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

Emilio Gutierrez† Adrian Rubli‡ José Tudón§

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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 develop a demand model with uncertainty in outcomes, for forward-looking consumers, and information revealed after the first interaction. We use data from a large cataract surgery provider in Mexico to estimate demand, and 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 efficient at increasing welfare and surgeries than persuasive advertising.

Keywords: demand estimation; uncertainty; experience goods; treatment choices; cataract surgery.

JEL: I11, L15, D83, C73.

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†Department of Economics, ITAM. Río Hondo 1, CDMX 01080, Mexico. Email: emilio.gutierrez@itam.mx.

‡Department of Business Administration, ITAM. Email: adrian.rubli@itam.mx.

§Department of Business Administration, ITAM. Corresponding author. Email: jtudon@itam.mx.

1 Introduction

In markets for experience goods, consumers are ex-ante unsure about product characteristics, such as quality (Nelson, 1970). This ex-ante uncertainty might be especially salient in markets where individuals or households only tend to consume one of these products at a time, and often consider purchases to be long-lasting, as is the case with durable goods, like electric vehicles or housing. However, many experience goods allow for potentially repeated interactions, such as prescription drugs, education services, entertainment, or some elective surgeries. Here, the consumer's decision for initial take-up might consider not only the inherent uncertainty, but the fact that information about the idiosyncratic benefits of consumption are revealed before having to make subsequent choices. Hence, take-up might be higher or lower depending on the degree of uncertainty, risk preferences, and the option value of the first choice.

This paper focuses on the market for cataract surgeries, a particularly important experience good in the healthcare industry, 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 private 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 to have more 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 the number of cataract surgeries.

Cataracts occur when the eye's natural (and normally clear) lens becomes cloudy, due to a breakdown of its proteins. Cataracts lead 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 to some degree in both eyes. Surgery to replace the clouded lens with an artificial intra-ocular lens is the only available treatment (Miller et al., 2022). 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 (Henderson and Schneider, 2012).

While cataracts are a common condition around the world, patients remain massively undertreated—particularly, in low- and middle-income countries (Lansingh et al., 2010; Congdon and Thomas, 2014). For instance, in Mexico, about 350,000 new cases are diagnosed each year, of which only about 50% undergo surgery, with similar numbers across the developing world.[1] Some commonly identified barriers to surgery include prices, access, and uncertainty (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, because most patients develop cataracts in both eyes, the number of potential repeated interactions is ex-ante known to the patient.[2] Second, it is very uncommon for patients to undergo surgery in both eyes simultaneously (in our data, none do so). Lastly, in our setting, patients are not given the option of scheduling surgery for both eyes simultaneously; 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 in two stages, with information revealed before having to decide on the second surgery (conditional on having chosen to operate in the first stage).

We analyze the decision-making process of 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 surgery. Our data contain all patients whose first contact with this provider occurred during 2018, and who 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 discount 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

[1] See `excelsior.com.mx` and Cataract surgical rates (2017). In this paper, urls are truncated, but their hyperlinks are not. Urls last accessed June, 2023.

[2] This is not always the case for these types of healthcare goods. 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.

first operation, which is only revealed after experiencing the first surgery. Then, all (knowable) information is known to the patient before having to decide on the second surgery. This setup implies consumers have an option value from the first surgery. In our estimation, we deal with endogenous prices with a control function that uses daily sales targets as an instrument, and we deal with potential selection into returning 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 decreasing marginal utilities for the second operation, flexible risk preferences, and control for patients' income, health, and other demographic characteristics. Thus, we identify the magnitude of the uncertainty shocks from discrepancies in estimated coefficients between the first and second surgery.[3]

We find elastic demand curves, and our estimates show that demand elasticities for the first operation are larger in absolute value than those for the second surgery. We also obtain a heterogeneous distribution of estimated uncertainty in the population, which suggests that the option value of the second surgery has an important role in the decision-making process of patients. 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 information provision (or 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 uncertain shock—that the patient takes as true—in an attempt to persuade patients about potential outcomes. Our simulations show that this intervention might be welfare-improving, as long as the size of the revealed information shock is large enough. That is, the champion must reveal a credible, sizable shock.

Our second set of counterfactual exercises consider revenue-neutral price changes, subsidizing the price of the first surgery but taxing the price of the

[3] Randomized trials have found that the second surgery leads to significant improvements in both visual acuity and quality of life (Javitt et al., 1995; Laidlaw et al., 1998; Castells et al., 2006). However, there is little evidence on whether the marginal utility decreases or not. One observational study found an only slightly lower marginal utility of the second surgery relative to the first (Busbee et al., 2003). However, another observational study found that marginal utility was increasing among US veterans (Shekhawat et al., 2017).

second, all while leaving the firm indifferent. A priori, it's not obvious if total surgeries would go up or down, because it depends on relative price elasticities. 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 to an increase in take-up for both 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).

Overall, these exercises suggest that persuasive advertising that reduces uncertainty will not be as effective, unless the firm is able to truly 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 affect the capacity of the firm to adapt and hinder customer reactions 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

Cataracts are a condition where the lens of the eye becomes clouded, leading to important declines in eyesight. Age is the biggest risk factor, in particular, due to the cumulative effects of ultraviolet radiation or oxidative damage (Hashemi et al., 2020). Other important risk factors include obesity, high blood pressure, and diabetes. Because cataracts are "an inevitable side effect of aging (Hashemi et al., 2020)," virtually all patients develop cataracts to some degree in both eyes. 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.[4]

While early symptoms may improve with glasses, advanced cataracts require

[4]See nei.nih.gov.

surgery to replace the lens with an artificial one. 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; usually, the small incision surgery is more appropriate for worse cataracts. An artificial lens, made of various materials, is then placed in the eye. Generally, the ophthalmologist decides the type of surgery and lens based on the medical and physiological needs of the patient.

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, which results in relatively high price elasticities of demand. Traditionally, large segments of the population do not have access to private care given their high prices and the lack of health insurance.

Estimates suggest that 30-40% of individuals in Mexico have cataracts, with 350,000 new cases per year. 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 international standards, but most surgeries cost between 1,300 and 1,500 USD per eye, which is equivalent to 1.5-1.7 times the median monthly household income in the Mexico City metropolitan area (ENIGH 2018).[8]

[5] See `excelsior.com.mx`. Recent estimates from public providers suggest that 15 to 20% of young adults are affected by cataracts in Mexico; see `imss.gob.mx`.

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

[7] According to clinical guidelines from IMSS, the largest public provider in Mexico, surgery is required once a patient "has difficulty performing daily activities such as recognizing familiar faces, has 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. Note that no single test can objectively define adequate thresholds for cataract surgery, as many considerations are patient-specific and self-reported (Miller et al., 2022). See `imss.gob.mx`.

[8] These quotes are based on posted prices on websites of the most common eye care clinics in

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. Their clinics are spread out over 20 locations, with a main clinic in downtown Mexico City, where the majority of surgical interventions are carried out. An important part of the firm's business is diagnosing and operating cataracts, with a target population made up of mostly lower-income patients.

Consumer's journey. When a patient arrives at the facilities of our partner firm, an ophthalmologist evaluates the patient's eyes, orders on-site lab analyses, and performs exams, some of which are conducted by in-house optometrists.[9] The physician diagnoses cataracts by assigning each eye 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, however, ocular comorbidities and physician practices may also play a role. Once a patient has been diagnosed by the physician and she has deemed that surgery is the recommended treatment, the physician emits a prescription with a recommendation for the type of surgery and type of intraocular lens. This recommendation is based on medical and physiological determinants, such as severity of cataracts, ocular health, and so on. Ophthalmologists do not have discretion over prices and cannot give price quotes. To get a quote, patients are then referred to a sales agent at the clinic.

Sales 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. Sales agents may offer discounts based on a menu of options that changes over time. However, the agents' commission is based on the sale price, creating an incentive to avoid using the discounts if possible. Patients take the physician's prescription as given, and rarely ask for alternatives; in our data, virtually no patient receives a price quote for a non-prescribed surgery, which is consistent with a literature that finds patients adhere to the physicians' recommendations, specially when patients lack expertise (Finkelstein et al., 2021; Johnson and

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.

Rehavi, 2016; Gruber and Owings, 1996).

If the patient chooses to go forward with the surgery, payment plans are discussed and a date is set. Importantly, 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. All patients in the data consider first a surgery on the eye with worse cataracts, because, in particular, physicians strongly recommend so.[10]

After the surgery, the patient returns, at the physician's discretion, for follow up appointments. If the patient wants another surgery for the second eye, the patient is again referred to a sales agent, who gives another price quote for the prescription of the second eye's surgery, and another date is set. On average, patients who undergo both surgeries do so within 74 days of each other.

3 Data

We obtained anonymized patient-level data directly from our partner firm spanning all patient visits from 2018 and 2019.[11] 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 time-invariant patient characteristics that include gender, age, whether they are covered by private insurance, whether they have access to public healthcare, and their zip code.

We also observe details from all patient visits. For each one, we observe the service provided by our partner firm, any diagnoses made, and all price quotes generated by sales agents. Physician and sales agent identifiers are included for each interaction. This effectively allows us to observe, for each patient visit, all relevant interactions with medical and non-medical staff, 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.

[10] 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.

[11] The data and replication files can be accessed here or at the authors' websites.

We exclude a small number of patients that had three cataract surgeries over this period, a few cataract surgeries that were not catalogued as either phacoemulsification or small incision surgery, and some pro-bono surgeries for which patients were not billed. Lastly, we exclude patients in the top one percent of the age distribution (i.e., aged 91 and older). Overall, we are left with a sample of 3,894 patients and a total of 4,699 patient-quote observations.

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. If cataracts were not reevaluated on a particular visit, we assign the cataract score from the patient's previous visit. Although we focus on patients with cataract diagnoses and surgery products, all patients are evaluated and receive a cataract score at least once during this period. As noted above, virtually all patients develop cataracts to some degree in both eyes, because age is the main risk factor (Hashemi et al., 2020). In our data, we find a high correlation in cataract scores between eyes; an increase of 1 in the cataract score of the most afflicted eye is associated with an increase of .4 in the healthier eye.

Table 1 shows summary statistics of individuals' characteristics and ocular health measures for patients in our sample and those who visited the clinic for non-cataract related reasons, and are thus not included in our sample. Appendix Table 6 describes these health measures in further detail. Note that 65% of our patient sample ends up having at least one cataract surgery in this time span. Cataract patients are older, less likely to be privately insured, more likely to have access to the public healthcare system, and more likely to not be covered by any type of healthcare (public or private). As expected, our patients have significantly worse cataract scores—taking the average over all measurements or simply the highest value in this time period. We also observe nine different eyesight measures for each eye which we take as a proxy for ocular health. In general, we find worse measures among the patients in our sample, perhaps due to a correlation of these measures with cataracts or simply the fact that they are older. From a medical perspective, these comorbidities make surgery the only recommended treatment (Lundström et al., 2015). In our estimations, we control for ocular health to allow for different marginal valuations of surgeries, depending on these characteristics.

We observe a total of 4,699 price quotes for cataract surgeries, of which 3,952 correspond to first surgeries and 747 to second surgeries. Of those who received a first quote, 2,526 underwent the surgery, and of those who returned for a second quote, 657 underwent the surgery.

TABLE 1: Patient summary statistics

Variable	(1) Cataract patients	(2) Non-cataract patients	(3) Difference
Has a cataract surgery	0.65 (0.48)	0	-
Age	69.24 (12.24)	46.88 (20.17)	-22.35 (0.33)
Female	0.61 (0.49)	0.61 (0.49)	0.00 (0.01)
Private insurance	0.07 (0.26)	0.15 (0.36)	0.08 (0.01)
Social security	0.22 (0.41)	0.20 (0.40)	-0.02 (0.01)
Uninsured	0.72 (0.45)	0.68 (0.47)	-0.05 (0.01)
Right eye cataract potential	2.68 (1.61)	0.43 (1.03)	-2.25 (0.02)
Left eye cataract potential	2.64 (1.61)	0.43 (1.03)	-2.20 (0.02)
Right eye maximum cataract potential	3.05 (1.58)	0.55 (1.18)	-2.50 (0.02)
Left eye maximum cataract potential	3.01 (1.59)	0.55 (1.19)	-2.46 (0.02)
Right eye far visual acuity count fingers	0.26 (0.44)	0.08 (0.27)	-0.18 (0.00)
Right eye far visual acuity hand motions	0.11 (0.31)	0.03 (0.16)	-0.09 (0.00)
Right eye far visual acuity light perception	0.05 (0.22)	0.02 (0.14)	-0.03 (0.00)
Right eye far visual acuity no light perception	0.01 (0.10)	0.01 (0.09)	-0.00 (0.00)
Left eye far visual acuity count fingers	0.23 (0.42)	0.08 (0.27)	-0.15 (0.00)
Left eye far visual acuity hand motions	0.09 (0.28)	0.03 (0.16)	-0.06 (0.00)
Left eye far visual acuity light perception	0.05 (0.22)	0.02 (0.14)	-0.03 (0.00)
Left eye far visual acuity no light perception	0.01 (0.11)	0.01 (0.09)	-0.00 (0.00)
Right eye ampliopia	0.03 (0.18)	0.01 (0.11)	-0.02 (0.00)
Right eye anisometropia	0.01 (0.11)	0.00 (0.06)	-0.01 (0.00)
Right eye astigmatism	0.62 (0.49)	0.57 (0.49)	-0.05 (0.01)
Right eye myopia	0.39 (0.49)	0.34 (0.47)	-0.04 (0.01)
Right eye presbyopia	0.35 (0.48)	0.23 (0.42)	-0.12 (0.01)
Right eye hypermetropia	0.23 (0.42)	0.20 (0.40)	-0.03 (0.01)
Right eye emmetropia	0.01 (0.08)	0.02 (0.13)	0.01 (0.00)
Left eye ampliopia	0.03 (0.17)	0.01 (0.11)	-0.02 (0.00)
Left eye anisometropia	0.01 (0.11)	0.00 (0.06)	-0.01 (0.00)
Left eye astigmatism	0.61 (0.49)	0.57 (0.50)	-0.04 (0.01)
Left eye myopia	0.37 (0.48)	0.34 (0.47)	-0.03 (0.01)
Left eye presbyopia	0.34 (0.47)	0.23 (0.42)	-0.11 (0.01)
Left eye hypermetropia	0.25 (0.43)	0.20 (0.40)	-0.05 (0.01)
Left eye emmetropia	0.01 (0.08)	0.02 (0.13)	0.01 (0.00)
Observations	3,894	39,151	43,045

Notes: Standard deviations in parentheses. Patient characteristics for those within our estimating sample (having at least one cataract-related visit) and those not in our sample. Cataract potential is a score based on a 0-6 classification. The maximum cataract potential is the largest score observed during the study period. All other ocular health measures are binary variables. Last column reports a difference-in-means test with standard errors in parentheses.

Importantly, our data allow us to proxy for risk aversion. Indeed, we observe all interactions and visits between patients and firm, so we observe how many visits it takes for a patient to obtain a price quote. At each visit, patients may obtain more information or reassurance about the procedure (i.e., information is weakly increasing in the number of visits between the initial diagnosis and obtaining the price quote). We thus make the reasonable assumption that, patients who are more averse register more visits before obtaining a price quote than patients who are less averse, all else equal. Therefore, as a proxy for risk aversion, we use the number of visits between initial diagnosis and obtaining a price quote, which is 3.9 on average in our sample.

For each surgery price quote, we observe the largely exogenous surgical characteristics, which were determined by medical reasons. At 65% of surgery quotes in our sample, phacoemulsification is more common than small incision surgeries, but is also more expensive. However, patient outcomes and complication rates are similar across both methods (Gogate et al., 2005; Riaz, de Silva and Evans, 2013). We also observe the type of artificial lens that replaces the natural lens and if patients pay for additional services (e.g., lab work) at the time of purchase.[12] Lastly, we observe whether the patient bought the surgery offered by the sales agent in the price quote. In our estimations, we include sales agent fixed effects.

Table 2 shows summary statistics at the patient-quote level and distinguishes between phacoemulsification and small incision quotes. As noted above, phacoemulsification is about 70% more expensive than small incision surgery. In our sample, phacoemulsification is also associated with slightly less severe cataract scores, younger patients, and more likely to be privately insured (which in turn signals a higher socioeconomic status). In our estimations, we control for surgical and patient characteristics, including type of insurance as proxy for income.

3.1 Evidence of learning

We document descriptive evidence consistent with consumer learning (though at this point we do not discard other explanations). First, we discuss raw statistics, and then we follow up with a more nuanced analysis.

The take-up rate for cataract surgery among patients returning for a second-eye quote is 87%, which is a higher rate than among patients deciding on their

[12] Patients with small incision surgeries are only fitted with one type of lens, while the physician has four options available for phacoemulsification.

TABLE 2: Summary statistics by type of surgical product

Surgical method:	SICS	Phaco.	Diff.
Age	70.97	68.48	-2.49
	(11.02)	(12.63)	(0.38)
Female	0.61	0.61	-0.00
	(0.49)	(0.49)	(0.02)
Private insurance	0.05	0.08	0.03
	(0.23)	(0.27)	(0.01)
Social security	0.25	0.20	-0.06
	(0.44)	(0.40)	(0.01)
Uninsured	0.70	0.73	0.03
	(0.46)	(0.44)	(0.01)
Right eye cataract potential	2.71	2.39	-0.33
	(1.68)	(1.70)	(0.05)
Left eye cataract potential	2.77	2.40	-0.37
	(1.69)	(1.66)	(0.05)
Price (MXN)	8920.59	15340.78	6420.20
	(2858.03)	(5411.24)	(146.62)
Observations	1,549	3,150	4,699

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 shows a difference-in-means test. During this period, 1 USD = 19.22 MXN.

first-eye surgery (63%). Hence, the firm might react strategically by raising prices of the second surgery. However, as an opposing pricing pressure, the second surgery might offer lower marginal improvements in vision, and therefore might be less valuable to patients. Overall, we find a lower average price for second surgeries (8% lower at 640 USD vs 697 USD), but we also find a lower standard deviation of prices for second surgeries (227 USD vs 301 USD). This lower variance for the second surgery is consistent with patients being more certain about their willingness to pay. Indeed, in the context of cataract surgeries, the medical literature has documented that patients update their beliefs after the first surgery (Cheung and Sandramouli, 2005; Henderson and Schneider, 2012).

Clearly, we have a selection problem when thinking about who returns for a second surgery. Therefore, consider the following thought experiment: compare two observationally equivalent patients who only differ in their first-eye cataract score. That is, Alice has a score of 4 in her first eye, and Bob has a 6, but they both have a 3 in their second eye. After their first surgery, they are observationally equivalent.

TABLE 3: Probability of second surgery as a function of first-eye score

Second eye cataract score is	≤ 2	3	4
First eye cataract score	-0.030***	-0.062**	0.017
	(0.008)	(0.025)	(0.083)
Observations	1,659	576	194
R-squared	0.048	0.104	0.181
Mean dependent variable	0.148	0.439	0.490

Notes: Sample restricted to patients who undergo the first surgery. Robust standard errors in parentheses. Regressions include controls for gender, age dummies, and insurance status fixed effects. p-value test for joint significance across columns is 0.000. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	Before first surgery		After first surgery	
	Alice	Bob	Alice	Bob
First eye score:	4	6	0	0
Second eye score:	3	3	3	3

However, Bob has probably learned more than Alice from the first surgery; as an extreme example, a person with very mild cataracts learns very little from the procedure. Therefore, if their likelihood of undergoing the second surgery differs, it must be because Bob learned differently. In other words, without learning, there should be no difference in their take-up rate.

We can test for differences in take-up rates as functions of the first-eye score by estimating

$$\mathbb{1}\left\{\text{Second surgery}_{is}\right\} = \alpha_s + \beta_s \text{First-eye score}_i + \gamma_s' \boldsymbol{x}_i + \varepsilon_{is},$$

for each patient i and for each second-eye cataract score $s = 1, \ldots, 6$, where $\mathbb{1}\left\{a\right\}$ is an indicator of the event a, and $\boldsymbol{x}_i$ is a vector of controls including gender, age dummies, and insurance status fixed effects (private, public, none), which proxy for income.

Table 3 shows the results for this estimation. We do find a difference between patients' take-up: negative and significant coefficients imply that worst scores in first eyes are associated with lower take-up rates for the second surgery. This finding is consistent with consumers who learn more about the surgery are dissuaded from returning.

A similar thought experiment consists of asking how the score of the second eye changes the propensity of undergoing the second surgery, conditional on the first eye score. That is, Alice and Bob both have a score of 6 in their first eye, but

TABLE 4: Probability of second surgery as a function of second-eye score

First eye cataract score is	3	4	≥ 5
Second eye cataract score	0.326***	0.203***	0.180***
	(0.035)	(0.030)	(0.016)
Observations	913	469	695
R-squared	0.173	0.173	0.242
Mean dependent variable	0.244	0.299	0.302

Notes: Sample restricted to patients who undergo the first surgery. Robust standard errors in parentheses. Regressions include controls for gender, age dummies, and insurance status fixed effects. $H_0 : \beta_3 = \beta_4 \Rightarrow p = .008$; $H_0 : \beta_3 = \beta_{\geq 5} \Rightarrow p = .000$; $H_0 : \beta_4 = \beta_{\geq 5} \Rightarrow p = .494$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

their second-eye scores are 3 and 5. After the first surgery, we can ask about the marginal effect of the second-eye score on their take-up rates. Without learning, the marginal effects should not be a function of the first-eye scores.

	Before first surgery		After first surgery	
	Alice	Bob	Alice	Bob
First eye score:	6	6	0	0
Second eye score:	3	5	3	5

In this case, we can estimate the following equation,

$$\mathbb{1}\left\{\text{Second surgery}_{if}\right\} = \alpha_f + \beta_f \text{Second-eye score}_i + \boldsymbol{\gamma}_f' \boldsymbol{x}_i + \varepsilon_{if},$$

for each patient i and for each first-eye cataract score $f = 1, \ldots, 6$. Table 4 shows the results of this estimation. Because the slopes are different across columns, the estimation suggests patients are learning from the experience.

Finally, a third thought experiment compares patients *before* their first surgery that have zero cataracts in their second eye vis à vis patients *after* their first surgery (that now have zero cataracts in their first eye). In other words, suppose Alice has 4 and 0 cataract scores in each eye, and Bob has 6 and 4. After Bob's first surgery, Bob now has 0 and 4, which makes Alice's first surgery comparable with Bob's second sugery. If Alice and Bob are observationally equivalent and patients do not learn, then we should see essentially the same take-up rates for Alice's first and Bob's second surgery.[13]

[13] Alice might still develop cataracts in her second eye eventually, which means that Alice still has some option value.

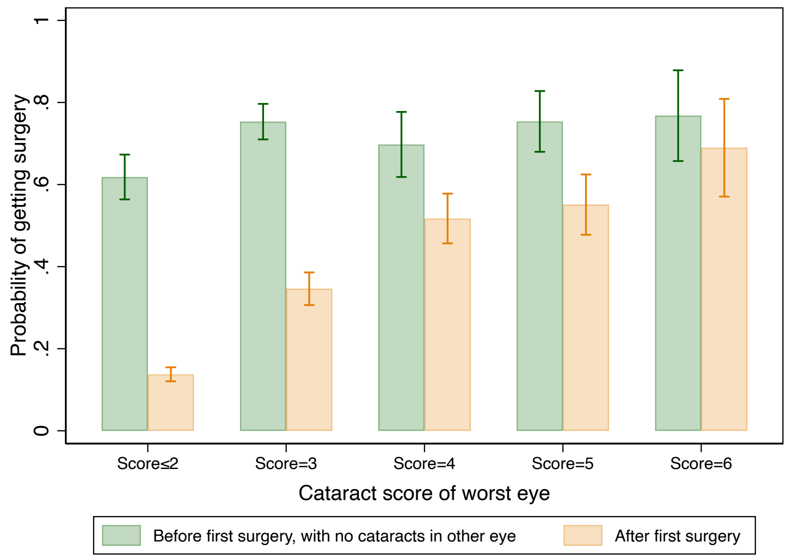

FIGURE 1: Probability of surgery, conditional on one eye having zero cataracts

	Before first surgery		After first surgery	
	Alice	Bob	Alice	Bob
First eye score:	4	6	0	0
Second eye score:	0	4	0	4

Figure 1 compares first-time patients with zero score in one eye versus returning patients. We can see returning patients have a lower propensity to operate.

To conclude, even if learning is not the cause of differential demands across observationally equivalent people, we know that something is changing. The model and estimations of section 4 disentangle the potential explanations, while taking care of addressing confounders. Interestingly, the results of this section seem to imply that learned consumers do not go ahead with the procedure, which in turn implies an important role for the option value.

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 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 and of herself. 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 uncertain component is no longer uncertain, because the consumer learns from the experience. The model allows for partial learning and flexible risk preferences. Moreover, the consumer knows that information is revealed after the first surgery, which implies an option value from it.

At each surgery opportunity, consumers face a binary choice of undergoing a surgery or not. That is, except for prices, the characteristics of the surgery are exogenous, and the consumers' consideration sets contain exactly two products: the surgery and the outside option. This assumption is realistic, because the main characteristics of the surgery are determined by the ophthalmologist for medical reasons, and is also consistent with a literature that documents patients adhere to physicians' prescriptions.[14] Moreover, because we study surgery take-up, our main counterfactual only requires us to model realistic substitution patterns towards the outside option.

4.1 Forward-looking consumer

Because we assume consumers are forward-looking, their demand for the first surgery takes into account it will reveal information about the second surgery. Let i index consumers. We represent the uncertain outcome of a surgery with α_i, an iid random shock across i. 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 the distribution of α_i.

We assume the uncertain component, α_i, is composed of a knowable and an unknowable component; that is,

$$\alpha_i \equiv \alpha_i^k + \alpha_i^u.$$

Therefore, we allow the consumer to only learn partially from the first surgery. The unknowable component is never revealed to the consumer, and can be thought of as long-term benefits or costs of the surgery which can only be learned through time.

Let $\boldsymbol{x}_{i1}$ and $\boldsymbol{x}_{i2}$ be patient and surgery characteristics, which are known in

[14]See Finkelstein et al. (2021) for the general case of physicians' recommendations, or Johnson and Rehavi (2016) and Gruber and Owings (1996) for the case of cesarean sections.

advance, and let shocks $\varepsilon_{i01}, \varepsilon_{i1}, \varepsilon_{i02}, \varepsilon_{i2}$ be iid.[15]

Define the (ex post) utility obtained from undergoing surgery t as

$$u_{it} \equiv \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{it} + \varepsilon_{it},$$

for $t = 1, 2$. The outside options are valued at $u_{i0t} = \varepsilon_{i0t}$.[16] Because the consumer does not learn about α_i^u, and does not observe it, we argue that the consumer de facto does not experience α_i^u, at least in the relevant time-frame for decision-making. Therefore, we set $\alpha_i^u = 0$, which implies that consumer welfare calculations must be interpreted as the welfare that consumers experience after the surgery, but which is relevant for them when they make decisions. Henceforth, we simply set $\alpha_i = \alpha_i^k$.[17]

Let $y_{it} \equiv \mathbb{1}\{i \text{ operates eye } t\}$, for surgeries $t = 1, 2$.

The timing is as follows:

1. Consumer i observes ε_{i01} and ε_{i1}.
2. i decides to operate eye 1 or not.
   (a) If $y_{i1} = 0$, utility is ε_{i01}. End.
   (b) If $y_{i1} = 1$, nature draws α_i from a distribution G_i and ε_{i2}.
3. i observes α_i, ε_{i02}, and ε_{i2}.
4. i decides to operate 2 or not.
   (a) If $y_{i2} = 0$, utility is $\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} + \varepsilon_{i02}$. End.
   (b) If $y_{i2} = 1$, utility is $\alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} + \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2}$. End.

For reference, the model tree can be found in section B in the appendix.

[15]The assumption of iid shocks across time is standard in the literature, where shocks commonly are assumed to have a Type-1 extreme value distribution. See, for instance, Gowrisankaran and Rysman (2012) or Arcidiacono and Ellickson (2011) for a review of common methods. We provide further details on identification in section 4.2.

[16]The reader might think that the outside option for the second surgery is not valued at ε_{i02}, because the patient might "carry" α_i^k with her to another provider. However, we assume α_i^k subsumes everything related to ocular health information, and $\alpha_i^u + \varepsilon_{i2}$ subsumes everything else. Therefore, we can interpret $\alpha_i^u + \varepsilon_{i2}$ as including remaining uncertainty from any of the outside options. This assumption is standard in the literature.

[17]Claude Monet's α. Monet is not a representative patient for our sample, but is the most famous cataracts patient, and his case is illustrative. Figure 9 in appendix C shows how Monet perceived the world before and after cataracts. Famously, Monet was advised by friends, family, and physicians to get a cataract surgery, but he was hesitant. After, presumably, their advice pushed his expected marginal utility into a positive sign, Monet underwent the surgery. Then, Monet went back and destroyed some paintings he had created while his vision was impaired. That is, Monet had a positive realization of the α shock, which made him regret some of his work ex post. See Gruener (2015).

Demands can be derived by backward induction. The consumer decides to get the second surgery if and only if

$$u_{i2} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2} > u_{i02} = \varepsilon_{i02}.$$

Therefore, conditional on the first surgery, the demand for the second surgery is

$$P\left[y_{i2} = 1 | y_{i1} = 1\right] = P\left[u_{i2} - u_{i02} > 0\right],$$

where we drop the conditional statement, because of independence.

Then, the expected marginal utility of the second surgery is

$$\mathbb{E}\left[u_{i2} - u_{i02}\right] = \mathbb{E}\left[u_{i2} - u_{i02} | u_{i2} - u_{i02} > 0\right] P\left[u_{i2} - u_{i02} > 0\right]$$

where the expectations are with respect to $\alpha_i + \varepsilon_{i2} - \varepsilon_{i02}$.

Therefore, before the first surgery, after ε_{i1} and ε_{i01} are known, but before α_i, ε_{i2}, and ε_{i02} are known, the expected marginal utility from the first surgery is

$$\mathbb{E}_{\alpha_i}[u_{i1} - u_{i01} + \mathbb{E}\left[u_{i2} - u_{i02}\right]] = \mathbb{E}_{\alpha_i}[\alpha_i] + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} - \varepsilon_{i01} + \mathbb{E}\left[u_{i2} - u_{i02}\right],$$

where the expectation with respect to α_i has been subscripted, and $\mathbb{E}\left[u_{i2} - u_{i02}\right]$ represents an option value conditional on undergoing the first surgery.

The consumer chooses the first surgery if and only if

$$\mathbb{E}_{\alpha_i}[u_{i1} - u_{i01} + \mathbb{E}\left[u_{i2} - u_{i02}\right]] > 0.$$

Therefore, the demand for the first surgery is

$$P\left[y_{i1} = 1\right] = P\left[\mathbb{E}_{\alpha_i}[u_{i1} - u_{i01} + \mathbb{E}\left[u_{i2} - u_{i02}\right]] > 0\right].$$

4.2 Identification and estimation

We take care of addressing important of threats to identification; namely, price endogeneity, selection bias, and confounders such as risk aversion, diminishing marginal returns, and income effects. We also discuss the identification argument for the variance of uncertainty shocks.

Price endogeneity. To identify the price coefficient, we use sales targets variables as instruments in a control function strategy described in detail in the appendix section D (Petrin and Train, 2010). 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. Specifically, the patient-specific demand shocks are uncorrelated with how far or close an agent is to her target on a given day. For instance, the patient's support system for post-operative care should be orthogonal to whether a particular day faced an unusually low demand. Generally, as long as the demand shocks are independent across patients, the exclusion restriction will hold.[18] 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 8 or more quotes in the data (Greene, 2004), which is more than 98% of quotes. Other patient controls include: log age, gender, type of insurance as a proxy for income, a risk aversion proxy, cataract score dummies, type of surgery, type of intra-ocular lens, and type of amenities.[19]

Risk aversion. As a potential confounder, it may be that patients who return are a selected sample of unobservably more risk averse individuals (the same reasoning applies to sicker or higher income patients). There are essentially two types of risk in this setting: First, there is a surgery-specific risk due to potential complications, such as infections; second, there is the uncertainty shock α_i, which represents an individual-specific surprise outcome. While the second type of risk is explicitly modeled, we need to address the first one, because, otherwise, it would be absorbed by the ε_{it} shocks. Our data allow us to measure a proxy for risk aversion, under the reasonable assumption that patients who engage in more visits before obtaining a price quote are more risk-averse than patients who do so in fewer visits, all else equal (including observable health characteristics). Hence, we control for (log) visits per price quote, which offers variation at the surgery- and individual-level.

Decreasing marginal returns. We allow for consumers to have different marginal valuations of surgeries as a function of health characteristics. For instance, the first surgery might be more valuable, because the patient might

[18]One possible violation of this assumption would be if, on a given day, there was unusually high traffic or roadblocks that made access to the clinic more difficult. However, it does not seem that many patients arrive by car, possibly due to the central location of the main clinic (a mix of both availability of public transportation and high parking costs).

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

recover a larger improvement in their vision from it. The second surgery might be less valuable, because the patient already has an improved vision. We provide flexibility for valuations to go either way by controlling for cataract scores of both eyes in both surgery demands, as well as for other patient and surgery characteristics.

Income effects. Because surgeries are relatively expensive, even at our partner firm, we might have income effects, where high-income consumers are less elastic, for example. In Mexico, high income is highly correlated with health insurance coverage (ENSANUT, 2020). Therefore, as a proxy for income we use type of insurance, which is observable in our data. Alternatively, we also observe zip codes, but we favor insurance type, because results are similar and less prone to incidental parameters problems.

Size of uncertainty shocks. 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. 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, whiches include log age, gender, cataract score dummies, and ocular health measures. More formally, we identify $\sigma_{\alpha,i}$ given that ε-shocks have the same variance: Conditional on observables, if the decision to undergo either surgery is the same between surgeries, except for the information set, then we have identification. In this context, we find this assumption to be reasonable, because we observe the major components of the decision; namely, prices, surgery characteristics, demographic characteristics (e.g., income), risk-aversion proxies, and ocular health measures. Moreover, the utility specification is flexible enough to account for a lower marginal utility for the second operation and for the role of severity in both eyes. Finally, this assumption is very common in the dynamic discrete choice models literature (Arcidiacono and Ellickson, 2011).

Selection bias. 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 the first one. 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, sales agents, optometrists, and ophthalmologists. We use a simple machine learning technique, LASSO, to predict prices; we find LASSO outperforms a linear regression in this setting, as measured by the mean prediction error, and achieves an R^2 of .72. We match the distribution of predicted prices to the empirical distribution of non-missing prices, as shown in Figure 10, which can be found in the appendix section E, along with further details of the algorithm.

Estimation. Estimation is performed in two steps. We first construct a control function. Then, we add the control function as an extra regressor, and we perform a maximum likelihood estimation as detailed below. We run 500 (panel) bootstraps of the whole process to calculate standard errors.

We begin by assuming distributions for the shocks. A common assumption is Type-1 extreme-valued ε-shocks, which yield a mixed logit model if we assume a normal distribution for α. However, because we have a binary choice model, we see no advantage of a mixed logit vis-à-vis normally distributed ε-shocks, but, if we assume normality, we can solve analytically for the equilibrium of the model.

We make the following simplifying assumption.

Assumption 1. *$\varepsilon_{i1} - \varepsilon_{i01}$ and $\varepsilon_{i2} - \varepsilon_{i02}$ are iid $\mathcal{N}(0,1)$, and α_i are iid $\mathcal{N}(\mu_{\alpha,i}, \sigma_{\alpha,i})$.*

Under assumption 1, we obtain

$$\mathbb{E}\left[u_{i2} - u_{i02}\right] = \left[\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)\right]\Phi\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)$$

$$P\left[y_{i1} = 1\right] = \Phi\left[\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \mathbb{E}\left[u_{i2} - u_{i02}\right]\right] \tag{1}$$

and

$$P\left[y_{i2} = 1 | y_{i1} = 1\right] = \Phi\left(\frac{\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i2}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right), \tag{2}$$

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. Section B in the appendix shows the derivations for these expressions.

From (1) and (2), 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 ex ante informed consumers who can correctly anticipate their mean utility level from surgeries.

Finally, let $s_{i1} \equiv P[y_{i1} = 1]$ and $s_{i2} \equiv P[y_{i2} = 1 | y_{i1} = 1]$, and recall our parametrization $\sigma_{\alpha,i} \equiv \exp(\boldsymbol{\theta}' w_i)$. Therefore, the log-likelihood of the data 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 $(\boldsymbol{\beta}, \boldsymbol{\theta})$.

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 bootstrap repetitions.

Table 5 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 $\sigma_{\alpha,i}$. Different columns offer different specifications of the σ equation and some add 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.

All columns include as controls: surgery characteristics, a proxy for income, and sales agents fixed effects.

As a benchmark, column 1 shows a standard IV-probit, where we do not allow for uncertainty shocks, α, nor we allow for an option value of the second surgery. Column 2 allows for uncertainty shocks, but does not address endogenous prices, and yields very elastic demand curves. Column 3 addresses price endogeneity.

TABLE 5: DEMAND ESTIMATIONS

DEP VAR: Operates$_{it}$	(1)	(2)	(3)	(4)
log price	-3.85	-0.93	-3.92	-3.92
	(0.068)	(0.077)	(0.070)	(0.071)
log Age	0.08	-0.11	0.07	0.05
	(0.074)	(0.084)	(0.078)	(0.104)
Female	-0.04	-0.09	-0.05	0.12
	(0.025)	(0.041)	(0.025)	(0.135)
Min cataract score	0.03	0.07	0.03	0.00
	(0.009)	(0.015)	(0.009)	(0.022)
Max cataract score	-0.01	0.02	-0.02	0.00
	(0.011)	(0.017)	(0.010)	(0.027)
Risk aversion proxy	0.01	1.17	0.01	0.00
	(0.034)	(0.032)	(0.033)	(0.035)
DEP VAR: $\sigma_{\alpha,i}$				
log Age				-1.98
				(0.243)
Female				-2.57
				(0.358)
Min cataract score				-1.95
				(0.172)
Max cataract score				-2.10
				(0.210)
RE health score				-2.02
				(0.174)
LE health score				-2.03
				(0.180)
cons		6.46	5.30	3.65
		(0.257)	(0.336)	(1.076)
ELASTICITIES				
ALL OPS	-3.64	-7.99	-6.31	-3.56
FIRST OPS	-3.72	-11.39	-8.62	-4.07
SECOND OPS	-3.57	-4.53	-3.96	-3.04
OTHER CONTROLS	YES	YES	YES	YES
CONTROLS ($\sigma_{\alpha,i}$)	NO	NO	NO	YES
CONTROL FUNCTION	YES	NO	YES	YES
MPE	0.43	0.41	0.39	0.34
R_p^2	-0.06	0.00	0.04	0.16
FIRST-STAGE IV'S F	50.48		50.48	50.48
PATIENTS	3,894	3,894	3,894	3,894
QUOTES	7,848	7,848	7,848	7,848

Notes: Bootstrapped standard errors clustered at individual level with 500 repetitions. Risk aversion proxy is (log) number of visits to obtain a price quote. Control functions for prices are constructed with daily percentage of operations sold up to the moment as an instrument (Petrin and Train, 2010). Other controls include: sales agents fixed effects, surgery characteristics, and type of insurance as proxy for income. In the $\sigma_{\alpha,i}$ equation, eye health scores count the number of comorbidities (ampliopia, anisometropia, astigmatism, myopia, presbyopia, hypermetropia, and emmetropia) present in each eye. MPE stands for mean prediction error. R_p^2 stands for pseudo-R^2, constructed as described in footnote 21. Price elasticities with respect to unconditional demands: $P\left[y_{it}=1\right]$, $t=1,2$.

Column 4 shows our preferred specification, which includes both the control variables in the σ equation and a control function approach. 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.[20]

As for the information shock, we find that older people, women, and patients with worse scores experience lower uncertainty from the first surgery. 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.

All columns support the existence of an information shock, where the null hypothesis is no information shock. 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.[21] Indeed, in the appendix F, we perform our estimations in a training set, consisting of a random sample of 50% of the data, and we test our estimations in the hold-out sample of the remainig 50%. We find our preferred specification outperforms the rest, and is not simply overfitting the data.

Our overall elasticities are in line with what one might expect: because patients mainly pay out-of-pocket and this is an elective procedure, we find elastic demands. These estimates are broadly consistent with other Latin American settings. For instance, Duarte (2012) exploits variation in Chile in public sector price caps that affect private insurance plans, finding that elasticities for elective procedures range from -0.3 to -2.1. In the US, researchers analyzing the seminal RAND health insurance experiment obtained very inelastic demands (Newhouse, 1993; Lurie et al., 1989). However, some of these elasticities have been revisited in various ways (see Aron-Dine, Einav and Finkelstein (2013) for a broad discussion). For instance, Kowalski (2016) uses a censored quantile instrumental variable estimator that leads to elasticities for medical care between -0.8

[20]The unreported estimates for surgery characteristics are significant. 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.

[21]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).

and -1.5, an order of magnitude larger than the RAND experiment elasticities.

We find that elasticities are consistently larger for the first operation compared to the second. In our preferred specification, we find that a 10% increase in the price leads to an overall decline of 35.6% in the probability of getting cataract surgery. However, for a 10% increase in the price of the first surgery, take-up goes down by 40.7%, while the same percentage change for the second surgery only leads to a decline of 30.4% in the probability of take-up.

We also note that our risk aversion proxy is insignificant, except when prices are not instrumented. This makes sense for at least two reasons. First, we actually were expecting patients not to worry too much about surgery-specific complications or secondary effects, because the procedure is overall very safe. Even in the developing world, complication are extremely rare (Miller et al., 2022); in our data, we didn't observe a single complication. Second, if price effects are not properly identified, then differential elasticities between operations have to be (erroneously) explained through differential risk attitudes. Indeed, to rationalized observed demands, column 2 finds that people who are more risk averse are also more willing to undergo surgery, which yields unrealistic price elasticities.

Figure 2 plots the distribution of our estimated uncertainty shock parameter. We find considerable heterogeneity, with bimodality (due to gender dummies), and a relatively long right tail (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 2.1 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 post utility from getting surgeries, and we transform consumer surplus into dollar terms by considering the marginal utility of income implied by the model. Specifically, given α_i, and ε-shocks, we compute the ex post surplus as

$$CS_i(\alpha_i, \varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i01}, \varepsilon_{i02}) \equiv \mathbb{1}\left\{u_{i1}^m + \mathbb{E}\left[u_{i2}^m\right] > 0\right\} \left(\frac{u_{i1}^m}{\frac{\partial u_{i1}^m}{\partial p_{i1}}} + \mathbb{1}\left\{u_{i2}^m > 0\right\} \frac{u_{i2}^m}{\frac{\partial u_{i2}^m}{\partial p_{i2}}} \right),$$

where $u_{it}^m \equiv u_{it} - u_{i0t}$ are the marginal utilities, and where we simulate 500 vectors of shocks, and average across them to find our estimate of consumer

[22] We obtain qualitatively similar results with ex ante computations of consumer surplus.

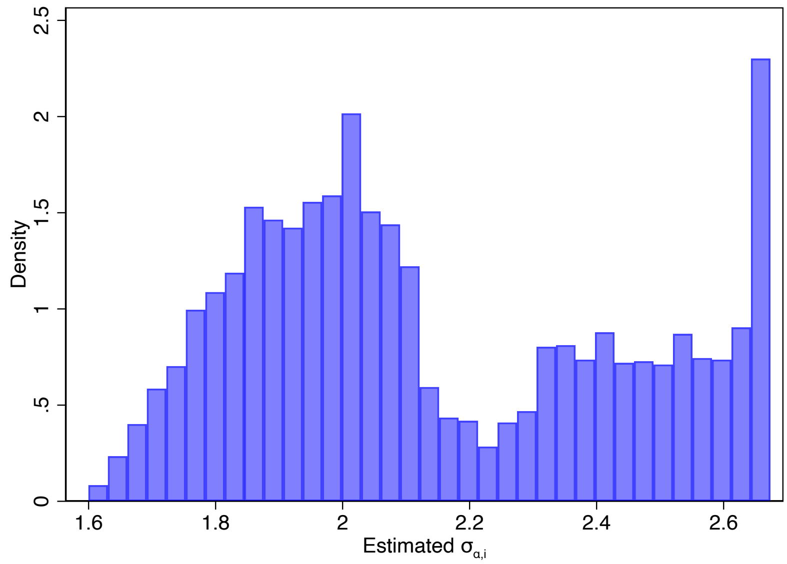

FIGURE 2: Distribution of $\widehat{\sigma}_{\alpha,i}$
Note: Distribution winsorised at 95th percentile.

surplus, CS_i.[22]

Figure 3 presents the distribution of the estimated ex post consumer surplus in US dollars, which is on average 92 USD.[23] The distribution presents a high dispersion. We therefore winsorize this plot at the 1st and 99th percentiles. A small percentage of patients have a negative estimated surplus, because they received a negative shock after the first surgery and did not exercise their option for the second surgery. As a reminder, the average price of cataract surgery at this provider is around 13,000 pesos or 700 USD (Table 2).

The interpretation of the consumer surplus is anchored by the outside option. That is, we estimate the marginal surplus with respect to the outside option. Then, the conservative interpretation is that we find a lower bound on the real consumer surplus from the surgery. However, for the vast majority of patients, the outside option is simply not getting a surgery.[24] Therefore, our estimated surplus is close to the real surgery surplus for these patients.

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

[24]The authors surveyed former patients by phone. Of those patients who were surveyed, about 10% of them report having a surgery outside our partner firm, which amount to 17% of patients who did not get a surgery with our partner firm.

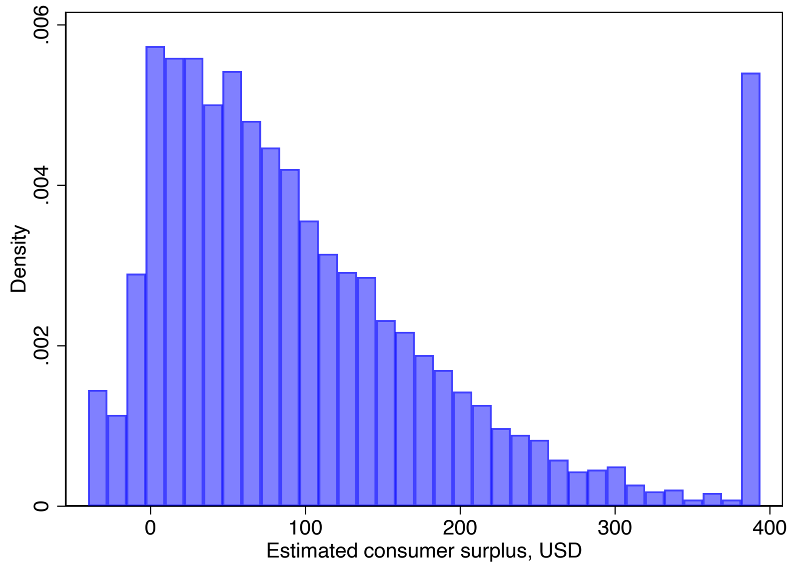

FIGURE 3: Distribution of estimated ex post consumer surplus
Note: Distribution winsorised at 1st and 99th percentiles.

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. Therefore, whether we have under or oversupply remains an empirical question.

With estimated preferences, we simulate two counterfactual policies. First, we quantify the welfare costs (or gains) from surprises in a counterfactual resolution of uncertainty. The medical literature is interested in these type of experiments; Mailu et al. (2020) offers a review.

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

[25] The reader might ask about an obvious counterfactual: tie-ins, that is, bundling both surgeries from the start at a single price. However, here is a simple argument against tie-ins: because the consumer is uncertain about outcomes, the consumer's dominant strategy is to consume sequentially. On the other hand, the firm would have to drop the price significantly to convince consumers to purchase the bundle, which is not optimal for the firm. Moreover, the authors have found no firm on the market which offers this option.

while taxing the second operation. Policymakers might find this counterfactual informative, because take-up increases through an efficient mechanism.

Throughout we analyze the heterogeneous effects of these policies.[25]

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. These types of interventions have been done in a variety of settings and have been experimentally evaluated by the medical literature (Mailu et al., 2020). For instance, a champion c might reveal their outcome $\alpha_c = \sigma_i/2$ to a potential consumer i. The potential consumer i might believe totally or partially in this information. For simplicity, we assume patients completely believe the champion's announcement, but the model can readily incorporate partial persuasion. We offer a range of possible outcomes based on the level of α_i that potential consumers might believe, including $\alpha_i = 0$, which would quantify the value of uncertainty.

That is, given a *revealed* α, we compute the ex post consumer surplus with known α as:

$$CS_i^{\alpha}(\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i01}, \varepsilon_{i02}) \equiv \mathbb{1}\left\{u_{i1}^m + \mathbb{E}\left[u_{i2}^m\right] > 0\right\} \left(\frac{u_{i1}^m}{\frac{\partial u_{i1}^m}{\partial p_{i1}}} + \mathbb{1}\left\{u_{i2}^m > 0\right\} \frac{u_{i2}^m}{\frac{\partial u_{i2}^m}{\partial p_{i2}}} \right)$$

where we set $\sigma_{\alpha,i} = 0$, and expectations are only with respect to demand shocks. In other words, if we set $\alpha_i = \alpha$, patients believe the shock to be α with probability 1, and the only remaining uncertainty at the time of the first surgery are the second surgery demand shocks. Then, a reduced option value remains. Again, we simulate a vector of shocks and take an average to find CS_i^{α}.

Figure 4 shows how consumer surplus changes from the status quo to a revealed information couterfactual. As expected, as the revealed shock increases, consumer surplus increases. Perhaps surprisingly, at $\alpha_i = 0$, this change is negative, which implies uncertainty is valuable for consumers. Intuitively, patients value uncertainty, because a bad draw from the surprise distribution can be mitigated by operating just once, but a good draw can be amplified by operating twice.[26] The reader could have anticipated these results, because in section 3.1

[26] In equilibrium, the firm would react to a counterfactual resolution of uncertainty by changing

we found "model-free" evidence consistent with consumers who learn more about the surgery are dissuaded from returning.

Therefore, for consumers to value certainty, the revealed information needs to be credible and sizable.

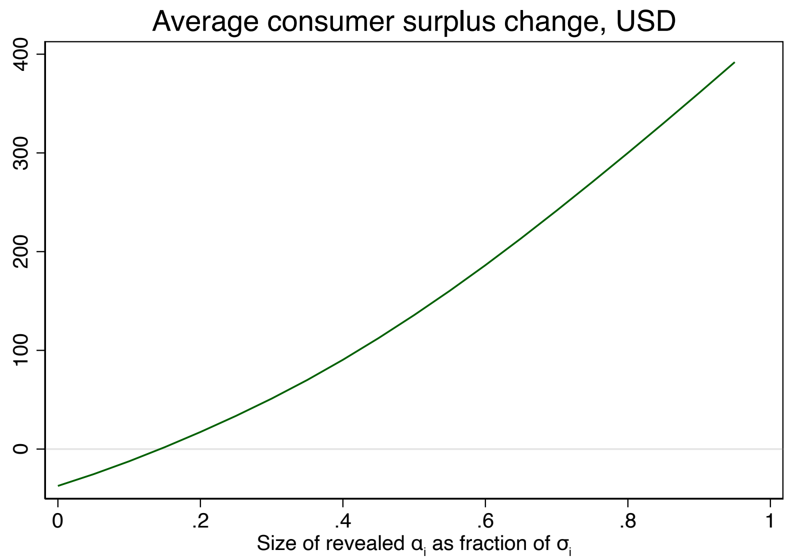

FIGURE 4: Quantifying uncertainty and champions policy

6.2 Revenue-neutral price changes

Now we consider how to increase surgeries in such a way that the firm remains indifferent. Policymakers—government, NGOs, or other third-parties—are interested in such interventions, because take-up might increase through simple price changes. Throughout these counterfactuals we consider ex post estimations of consumer surplus, demand, and revenue, and we focus on revenue-neutral policies.[27]

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

prices. For instance, if the option value is high, then prices for the first surgery would be high as well, because willingness-to-pay for the first surgery is high. Without uncertainty, the option value drops, because the consumer has less to learn.

[27]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.

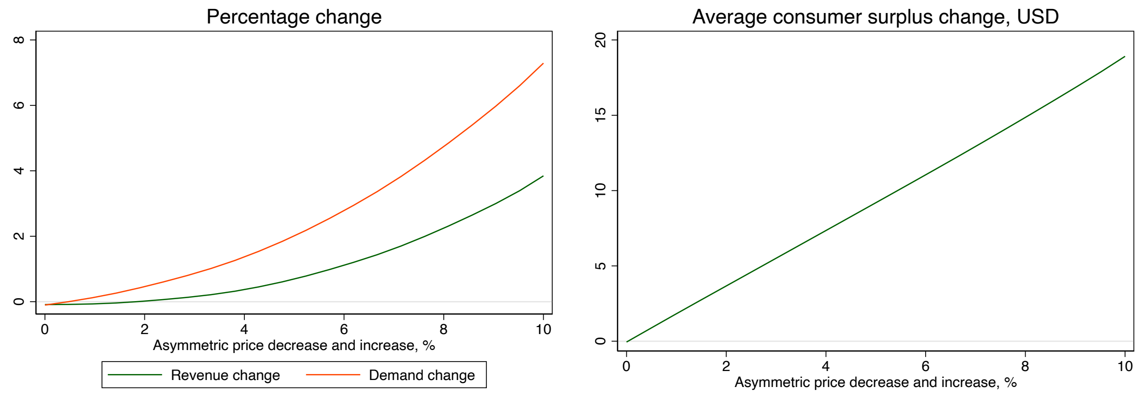

FIGURE 5: Asymmetric, revenue-neutral change in pricing policy

Note: Counterfactual increase of second surgery prices is 2 times the decrease of first surgery prices. For example, if p_1 drops in 1%, then p_2 increases in 2%.

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 total demand is the elasticity for the first surgery. Therefore, it's not obvious if a demand-increasing, budget-neutral price change can be found. But, if the demand for the second surgery is less elastic, we might find a pricing schedule where welfare increases through cross-subsidizing.

Figure 5 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 $2x$%. The firm is roughly indifferent, but take-up increases, and consumers are significantly better off.

Figure 6 shows a symmetric price change: if p_1 decreases by x%, then p_2 increases by x%. In this case we find both the firm's revenues and the consumer surplus are even higher. In particular, take-up increases to a greater extent.

In both cases, new consumers undergo the surgery. Figure 7 shows a breakdown of changes in demand by first and second surgeries. We can see the increase in the extensive margin is mainly due to an increase in the take-up of the first surgery.

In light of these results, a natural question may be why the firm has not implemented these pricing schedules yet. We posit two hypotheses, but are unable to test for them within our model. First, the firm is presumably already near an optimum: In fact, our estimations imply the firm profits about 10% of

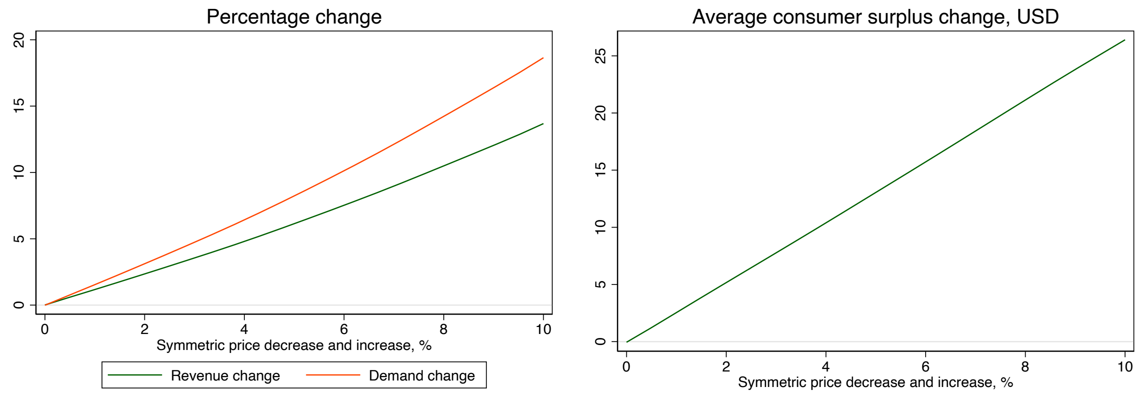

FIGURE 6: Symmetric, revenue-neutral change in pricing policy

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%.

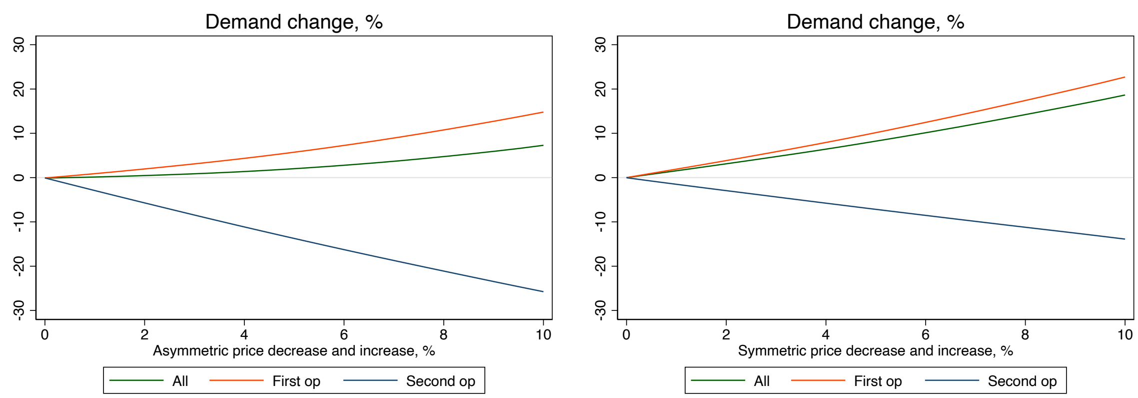

FIGURE 7: Demand changes by surgery, revenue-neutral change in pricing policy

Note: For the asymmetric price change, counterfactual increase of second surgery prices is 2 times the decrease of first surgery prices. For example, if p_1 drops in 1%, then p_2 increases in 2%.

the surgery's price on average, which is coincides with their declared business model. With slim profit margins, the firm might not be able to justify the potential backlash from an ill-executed price hike in the second surgery, including a negative impact on reputation. Second, the firm might find hard to implement this type of price discrimination in practice. Indeed, the industry standard appears to be independent, sequential pricing.

Therefore, we think there is room for policy. For instance, the government or an NGO might intervene by offering vouchers or cross-subsidies. These third-parties should find the firm is willing to cooperate, because the firm remains roughly indifferent, while take-up increases.

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 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, which is of interest to policymakers.

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 interventions.

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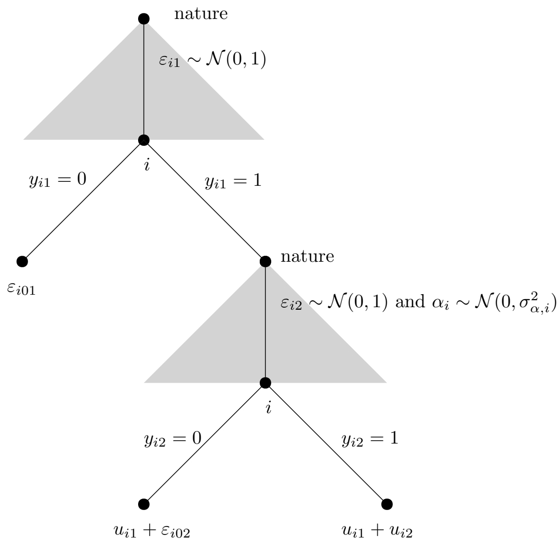
A Details on ocular health measures

TABLE 6: Description of ocular health measures

Measure	Description
Far visual acuity	A measure of a person's vision, typically set at "optical infinity", which is approximated at 20 feet.
Near visual acuity	A measure of a person's vision, defined as a comfortable reading distance of around 18 inches.
Amblyopia	Vision that does not develop properly during childhood. Also referred to as lazy eye.
Anisometropia	A condition in which the eyes have unequal refractive power, meaning the degree to which the lens converges or diverges light.
Astigmatism	Distorted shape of the cornea and/or lens that causes improper light refraction, leading to blurry and distorted vision of both near and far objects.
Myopia	Refractive error caused by the eye not focusing light properly on the retina, leading to blurry vision for distant objects. Also called nearsightedness.
Presbyopia	An increased rigidity in the lens caused by aging, which leads the eye to lose the ability to see things clearly up close.
Hypermetropia	A refractive error due to an eye focusing problem that causes close objects to appear blurred. Also called hyperopia or farsightedness.
Emmetropia	A state of vision without refractive error, leading to a sharp focus of objects that are far away, typically around 20 feet. The presence of a refractive error of this type is called ametropia.

Notes: This table describes the ocular health measures included in the summary statistics of main text Table 1. Information in this table is taken directly from the American Academy of Ophthalmology, www.aao.org.

B Model tree and demand derivations



1. Nature draws shock ε_{i1}
2. Given ε_{i1}, i operates or not
3. Nature draws shocks $\varepsilon_{i2}, \alpha_i$
4. Given $\varepsilon_{i2}, \alpha_i$, i operates or not
5. Payoffs

$$u_{i1} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1}$$
$$u_{i2} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2}$$

FIGURE 8: Model tree and basic timing

Assuming normal errors (assumption 1), we can simplify,

$$\begin{aligned}
&\mathbb{E}\left[u_{i2} - u_{i02} | u_{i2} - u_{i02} > 0\right] \\
&= \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\,\mathbb{E}\left[\frac{\alpha_i + \varepsilon_{i2} - \varepsilon_{i02} - \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\middle| \frac{\alpha_i + \varepsilon_{i2} - \varepsilon_{i02} - \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}} > -\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right], \\
&= \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\,\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right), \qquad (3)
\end{aligned}$$

conditional on the first surgery. Also,

$$\begin{aligned}
P\left[u_{i2} - u_{i02} > 0\right] &= P\left[\alpha_i + \varepsilon_{i2} - \varepsilon_{i02} + \boldsymbol{\beta}'\boldsymbol{x}_{i2} > 0\right] \\
&= \Phi\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right).
\end{aligned}$$

Then,

$$\begin{aligned}
&\mathbb{E}_{\alpha_i}\left[u_{i1} - u_{i01} + \mathbb{E}\left[u_{i2} - u_{i02}\right]\right] \\
&= \mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1} - \varepsilon_{i01} \\
&+ \left\{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)\right\}\Phi\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right),
\end{aligned}$$

and,

$$\begin{aligned}
&P\left[y_{i1} = 1\right] \\
&= P\left[\mathbb{E}_{\alpha_i}\left[u_{i1} - u_{i01} + \mathbb{E}\left[u_{i2} - u_{i02}\right]\right] > 0\right] \\
&= \Phi\left[\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \left\{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i} + \sqrt{1+\sigma^2_{\alpha,i}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)\right\}\Phi\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2} + \mu_{\alpha,i}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)\right].
\end{aligned}$$

Also, once α_i is known to the consumer, the unconditional 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

$$P\left[y_{i2} = 1 | y_{i1} = 1\right] = P\left[u_{i2} - u_{i02} > 0\right] = \Phi\left(\frac{\mu_{\alpha,i} + \boldsymbol{\beta}'\boldsymbol{x}_{i2}}{\sqrt{1+\sigma^2_{\alpha,i}}}\right)$$

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.

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,

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

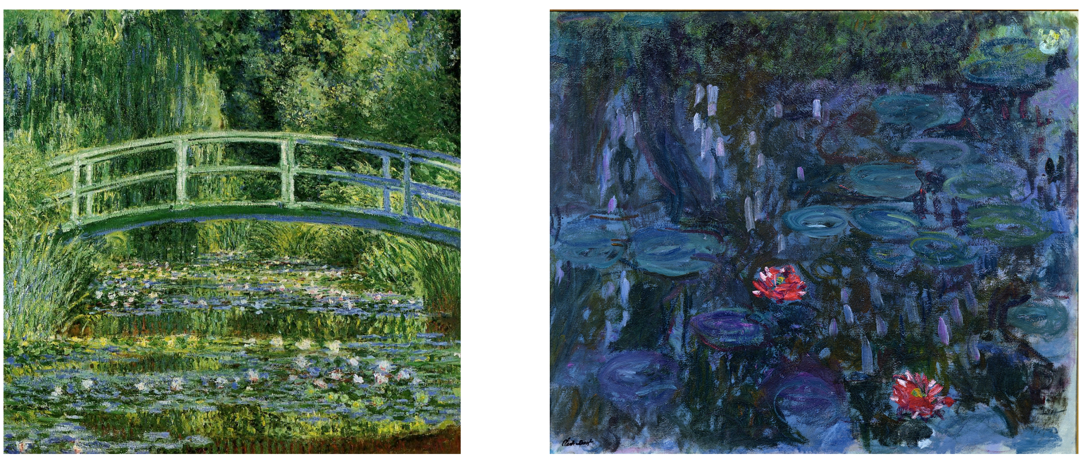
Finally, because the expected demand of consumer i is $D_i = s_{i1} + s_{i1}s_{i2}$, price elasticities of demand are defined as

$$\epsilon_{i1} \equiv \frac{\partial s_{i1}}{\partial p_{i1}}\frac{p_{i1}}{s_{i1}} \quad \text{and} \quad \epsilon_{i2} \equiv \frac{\partial s_{i1}s_{i2}}{\partial p_{i2}}\frac{p_{i2}}{s_{i1}s_{i2}}.$$

It can be shown that

$$\frac{\partial D_i}{\partial p_{i1}}\frac{p_{i1}}{D_i} = \epsilon_{i1} \quad \text{and} \quad \epsilon_{i2} = \frac{\partial s_{i2}}{\partial p_{i2}}\frac{p_{i2}}{s_{i2}} + \epsilon_{i1}s_{i2}.$$

C Claude Monet's α



(A) Water lilies and Japanese bridge

(B) Nymphéas reflets de saule

FIGURE 9: Two of Monet's paintings: Giverny period c.1897 (left) and with cataracts c.1916 (right)

D Price endogeneity and control function

To deal with endogenous prices, we use a control function (Petrin and Train, 2010). We assume:

Assumption 3. Shocks can be decomposed as $\varepsilon - \varepsilon_0 = \gamma\rho + \widetilde{\varepsilon}$, where prices $p \perp \widetilde{\varepsilon}$, and ρ is correlated with prices, with $\mathbb{V}[\rho] = 1$.

Then,

$$\mathbb{V}\left[\varepsilon-\varepsilon_0\right]=1=\gamma^2+\mathbb{V}\left[\widetilde{\varepsilon}\right]\Rightarrow\mathbb{V}\left[\widetilde{\varepsilon}\right]=1-\gamma^2.$$

Define

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

Therefore, by decomposing $\varepsilon-\varepsilon_0$ in the preceding derivations, we have

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

and

$$\begin{aligned}&\mathbb{E}\left[u_{i2}-u_{i02}|u_{i2}-u_{i02}>0\right]\\&=\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\gamma\rho_{i2}+\mathbb{E}\left[\alpha_i+\widetilde{\varepsilon}_{i2}|\alpha_i+\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\gamma\rho_{i2}+\widetilde{\varepsilon}_{i2}>0\right]\\&=\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\gamma\rho_{i2}+\sigma_{\widetilde{\varepsilon}}\sqrt{1+\frac{\sigma^2_{\alpha,i}}{\sigma^2_{\widetilde{\varepsilon}}}}\lambda\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i2}+\gamma\rho_{i2}}{\sigma_{\widetilde{\varepsilon}}\sqrt{1+\frac{\sigma^2_{\alpha,i}}{\sigma^2_{\widetilde{\varepsilon}}}}}\right).\end{aligned}$$

Then,

$$\begin{aligned}P\left[y_{i1}=1\right]&=P\left[\mathbb{E}_{\alpha_i}\left[u_{i1}+\mathbb{E}\left[u_{i2}-u_{i02}|u_{i2}-u_{i02}>0\right]P\left[y_{i2}=1\right]\right]>0\right]\\&=P\left[\boldsymbol{\beta}'\boldsymbol{x}_{i1}+\gamma\rho_{i1}+\widetilde{\varepsilon}_{i1}+\mathbb{E}\left[u_{i2}-u_{i02}|u_{i2}-u_{i02}>0\right]P\left[y_{i2}=1\right]>0\right],\\&=\Phi\left[\frac{\boldsymbol{\beta}'\boldsymbol{x}_{i1}+\gamma\rho_{i1}+\mathbb{E}\left[u_{i2}-u_{i02}|u_{i2}-u_{i02}>0\right]P\left[y_{i2}=1\right]}{\sigma_{\widetilde{\varepsilon}}}\right].\end{aligned}$$

Therefore, 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

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

E Details on unobserved price predictions

In order to predict the missing price quotes on second surgeries, we employ a least absolute shrinkage selector operator (LASSO). Specifically, we predict log prices using:

- Patient's characteristics: age, gender, access to private insurance, social security, cataract scores, and ocular conditions, namely, ampliopia, anisometropia, astigmatism, myopia, presbyopia, hypermetropia, and emmetropia.
- Surgery's characteristics: type of intraocular lens and type of surgery.
- Personnel: identity of sales agents, optometrists, and ophthalmologists who interacted with the patient.

These covariates amount to a total of 291 predictors, of which 156 were selected by LASSO. The penalty parameter was selected by cross-validation, using 10 folds. We use all observed price quotes for this estimation. We find a mean prediction error of .07, which is small, given the average log price is about 9.4.

Figure 10 shows the price histograms of observed prices for first and second surgeries, and the predicted price distribution for the unobserved second surgery prices. The graph and the mean prediction error give us confidence in our procedure to predict the missing data.

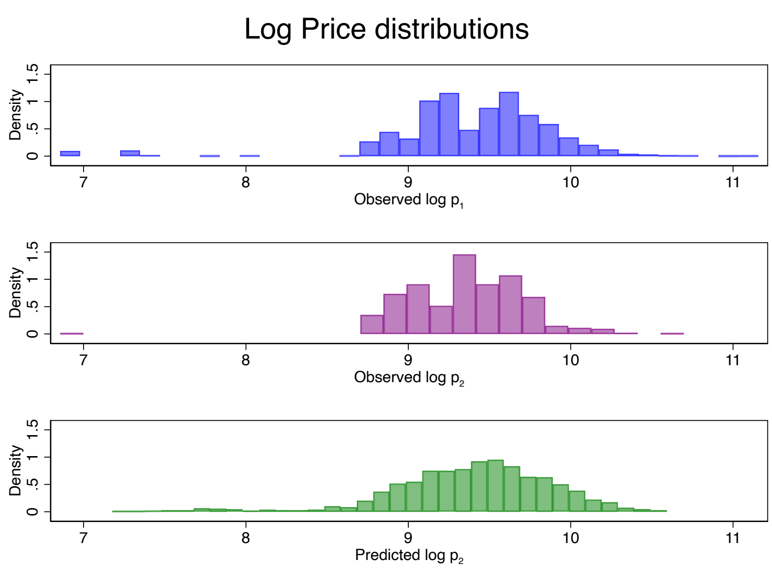


FIGURE 10: Observed and predicted (log) price distributions

F Robustness checks

TABLE 7: DEMAND ESTIMATIONS IN TRAINING SET

DEP VAR: Operates$_{it}$	(1)	(2)	(3)
log price	-3.85	-3.96	-3.96
	(0.106)	(0.116)	(0.216)
log Age	0.14	0.11	0.12
	(0.085)	(0.089)	(0.120)
Female	-0.08	-0.09	0.06
	(0.037)	(0.039)	(0.143)
Min cataract score	0.03	0.04	0.00
	(0.013)	(0.014)	(0.026)
Max cataract score	0.00	-0.02	-0.03
	(0.015)	(0.016)	(0.034)
Risk aversion proxy	0.03	0.02	0.01
	(0.053)	(0.051)	(0.052)
DEP VAR: $\sigma_{\alpha,i}$			
log Age			-2.08
			(0.449)
Female			-2.51
			(0.516)
Min cataract score			-1.97
			(0.390)
Max cataract score			-2.06
			(0.400)
RE health score			-2.06
			(0.399)
LE health score			-2.07
			(0.399)
cons		5.40	3.93
		(0.671)	(1.118)
ELASTICITIES			
ALL OPS	-3.68	-6.52	-3.84
FIRST OPS	-3.75	-8.94	-4.62
SECOND OPS	-3.61	-4.07	-3.05
OTHER CONTROLS	YES	YES	YES
CONTROLS ($\sigma_{\alpha,i}$)	NO	NO	YES
CONTROL FUNCTION	YES	YES	YES
MPE (TEST SET)	0.43	0.39	0.35
R_p^2 (TEST SET)	-0.04	0.04	0.14
FIRST-STAGE IV'S F	28.05	28.05	28.05
PATIENTS	1,910	1,910	1,910
QUOTES	3,851	3,851	3,851

Notes: Bootstrapped standard errors clustered at individual level with 500 repetitions. Models trained on a random subsample of 50% of the original data, and tested on the remaining 50%. Control functions for prices are constructed with daily percentage of operations sold up to the moment as an instrument (Petrin and Train, 2010). Other controls include: sales agents fixed effects, surgery characteristics, and type of insurance as proxy for income. In the $\sigma_{\alpha,i}$ equation, eye health scores count the number of comorbidities (ampliopia, anisometropia, astigmatism, myopia, presbyopia, hypermetropia, and emmetropia) present in each eye. MPE stands for mean prediction error, computed on the test set. R_p^2 stands for pseudo-R^2, constructed as described in footnote 21. Price elasticities with respect to unconditional demands: $P[y_{it}=1]$, $t=1,2$.