1} + \mathbb{E}\left[u_{i2}|u_{i2} > 0\right] > 0, \alpha\right],$$

where $\sigma_{\alpha,i} = 0$, and expectations are only with respect to demand shocks. In other words, when $\alpha_i = 0$, patients believe the shock to be 0 with probability 1; or, when $\alpha_i = \sigma_i$, patients believe the shock to be (their estimated) σ_i with probability 1.

Figure 3 shows how consumer surplus changes from the status quo to a revealed information couterfactual. At $\alpha_i = 0$, this change is negative, which implies uncertainty is valuable for consumers. That is, patients have a preference for risk. Recall that patients do not observe ε_{i2} at $t = 1$, therefore, the option value remains in the form of an inverse Mill's ratio, which is convex. Intuitively, patients value uncertainty, because a bad draw can be mitigated by operating just once, but a good draw can be amplified by operating twice.

Finally, as expected, as the revealed shock increases, consumer surplus increases. Therefore, for consumers to value certainty, the revealed information needs to be credible and sizable.

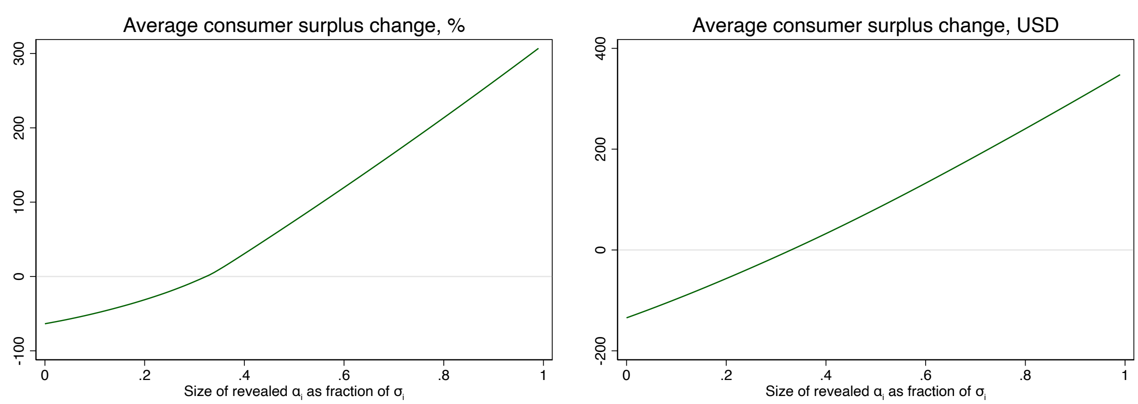


FIGURE 3: Quantifying uncertainty and champions policy

6.2 Revenue-neutral price changes

Now we consider how to increase surgeries in such a way that the firm remains indifferent. Throughout these counterfactuals we focus on revenue-neutral policies.[19]

For a forward-looking consumer, price hikes on the second surgery reduce the option value. However, price reductions on the first surgery increase demand through both the first and second surgery. Indeed, if the expected demand of consumer i is $D_i \equiv s_{i1} + s_{i1}s_{i2}$, then,

$$\frac{\partial D_i}{\partial p_{i1}} \frac{p_{i1}}{D_i} = \frac{\partial s_{i1}}{\partial p_{i1}} \frac{p_{i1}}{s_{i1}},$$

where we see the elasticity for the first surgery is the elasticity for total demand. Moreover, if the elasticity for the second surgery is less elastic, we might find a pricing schedule where welfare increases through cross-subsidizing.

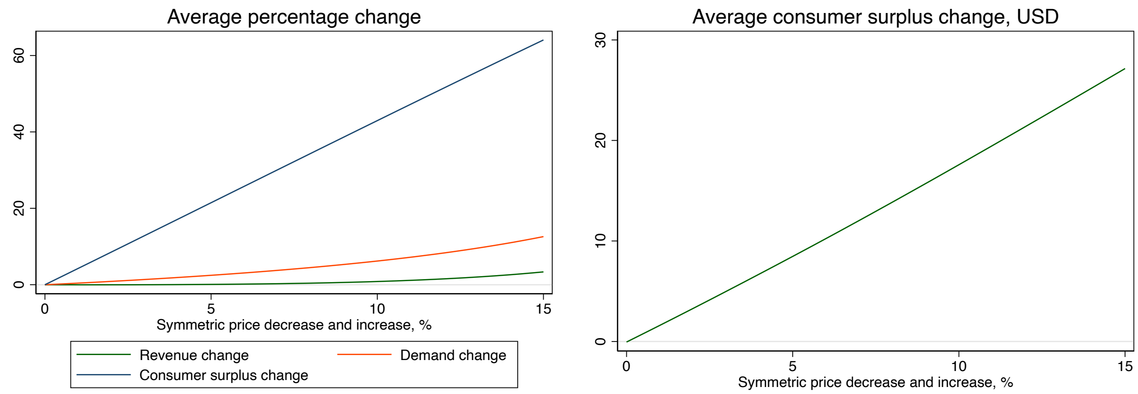
Figure 4 shows a counterfactual discount for the first surgery accompanied by an offsetting price increase in the second surgery. In this exercise, if p_1 decreases by x%, then p_2 increases by x%. In this symmetric case, we find the firm is roughly indifferent, but consumers are significantly better off. On the extensive margin, new consumers undergo the surgery, which is captured by the absolute change in consumer surplus.

Figure 5 shows an asymmetric price change: if p_1 decreases by x%, then p_2 increases by $.5x$%. In this case we find both the firm and the consumer are better off, mainly due to gains from trade.

7 Concluding remarks

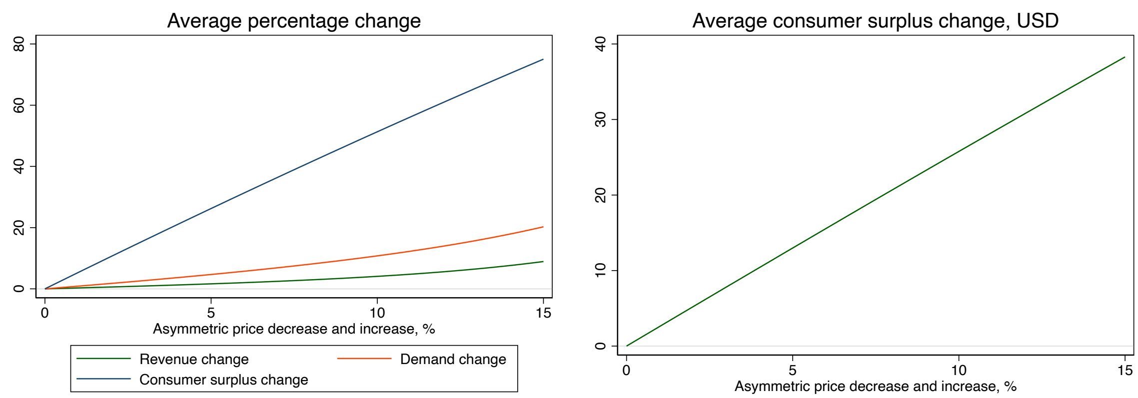
In many experience goods markets, the number of potential repeated purchases might be small and limited. Such is often the case with durable goods or elective healthcare treatment procedures. Given this feature, classic insights about the value of learning on demand and the efficacy of policies that may increase initial take-up may not necessarily hold true. With these limits on repeated interactions, firms may not be able to successfully adapt their pricing and advertising strategies in order to increase market share, and potential customers may be constrained in their ability to exploit these consumption dynamics. Understanding

[19] We assume constant marginal costs, which is sensible in this context. The firm has relatively low marginal costs from surgeries, mainly because they pay surgeons by day, not by surgery.



Note: Counterfactual decrease in first surgery prices in same percentage as increase of second surgery prices. For example, if p_1 drops in 1%, then p_2 increases in 1%.

FIGURE 4: Symmetric change in pricing policy



Note: Counterfactual increase of second surgery prices is .5 times the decrease of first surgery prices. For example, if p_1 drops in 1%, then p_2 increases in .5%.

FIGURE 5: Asymmetric change in pricing policy

these factors as well as the size and value of the initial uncertainty is therefore important for quantifying welfare.

To shed light on these issues, we focus on modeling and estimating demand for cataract surgeries. Exploiting a rich dataset from a large private provider in Mexico City and leveraging sales targets set by the firm for its sales agents, we identify structural demand parameters detailing price elasticities for each of two potential surgeries as well as the value of the uncertainty shock. Our results show that the estimated elasticities are larger for the first surgery and that there is considerable heterogeneity in the idiosyncratic uncertainty parameter. This suggests that the option value of the first surgery is large. We also find heterogeneity in our measure of consumer surplus.

With our parameters, we then ask how efficient the equilibrium amount of surgeries is by estimating a series of counterfactuals inspired by experimental insights from the medical literature. The first set of simulations considers informational interventions akin to persuasive advertising, where the objective is to resolve the uncertainty. We find that reducing uncertainty is only welfare-improving if the firm is able to convince patients of a very positive outcome. Our second set of counterfactuals considers instead revenue-neutral price changes that subsidize the price of the first surgery and tax the second. These interventions unequivocally lead to welfare improvements, that may even increase revenues for the firm.

Our findings suggest that uncertainty in these interactions is large and heterogeneous across patients, which in turn makes subsidizing initial take-up more efficient than implementing persuasive advertising. This suggests that even in a setting with limited repeat purchases, the value of revealed uncertainty may allow for welfare-improving price changes.

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