

Diagnosing Quality: Learning, Amenities, and the Demand for Health Care*

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Abstract

We study the role of amenities in increasing demand for underutilized healthcare services. We evaluate the offer of a high-amenity diagnostic consultation for cataracts with a randomized price and find that a lower price for the high-amenity consultation increases surgery take-up by more than 50%. Structural estimates from a model of patient demand show that patients' update to surgery valuation from experienced amenities is large (three-quarters of the update effect of wait time), and that price effects (e.g., sunk cost accounting or gift exchange) are much smaller, suggesting that providing amenities in initial interactions can increase adoption of underutilized services.

Keywords: health care demand, amenities, learning, health care quality, cataracts, surgery, Mexico
JEL Codes: D83, I12, L15

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1 Introduction

Information frictions play a fundamental role in health care markets (Arrow, 1963). One oft-cited problem is consumers' limited information when making choices related to health care services and insurance plans (Dranove and Satterthwaite, 1992, 2000; Handel and Kolstad, 2015; Kolstad, 2013; Kolstad and Chernen, 2009; Sofaer and Firinginger, 2005). Yet, despite these substantial frictions, recent evidence suggests health care markets function relatively well, allocating greater market share to higher quality producers (Chandra et al., 2016). This indicates that consumers are indeed able to (at least partially) discern quality differentials and make choices accordingly.

One mechanism through which this differentiation might take place is through repeat interactions with providers, which are commonplace across a wide variety of health care settings; patients often rely on these interactions to reduce uncertainty regarding quality (Chintagunta et al., 2009; Crawford and Shum, 2005; Dickstein et al., 2014; Dranove et al., 2003; Leonard, 2007; Leonard et al., 2009). This process is particularly effective for nontechnical amenities – for example, whether a clinic appears to operate efficiently or whether a physician is respectful and speaks clearly – and, notably, not effective at revealing the technical quality of care, e.g., whether the physician uses evidence-based treatment protocols (Frank, 2004). This distinction is important because the quality of health care inputs is a key driver of differences in health outcomes across providers, but may be difficult to observe even after repeated interactions (Adhvaryu and Nyshadham, 2015; Chandra and Staiger, 2007; Doyle, 2011). Amenities, on the other hand, are relatively easily observed signals, but do not directly influence health outcomes (Manary et al., 2013).

What role can amenities play in stimulating the demand for health care? Specifically, can improving amenities increase demand for “underutilized” services? We study these questions in the context of elective surgery, which commonly involves initial interaction between patients and providers through diagnostic consultations (Hoffer Gittell et al., 2000; Kim et al., 2004). We hypothesize that more amenities during the diagnostic consultation phase may increase patients' demand for surgery conditional on a positive diagnosis.

We evaluate this hypothesis in the setting of cataract surgery in Mexico City. A cataract is a clouding of the eye's lens. Cataracts are associated with aging, and if severe enough, can cause blindness. Indeed, the majority of blindness in old age is attributed to cataracts in low-income countries (Flaxman and Bourne, 2017; Lewallen, 2008; Liu et al., 2017). The only recourse for severe cataracts is surgery to

replace the clouded lens with an artificial one. Cataract surgery dramatically improves vision, but despite high need in many low-income contexts, surgery take-up is low (Congdon and Thomas, 2014; Rabiou, 2001; Zhang et al., 2014).

To inform whether greater access to amenities during initial interactions with the provider might increase surgery take up, we study a price experiment at a private cataract surgery clinic in Mexico City. The clinic's model is to provide high quality surgical services at substantially reduced prices (less than 50% the next cheapest provider), and generate most of its revenue via the offer of upcharge features for those willing to pay.¹ Clinic leadership believed that offering a more comfortable experience at the diagnostic consultation stage might increase surgery take-up among those diagnosed with operable cataracts. We evaluate a "premium" (high-amenity) diagnostic consultation with a randomized price. The consultation offered patients a chance to wait less and be seen in an upgraded room with additional amenities. These additional amenities were essentially frills: a comfortable couch to sit on and beverages.

Demand for the premium consultation varied substantially with randomized price. Roughly a quarter of patients received a positive diagnosis for cataracts, and diagnosis was not significantly different across choice of premium consultation.² Those who had operable cataracts were offered the opportunity to schedule a surgery at the clinic. Reduced form estimates show an increase of more than half in surgical rates among those offered lower premium consultation prices.

We then estimate a structural model of patient choice to elucidate potential mechanisms for this increase. Putting structure on the patient's dynamic decision-making allows us to measure the extent to which surgery take-up is driven by changes in patients' valuation of surgery induced by the amenities – as well as the wait times – they experienced in the diagnostic stage. A positive association between amenities and technical health care quality may arise as an equilibrium outcome if amenities function as a costly signal of underlying quality (Akerberg, 2003; In and Wright, 2017; Kihlstrom and Riordan, 1984; Milgrom and Roberts, 1986; Nelson, 1974; Wolinsky, 1983).³ We identify these effects separately from effects due to the price paid for the consultation, e.g., the role of price in screening, sunk costs, or gift exchange.⁴

¹Eligible patients can see public providers under one of three public insurance schemes (IMSS, ISSSTE, and *Seguro Popular*) if they pay a sliding scale premium, but face wait times of more than 6 months on average.

²This suggests that patients may not have had precise beliefs about their specific eye conditions and were thus unlikely to have self-selected into the premium consultation on the basis of condition.

³This fact is echoed to a certain extent in the literature on patient satisfaction and health care quality; see, e.g., Cleary and McNeil (1988); Manary et al. (2013).

⁴Targeting can have large impacts on the welfare-enhancing value of health resources (Finkelstein and Notowidigdo, 2019; Lieber and Lockwood, 2019). In our context, consultation price might serve to screen patients into surgery on the basis of private valuation or willingness to pay. On the other hand, sunk costs have been shown in a large body of work spanning

Estimating the structural model reveals that the driving mechanism in our setting was updating in surgery valuation from experienced amenities (approximately 75% of the magnitude of the updating from experienced wait time). Price effects (i.e., the combined effect of screening, sunk cost accounting, and gift exchange) collectively play a considerably smaller role in the link between consult choice and subsequent surgery take-up (about 25% of the marginal effect of wait time). Taken together, structural estimates suggest that providers can meaningfully drive up adoption of underutilized care like cataracts surgery by providing extra amenities in early interactions with patients at low prices.

This study is, to our knowledge, the first randomized assessment of the value of amenities in spurring subsequent health care demand. A rich descriptive literature has documented patients' abilities to discern the quality of amenities (in contrast to technical aspects of the quality of care) (Frank, 2004). What is less clear is how experienced amenities impact future demand for health care services. The need for exogenous variation in the level of amenities in order to answer this question is clear: patients' experiences regarding amenities and their subsequent health care utilization is likely jointly determined by unobserved factors like preferences and underlying health status (Dupas and Miguel, 2017). We answer this question using randomized variation in access to amenities in a setting that naturally lends itself to repeated interaction with the health care provider.

Our work also relates to studies on information provision in health care markets. Better information has the potential to shift out the demand for health care and significantly affect patient welfare (Dranove et al., 2003). Much of this literature has focused on quality revelation through report cards grading the performance of health care providers, surgeons, and hospitals. Interestingly, consistent with the idea that consumers do not revise beliefs markedly when it comes to technical aspects of care, this literature generally finds little change in consumer demand even though actual quality measures improve as a result of report cards (Dranove and Sfekas, 2008; Epstein, 2010; Kolstad, 2013; Mukamel et al., 2004). A related literature examines how patients learn about quality through their repeated experiences with providers (Leonard, 2007; Leonard et al., 2009). We add to these strands of work by identifying the specific role of experienced amenities in driving subsequent demand for care. Our structural estimates confirm that experienced amenities are an economically (and statistically) significant driver of patient valuations of surgery and, consequently, demand.

psychology and economics to factor into decision-making, both in laboratory and real-world contexts (Arkes and Blumer, 1985; Thaler, 1980), with some studies focusing on whether price-driven screening might be confused for sunk cost accounting (Ashraf et al., 2010; Cohen and Dupas, 2010). Finally, specifically in healthcare interactions in developing country settings, studies have shown that gift exchange can elicit higher effort from providers, suggesting that paying higher prices for the same care might do the same in our context (Currie et al., 2013).

Finally, we contribute to the body of work on the nuanced role of pricing in determining healthcare demand, particularly in the developing world (Kremer and Holla, 2009). This literature has focused on the fact that while demand is downward sloping in price, often steeply so, behavioral factors may intervene to alter which pricing strategies can stimulate high demand for necessary products and services. Consistent with previous studies of pricing for health care products in low-income contexts, we find that demand is downward sloping for amenities as well and there is little evidence of screening, sunk cost, or gift exchange effects (Ashraf et al., 2010; Currie et al., 2013; Dupas, 2014). This study suggests that providing improvements in amenity levels in initial interactions at little or no cost is ideal for stimulating significantly more usage of healthcare services.

The rest of the paper is organized as follows. Section 2 provides details on the context and the price experiment. Section 3 describes the data and balance checks. Section 4 presents the results of the experiment. Section 5 lays out a structural model to aid in the interpretation of the experiment and presents the resulting estimates. Finally, section 6 concludes.

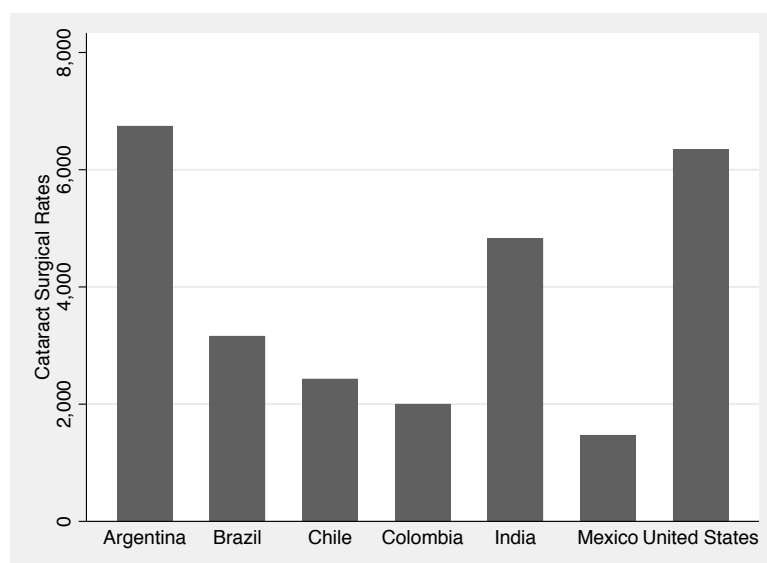
2 Context and Experiment

2.1 Cataract Surgery

A cataract is an occlusion of the eye's lens, typically manifesting at later ages (50 and older). If severe, cataracts can decrease visual acuity, cause difficulty in filtering light, and, if left untreated, eventually cause blindness. In low-income country contexts, where the vast majority of cataracts are untreated, cataracts are the leading cause of blindness in the elderly (Chao et al., 2014). The determinants of low take-up of cataract surgery are likely multifactorial. Access to high quality ophthalmic surgeons is limited in many parts of the developing world; price is often prohibitively high for low-income households; and the costs and benefits of surgery are not widely known (Grimes et al., 2011).

Despite strong evidence from developing countries that cataract surgery can dramatically improve both quality of life and socioeconomic outcomes (see, e.g., Finger et al. (2012)), treatment utilization remains low in much of the developing world. Figure 1 compares the rate of cataract surgery (defined as the total number of cataract surgeries per million inhabitants) across several Latin American countries, India and the United States. As is evident from the Figure, the rate of cataract surgery per capita is fairly low in Latin American countries – and lowest of all countries pictured in Mexico. Prevalence of cataracts varies with demographic composition of the country (for example, with proportion of population of

Figure 1: Cataract Surgical Rates by Country, 2013



Notes: Cataract surgical rates are the total number of cataract surgeries per million inhabitants. Rates for India and the USA correspond to 2014 and 2010 numbers, respectively. Source: <http://atlas.iapb.org/about-vision-atlas/iapb/>

advanced age). Accordingly, a higher rate in the US in part reflects the increased prevalence of cataracts due to a larger fraction of elderly in the population. However, even among countries with similar demographic compositions, GDPs per capita, and public health infrastructures, Mexico has the lowest rate among countries shown. Figure 1 suggests that evidence on ways to stimulate demand for cataract surgery would have important implications for many other developing country settings, given similar patterns of need and underutilization.

2.2 The Mexican Market

In Mexico's health care system, several public sector institutions co-exist with private providers. According to the 2012 Health and Nutrition Survey (ENSANUT), three-quarters of the population is eligible to be served by a public provider: 30% of the population is affiliated with the Mexican Social Security Institute (IMSS), 37% is affiliated with the Ministry of Health (*Seguro Popular*), and an additional 8 percent receives healthcare services from other public institutions. If willing to be treated in the public sector, individuals must seek treatment at the clinics and hospitals associated with the institution with which they are affiliated. Outside of public health coverage, 25% of the population is uninsured, and less than 1% has private health insurance coverage of any kind.

IMSS, which covers workers in the formal sector and their families, is the subsystem where most

surgeries are performed, including cataract surgeries. In 2004, there were over 1.4 million total surgeries performed at IMSS (64 thousand eye surgeries).⁵ Hospitals administered by *Seguro Popular* performed 320,000 surgeries in that year, but only covered cataract surgeries for patients over the age 65. Access to specialized care in the public system is associated with long wait times (23 weeks on average – 4.7 weeks to be seen by a specialist plus 18.2 weeks from diagnosis to surgery), and the quality of service is generally rated poorly.⁶ As a result, a relatively large fraction of individuals with access to public healthcare turn to private providers for relatively low-cost procedures to avoid long waits and low quality.⁷ According to a recent Deloitte study,⁸ 47% of all treatment costs for eye diseases in Mexico is covered directly by patients, while 49% is covered by the public healthcare system (only 4% is covered by private insurers).

2.3 The Partner Clinic and Experiment Details

We partnered with a cataract surgery clinic serving mostly low-income elderly patients in Mexico City to evaluate a randomized price experiment to study how take-up of cataract surgery may be influenced by the provision of amenities in early stages of the patient-provider interaction. The clinic with which we partnered for the experiment offers substantial benefits over the public sector (care meeting international standards and substantially reduced wait times), and is relatively attractive to patients seeking care in the private market because the price of the most basic surgery is set well below competitors' prices.⁹ The clinic's business model consists of guaranteeing high-quality basic service (diagnostic consultations and cataract surgeries) at the lowest price in the market, and giving consumers the choice (when medically possible and advisable) to opt for additional amenities for these services at higher prices. Scale economies allow the clinic to remain profitable.

While consultations represent a large fraction of physicians' time, surgeries represent a considerably larger fraction of the clinic's profits. When we were first approached by the clinic, they were particularly

⁵INEGI. Estadísticas de Salud en Establecimientos Particulares. <https://www.inegi.org.mx/programas/salud/>

⁶Centro de Investigación en Sistemas de Salud. "Tiempos de Espera y Productividad en Rastreadores Clínicos Seleccionados en Hospitales del Sector Público." Morelos-México: Instituto Nacional de Salud Pública. Available here: http://www.dged.salud.gob.mx/contenidos/dged/descargas/estudios/IF_TE_11.pdf

⁷In 2004, the private sector performed in total 800,000 surgeries.

⁸<https://www2.deloitte.com/au/en/pages/economics/articles/economic-cost-eye-disease-preventable-blindness.html>

⁹Wait time between diagnosis and surgery could be as little as 2 days and was guaranteed to be at least 40% shorter than public providers (which averaged more than 4 months). Basic surgery started at 6,400 pesos as compared to private competitors' prices ranging from 15,000 to 35,000 pesos. Public insurance annual premiums averaged roughly 2,400 pesos for Mexico City, but could be more than 10,000 pesos depending income, making 6,400 pesos competitive if little other care is expected over the year. http://seguropopular.guanajuato.gob.mx/archivos/CAUSES_2014.pdf http://www.imss.gob.mx/sites/all/statics/pdf/informes/20132014/20_Anexos.pdf

interested in maximizing surgery take-up among patients with a positive diagnosis of cataracts. The monetary price of the basic consultation was 50 pesos (roughly 4 USD)¹⁰, and patients had the option to pay a fee to reduce the time spent in the waiting room before being seen by the physician. Clinic management was under the impression that patients that paid the fee to reduce waiting during the first consultation were significantly more likely to take-up the surgery, and believed this pattern may be attributable to the fact that these patients' first interaction with the clinic was (relatively) pleasant.

For this reason, the clinic invested in building a "premium consultation" facility across the street from the main clinic, in which patients would be offered a more comfortable waiting area. A premium consultation was designed to include free soft drinks and the same reduced wait time offered in the original facility, in addition to the more comfortable sitting room across the street. Prior to the experiment, the clinic piloted a version of this premium consultation at a price of 400 pesos, but take-up was very low. Accordingly, clinic management decided to experiment with the price of the premium consultation to see if greater take-up could be achieved.

The experiment would consist of offering the premium consultation at randomized, promotional prices, subject to some constraints. First, the promotional price offered to all patients had to be higher than 200 pesos (the price at which the shorter waiting time consultation in the main clinic was offered). Second, of course, this promotional price should be lower than the pilot price of 400 pesos. And finally, because take-up rates were very low at the 400 pesos price, the clinic wanted to randomize a relatively small percentage of individuals into the highest promotional price point: 350 pesos.

The experiment took place from January to April 2013. During this period, each patient that arrived for a diagnostic consultation was enrolled in the study. The receptionist who greeted patients explained the variety of consultations available. There were three types of diagnostic consultation available to patients:

- *Basic* (50 pesos): standard wait time, diagnosis in a standard room, no amenities
- *Reduced wait time* (200 pesos): reduced wait time, diagnosis in a standard room, no amenities
- *Premium* (randomized price – 250, 300, or 350): reduced wait time, upgraded room, additional amenities

Once the options were made known, the receptionist handed a promotion card in a closed envelope

¹⁰This represents 75% of the daily minimum wage and 18% of the average daily wage among Mexico City inhabitants covered by a public insurance scheme.

to each patient from a previously randomly ordered stack.¹¹ The ticket reported the randomized price of the premium consultation cost (250, 300 or 350 pesos). The patient was told that she was able to access the premium consultation at the price assigned by the ticket, and was also told the approximate wait time.¹² The average daily number of patients was about 80, with a maximum daily number over the experimental period of roughly 150. Expected waiting time for the consultation was calculated based on the number of patients who arrived before and were still waiting, consult duration, and the number of diagnosticians available that day. The average expected wait time was about 3.5 hours. Though this was a substantial wait time, same day walk-in consultation still represented a significant improvement on the over month long wait at public providers. Accordingly, no patient, after receiving a randomized price and being told the expected wait time, left the clinic without completing a consultation.

Patients paying for the premium consultation were sent directly to the premium facility across the street for their consultation after registration at the reception desk. In the premium consultation building, patients were seen in a more comfortable consultation room, but the procedure for cataract detection was exactly the same as the one performed in the regular clinic. If diagnosed with cataracts, patients were then sent to see a “counselor,” a person different from the diagnostician who gave them the diagnosis, who explained options for surgery and prices and gave the opportunity to schedule surgery at the clinic. All diagnosed patients, irrespective of type of consultation, were seen by the same counselor.¹³ Counselors were not informed if patients paid for the premium consultation, and followed the same protocol for providing information about available surgery options to all patients.

3 Data and Summary Statistics

3.1 RCT Data Description

We received data on the offered randomized price for the premium consultation, the estimated waiting time that was reported to each patient, as well as her choice of consultation. We also have data on the diagnosis received following the consultation, and whether she decided to undergo surgery in cases

¹¹The cards were printed 8 to a page. Given the above-mentioned constraints imposed by clinic management, on each page, 3 cards had a promotional price of 250 pesos, 3 had a price of 300, and 2 had a promotional price of 350. The printing firm then took care of shuffling, numbering and stacking the cards with different promotional prices, which were given to the reception desk at the clinic during the experiment.

¹²Registration at the reception desk took place in a relatively private environment, as all previous patients in line were already sitting in one of the waiting rooms and patients waited in line outside the clinic before approaching the reception desk one by one. Unsurprisingly, no patient complained that the promotional price offered to them was higher than that offered to others.

¹³At any given time, there was one active counselor seeing all patients with a cataract diagnosis in the clinic.

when the diagnosis indicated the presence of operable cataracts. The total sample for the consultation is 2085 patients.

3.2 Summary Statistics

Table 1 reports summary statistics by randomized price for the premium consultation for the full sample of patients who were enrolled in the experiment in Panel A. We also present a balance test between the three groups defined by the randomized prices for each variable using ANOVA. The average wait time was 3.5 hours. The share of patients diagnosed with cataracts is around 21%. About 37% of patients were male, and patients were on average 58 years old. Means and standard deviations of these three variables are very similar across the three randomized prices. ANOVA shows that none of these means are statistically different across the three groups defined by the randomized prices. Table 1 also presents summary statistics for the sample of patients diagnosed with cataracts in Panel B. Note that the average age for patients diagnosed with cataracts is around 11 years more than the average of the whole sample, while the share of males and the average wait time are similar for both samples.

Table 1: Summary Statistics

	Full Sample		Price 250		Price 300		Price 350		Anova	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	F-stat	p-value
Panel A: All Patients										
Waiting time (hours)	3.494	1.627	3.485	1.618	3.475	1.653	3.531	1.607	0.210	0.812
Positive Diagnosis (cataract)	0.211	0.408	0.221	0.415	0.207	0.406	0.201	0.401	0.430	0.654
Male	0.370	0.483	0.352	0.478	0.388	0.488	0.373	0.484	1.060	0.347
Age	57.755	18.140	56.945	18.709	58.079	17.720	58.459	17.873	1.320	0.268
N	2085		782		747		556			
Panel B: Patients Diagnosed with Cataracts										
Waiting time (hours)	3.424	1.614	3.587	1.629	3.412	1.625	3.189	1.557	2.08	0.13
Male	0.405	0.492	0.405	0.492	0.426	0.496	0.378	0.487	0.30	0.74
Age	69.918	11.625	69.965	11.679	69.561	11.954	70.339	11.156	0.15	0.86
N	440		173		155		112			

Note: All prices are in 2013 Mexican pesos. Randomization is at individual level. Waiting time is the estimated waiting time in hours before the first available time slot for basic consultation. It is announced to the patient upon arrival at the clinic. Positive Diagnosis (cataract) is an indicator variable, which equals 1 if a patient was diagnosed with a cataract and 0 otherwise. Age refers to the age of a patient in years. Male is an indicator variable, which equals 1 if patient is male and 0 if patient is female. Balance Anova tests were estimated across the three groups defined by the randomized prices for each variable.

In addition to establishing that the price randomization was well executed, Table 1 also demonstrates that the expected wait time, which prevailed at the time that each patient made decisions regarding choice of consult type, provides an independent source of variation in the relative benefit of choosing

one of the reduced wait time options.¹⁴ We leverage this additional variation to identify the structural model below and provide richer interpretation of the effects of consult experience on subsequent surgery take up.

4 Experimental Results

We first present estimates of the effects of the randomized price, as well as expected wait time, on consult choice. We then present estimates of the pass through effects of these determinants of consultation choice on surgery implementation. Table 2 shows results of regressions of premium consultation take-up on randomized prices and waiting time. We find that being assigned a low price for the premium consultation resulted in roughly a 13 percentage point increase in the likelihood of take-up, relative to the 350 price group. The coefficient is unchanged when we include waiting time, gender and age.

Note that a higher expected waiting time increases the demand for the premium consultation as well. Each additional hour of expected wait time increases the likelihood of choosing the premium consultation by nearly 3 percentage points. Table A2 in the Appendix shows analogous results on take-up of the reduced wait time consultation, whose price was fixed at 200 pesos. As expected, when the randomized incremental price for the additional amenities is lower, patients are less likely to select the consultation involving reduced wait time alone.

Having established that both the randomized price for the premium consultation and the expected waiting time impact consultation take up for both the premium and reduced wait time consultations, we now examine effects on surgery implementation. We find that being randomized into a lower price for the premium consultation increases the probability of surgery implementation by more than half (an increase of between 5 and 6.5 percentage points from a mean of roughly 9% surgery take-up). These results are presented in Panel B of Table 2. Once again, we see little substantive change in the coefficients across specifications.

5 Interpretation

Note that we have not simply estimated second stage effects of premium consult take-up on surgery implementation using the randomized price as an instrument for consultation choice for two main

¹⁴In the Appendix, we present additional evidence of the distributional equivalence of wait time across randomized price groups.

Table 2: Premium Consultation Take-up

VARIABLES			
	Panel A: Premium Consultation, All Patients		
1[Randomized Price = 250]	0.132 (0.013)	0.133 (0.013)	0.133 (0.013)
1[Randomized Price = 300]	0.126 (0.013)	0.128 (0.013)	0.127 (0.013)
Waiting time (Hours)		0.029 (0.004)	0.029 (0.004)
Male			0.011 (0.014)
Age			0.0002 (0.0003)
Constant	0.009 (0.00401)	-0.092 (0.0151)	-0.110 (0.0255)
Observations	2085	2085	2075
Mean of Premium Consult.	0.104	0.104	0.103
	Panel B: Surgery Implemented, Patients Diagnosed with Cataracts		
1[Randomized Price = 250]	0.054 (0.030)	0.050 (0.030)	0.050 (0.030)
1[Randomized Price = 300]	0.065 (0.032)	0.063 (0.031)	0.064 (0.031)
Waiting time (Hours)		0.009 (0.009)	0.010 (0.010)
Male			0.005 (0.028)
Age			0.002 (0.001)
Constant	0.044 (0.0196)	0.018 (0.0381)	-0.154 (0.0819)
Observations	440	440	439
Mean of Premium Consult.	0.088	0.088	0.088

Note: Robust standard errors in parenthesis. Randomization is at individual level. Waiting time is the estimated waiting time in hours before the first available time slot for basic consultation. It is announced to the patient upon arrival at the clinic. Male is an indicator variable, which equals 1 if patient is male and 0 if patient is female. Age refers to the age of a patient in years. The premium consultation differs from the basic consultation in reducing waiting and adding some auxiliary services, not related to the quality of medical diagnosis.

reasons: 1) there are multiple consultation choices at the diagnostic stage and multiple drivers of choice (i.e., price, wait time, prior on likelihood of cataract); and 2) randomized price might impact surgery adoption both directly and by way of consultation choice. Accordingly, we develop and structurally estimate a model of two-stage patient-provider interactions to account for this complexity.¹⁵ In section B of the Appendix, we model the patient's decision in each stage and allow for the consultation choice to impact the surgery decision by way of experienced amenities and waiting time in the first stage, as well as the direct effect of price paid for the selected consultation type (e.g., screening, sunk cost accounting, or gift exchange effects). Below we present the derived estimating equations and assumptions needed for identification.

5.1 Estimating Equations and Stochastic Assumptions

We describe a patient by a vector of characteristics, $\Xi = (x, wt, p, \varepsilon_s, \varepsilon_u, \varepsilon_q)$ where x includes demographic characteristics (e.g., age, gender), wt is the waiting time, and p is the price of premium consultation. The scalar characteristics $\varepsilon_s, \varepsilon_u$ and ε_q are unobserved. First, when individuals arrive at the clinic they have a prior of having a cataract, s^* . We assume this is well approximated by a linear relationship:

$$s^* \approx x'\gamma + \varepsilon_s. \quad (1)$$

Then, cataract diagnosis is as follows:

$$s = \begin{cases} 1 & \text{if } s^* \geq 0 \\ 0 & \text{otherwise} \end{cases}. \quad (2)$$

Based on their probability of having a cataract, individuals will choose consultation $k \in \{p, w, b\}$ (where p denotes the premium consult, w denotes the reduced wait time consult, and b denotes the basic consult) as follows:

$$u_{1|s} = \begin{cases} p & \text{if } x'\alpha_x + \alpha_w wt + \alpha_p p + \alpha_s s^* + \varepsilon_u > \mu_p \\ b & \text{if } x'\alpha_x + \alpha_w wt + \alpha_p p + \alpha_s s^* + \varepsilon_u < \mu_b \\ w & \text{otherwise} \end{cases}. \quad (3)$$

Note that the parameters α_w, α_p and α_s , measure the sensitivity of the consultation decision to changes in the waiting time (wt), price of the premium consultation (p) and the prior probability of

¹⁵The model draws on Vera-Hernandez (2003) and Einav et al. (2012) among others.

being diagnosed with cataract (s^*), respectively.

Finally, if an individual chose consultation k in period 1 and is diagnosed with cataract, her surgery implementation decision is as follows:

$$u_{2|k,s} = \begin{cases} 1 & x'\beta_x + u_{1,k} + \beta_p p + \varepsilon_q \geq 0 \\ 0 & \text{otherwise} \end{cases}, \quad (4)$$

where $u_{1,b}$ is normalized to 0. Here $u_{1,k}$ means that the probability of undergoing cataract surgery increases as the additional utilities from reduced waiting time and extra amenities increase.

From our patient's decision choice model, the unobservables components, $(\varepsilon_s, \varepsilon_u, \varepsilon_q)$, are normally distributed with mean zero and variance-covariance matrix,

$$\Sigma = \begin{pmatrix} \sigma_s^2 & \rho_{su}\sigma_s\sigma_u & \rho_{sq}\sigma_s\sigma_q \\ \rho_{su}\sigma_s\sigma_u & \sigma_u^2 & \rho_{uq}\sigma_q\sigma_u \\ \rho_{sq}\sigma_s\sigma_q & \rho_{uq}\sigma_q\sigma_u & \sigma_q^2 \end{pmatrix}. \quad (5)$$

The correlation parameters ρ_{su} and ρ_{sq} characterize the relationship between the patient's unobserved prior of having cataract and her subsequent motives for different consultations and surgery take up behavior. The correlation parameter ρ_{uq} characterizes the relationship between patients unobserved motive for different consultations and her subsequent surgery take up behavior. Finally, the variance parameters σ_s , σ_u , and σ_q capture the importance of unobserved characteristics relative to observed characteristics in the prior of having cataract, and consultation and surgery take up patient decisions.

5.2 Identification and Estimation

We take the model directly to the data observed from the experiment. The model can be thought of as a system of three equations: (i) a probit cataract equation, (ii) an ordered probit consultation equation, and (iii) a probit surgery decision equation. This system maps the observed and unobserved characteristics of the each patient, along with the wait time and the randomized price, into realizations of cataract diagnosis, consultation choice and the cataract surgery decision. The maximizations of these three equations are standard but cumbersome since we need to integrate over unobservables.¹⁶

The data contain demographic characteristics of each patient, the expected waiting time when they

¹⁶In Appendix B we provide the details of the derivation of the estimating equations 2, 3, and 4. Using these estimating equations and the stochastic assumptions in (5), we compute the likelihood function of the observed decisions.

arrive at the clinic, the randomized price of the premium consultation, their corresponding selection of the type of consultation, the medical diagnosis (i.e., if the patient has an operable cataract or not), and their ultimate decision to schedule and undergo the surgery conditional on a positive diagnosis. These conditional probabilities provide all the information needed to estimate the model, subject to some additional assumptions. In estimating the probit cataract equation, γ is only identified up to a scale, so we set $\sigma_s^2 = 1$. For the ordered probit consultation equation, we need two identification constraints: 1) to suppress the intercept in order to recover μ_p and μ_b , and 2) to fix $\sigma_u^2 = 1$. Analogously, for the probit surgery equation, we fix $\sigma_q^2 = 1$. We can then also recover the correlations between the unobservables that affect the probability of having cataract, ε_s , and the unobservables that affect consultation choice and surgery decision, ε_u and ε_q , respectively.

5.3 Structural Estimates

In Table 3, we show that the model fit is good for all choice variables across both stages. The model fit moments are computed based on equations 2, 3, and 4. Raw data moments are computed directly from the estimating sample.

Table 3: Model Fit

	Model Fit	Raw Data
Cataract	0.212	0.220
Consulta Plus	0.105	0.103
Consulta Azul	0.064	0.065
Consulta Uno	0.831	0.832
Surgery / Consulta Plus	0.251	0.250
Surgery / Consulta Azul	0.120	0.110
Surgery / Consulta Uno	0.065	0.066

In Table 4 we report marginal effects of drivers in each stage of the model. As expected, age is a significant predictor of a positive cataract diagnosis. Consistent with reduced form evidence presented

Table 4: Marginal Effects

	Probability of Cataract		Probability of Consulta Plus		Probability of Surgery Take-up	
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
Age	0.009	0.001	0.023	0.058	0.003	0.005
Gender	0.034	0.019	0.015	0.014	0.002	0.032
Premium Consult. Price			-0.040	0.004	-0.030	0.024
Waiting Time			0.036	0.004		
Valuation Update (Waiting)					0.136	0.082
Valuation Update (Amenities)					0.103	0.062

Note: The model estimates are based on the econometric model described in sections 5.2 and 5.3. The sample for the probability of having cataract and the ordered probit consultation equation is 2,085 and the sample for the probit surgery equation is 439 (see Table 1). Reported marginal effects present the effect of a unit change in each explanatory variable: For the dummy variables we follow Einav et al. (2012) and compute the marginal effect by taking the difference when the explanatory variable is equal 1 and when the variable is equal to 0. For continuous variables we use the numerical derivative with respect to the explanatory variable. Bootstrap standard errors reported in the next column to the marginal effects.

above, demand for the premium consult is downward sloping in price and increasing in wait time.

We then report marginal effects of the impacts of experiencing amenities and waiting time on surgery take, as well as the composite direct effects of the price of the premium consultation (e.g., screening, sunk cost accounting, and gift exchange effects). Note first that the marginal effect of experiencing better amenities (0.103) is both economically and statistically significant. Using the marginal effect of waiting (0.136), which has been well-established as an important determinant of healthcare utilization, as a benchmark we see that experiencing amenities increases patients' surgery valuations by approximately 75% of the effect of wait times on surgery valuation.

Price effects appear to matter as well but less so (-0.030), with a magnitude about 25% the size of the marginal effect of wait times on surgery valuation. Taken together these results confirm that updating in the patient valuation of surgery from experienced amenities is a strong determinant of ultimate surgery implementation and the primary mechanism linking experience in the initial diagnostic stage to later stage utilization. Our estimates indicate that providers can meaningfully drive up adoption of underutilized care like cataracts surgery by providing extra amenities at low cost in early interactions.

6 Conclusion

Health care markets are prone to asymmetric information, which can have substantial implications for market functioning and as a result the choices and welfare of consumers. Patients often attempt to remedy lack of information about potential providers by learning from their own past experiences. This learning process seems particularly useful for nontechnical amenities, which patients can discern quite readily. This stands in contrast to learning about the technical quality of care, which ultimately is what matters for health outcomes. But these two may be correlated in equilibrium if amenities function as a signal of the underlying (technical) quality of care.

Under this premise, improving amenities in early stages of patient-provider interaction in health care services might be useful in spurring increased demand for underutilized health care services. We study this hypothesis in the context of cataract surgery in Mexico City. We evaluate demand for a high-amenity premium consultation with a randomized price, and document effects on subsequent demand for surgery for those patients who ended up having operable cataracts.

We find that demand for the premium consultation was sensitive to price and that there were indeed pass-through effects on surgery take-up. We then estimate a structural model that quantifies the impact of experienced amenities, relative to wait time, on subsequent surgery demand, as well as the importance of any direct price effects. We find that demand for cataract surgery is sensitive to amenities provided in the first stage of patient-provider interaction, and that composite price effects (e.g., screening, sunk cost accounting, and gift exchange effects) matter as well, but substantially less so. This is to our knowledge the first rigorous evidence of the value of amenities in increasing health care demand.

This work has potentially important policy implications. Preventative health care products and services are underutilized in many settings around the world, particularly in low-income countries. This work suggests that one way to raise the demand for such products and services is to increase the level of felt amenities in initial stages of patients' interactions with service providers.

References

- Akerberg, D. A. (2003). Advertising, learning, and consumer choice in experience good markets: an empirical examination. *International Economic Review*, 44(3):1007–1040.
- Adhvaryu, A. and Nyshadham, A. (2015). Return to treatment in the formal health care sector: Evidence from tanzania. *American Economic Journal: Economic Policy*, 7(3):29–57.
- Arkes, H. R. and Blumer, C. (1985). The psychology of sunk cost. *Organizational behavior and human decision processes*, 35(1):124–140.
- Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *The American economic review*, 53(5):941–973.
- Ashraf, N., Berry, J., and Shapiro, J. M. (2010). Can higher prices stimulate product use? evidence from a field experiment in zambia. *American Economic Review*, 100(5):2383–2413.
- Bücker, H. M., Corliss, G., Hovland, P., Naumann, U., and Norris, B. (2006). *Automatic differentiation: applications, theory, and implementations*, volume 50. Springer Science & Business Media.
- Chandra, A., Finkelstein, A., Sacarny, A., and Syverson, C. (2016). Health care exceptionalism? performance and allocation in the us health care sector. *American Economic Review*, 106(8):2110–44.
- Chandra, A. and Staiger, D. O. (2007). Productivity spillovers in health care: evidence from the treatment of heart attacks. *Journal of Political Economy*, 115(1):103–140.
- Chao, T. E., Sharma, K., Mandigo, M., Hagander, L., Resch, S. C., Weiser, T. G., and Meara, J. G. (2014). Cost-effectiveness of surgery and its policy implications for global health: a systematic review and analysis. *The Lancet Global Health*, 2(6):e334–e345.
- Chintagunta, P. K., Jiang, R., and Jin, G. Z. (2009). Information, learning, and drug diffusion: The case of cox-2 inhibitors. *QME*, 7(4):399–443.
- Cleary, P. D. and McNeil, B. J. (1988). Patient satisfaction as an indicator of quality care. *Inquiry*, pages 25–36.
- Cohen, J. and Dupas, P. (2010). Free distribution or cost-sharing? evidence from a randomized malaria prevention experiment. *Quarterly journal of Economics*, 125(1):1.

- Congdon, N. and Thomas, R. (2014). How can we solve the problem of low uptake of cataract surgery? *Ophthalmic Epidemiology*, 21(3):135–137.
- Crawford, G. S. and Shum, M. (2005). Uncertainty and learning in pharmaceutical demand. *econometrica*, 73(4):1137–1173.
- Currie, J., Lin, W., and Meng, J. (2013). Social networks and externalities from gift exchange: Evidence from a field experiment. *Journal of public economics*, 107:19–30.
- Dickstein, M. J. et al. (2014). Efficient provision of experience goods: Evidence from antidepressant choice. *Unpublished, Stanford University*. [1323].
- Doyle, J. J. (2011). Returns to local-area health care spending: evidence from health shocks to patients far from home. *American Economic Journal: Applied Economics*, 3(3):221–43.
- Dranove, D., Kessler, D., McClellan, M., and Satterthwaite, M. (2003). Is more information better? the effects of “report cards” on health care providers. *The Journal of Political Economy*, 111(3):555–588.
- Dranove, D. and Satterthwaite, M. A. (1992). Monopolistic competition when price and quality are imperfectly observable. *The RAND Journal of Economics*, pages 518–534.
- Dranove, D. and Satterthwaite, M. A. (2000). The industrial organization of health care markets. *Handbook of health economics*, 1:1093–1139.
- Dranove, D. and Sfekas, A. (2008). Start spreading the news: a structural estimate of the effects of new york hospital report cards. *Journal of health economics*, 27(5):1201–1207.
- Dupas, P. (2014). Getting essential health products to their end users: Subsidize, but how much? *Science*, 345(6202):1279–1281.
- Dupas, P. and Miguel, E. (2017). Impacts and determinants of health levels in low-income countries. In *Handbook of economic field experiments*, volume 2, pages 3–93. Elsevier.
- Einav, L., Jenkins, M., and Levin, J. (2012). Contract pricing in consumer credit markets. *Econometrica*, 80(4):1387–1432.
- Epstein, A. J. (2010). Effects of report cards on referral patterns to cardiac surgeons. *Journal of health economics*, 29(5):718–731.

- Finger, R. P., Kupitz, D. G., Fenwick, E., Balasubramaniam, B., Ramani, R. V., Holz, F. G., and Gilbert, C. E. (2012). The impact of successful cataract surgery on quality of life, household income and social status in south india. *PLoS one*, 7(8):e44268.
- Finkelstein, A. and Notowidigdo, M. J. (2019). Take-up and targeting: Experimental evidence from snap. *The Quarterly Journal of Economics*, 134(3):1505–1556.
- Flaxman, S. and Bourne, R. (2017). Global causes of blindness and distance vision impairment 1990–2020: a systematic review and meta-analysis. *The Lancet Global Health*, 5(12).
- Frank, R. G. (2004). Behavioral economics and health economics. Technical report, National Bureau of Economic Research.
- Grimes, C. E., Bowman, K. G., Dodgion, C. M., and Lavy, C. B. (2011). Systematic review of barriers to surgical care in low-income and middle-income countries. *World journal of surgery*, 35(5):941–950.
- Handel, B. R. and Kolstad, J. T. (2015). Health insurance for “humans”: Information frictions, plan choice, and consumer welfare. *American Economic Review*, 105(8):2449–2500.
- Hoffer Gittel, J., Fairfield, K. M., and Bierbaum, B. (2000). Impact of relational coordination on quality of care, postoperative pain and functioning, and length of stay: A nine-hospital study of surgical patients. *Medical Care*, 38(8):807–819.
- In, Y. and Wright, J. (2017). Signaling private choices. *The Review of Economic Studies*, 85(1):558–580.
- Kihlstrom, R. E. and Riordan, M. H. (1984). Advertising as a signal. *Journal of Political Economy*, 92(3):427–450.
- Kim, S., Kaplowitz, S., and Johnston, M. (2004). The effects of physician empathy on patient satisfaction and compliance. *Evaluation & the Health Professions*, 27(3):237–251.
- Kolstad, J. T. (2013). Information and quality when motivation is intrinsic: Evidence from surgeon report cards. *American Economic Review*, 103(7):2875–2910.
- Kolstad, J. T. and Chernew, M. E. (2009). Quality and consumer decision making in the market for health insurance and health care services. *Medical Care Research and Review*, 66(1_suppl):28S–52S.

- Kremer, M. and Holla, A. (2009). Pricing and access: lessons from randomized evaluations in education and health. *What Works in Development: Thinking Big and Thinking Small*, pages 91–129.
- Leonard, K. L. (2007). Learning in health care: evidence of learning about clinician quality in tanzania. *Economic Development and Cultural Change*, 55(3):531–555.
- Leonard, K. L., Adelman, S. W., and Essam, T. (2009). Idle chatter or learning? evidence of social learning about clinicians and the health system from rural tanzania. *Social science & medicine*, 69(2):183–190.
- Lewallen, S. (2008). Poverty and cataract – a deeper look at a complex issue. *PLoS Med*, 5(12).
- Lieber, E. M. and Lockwood, L. M. (2019). Targeting with in-kind transfers: Evidence from medicaid home care. *American Economic Review*, 109(4):1461–85.
- Liu, Y.-C., Wilkins, M., Kim, T., Malyugin, B., and Mehta, J. (2017). Cataracts. *Lancet*, 390:600–612.
- Manary, M. P., Boulding, W., Staelin, R., and Glickman, S. W. (2013). The patient experience and health outcomes. *New England Journal of Medicine*, 368(3):201–203.
- Milgrom, P. and Roberts, J. (1986). Price and advertising signals of product quality. *Journal of political economy*, 94(4):796–821.
- Mukamel, D. B., Weimer, D. L., Zwanziger, J., Gorthy, S.-F. H., and Mushlin, A. I. (2004). Quality report cards, selection of cardiac surgeons, and racial disparities: a study of the publication of the new york state cardiac surgery reports. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 41(4):435–446.
- Nelson, P. (1974). Advertising as information. *Journal of political economy*, 82(4):729–754.
- Rabiu, M. (2001). Cataract blindness and barriers to uptake of cataract surgery in a rural community of northern nigeria. *British Journal of Ophthalmology*, 85(7):776–780.
- Sofaer, S. and Firminger, K. (2005). Patient perceptions of the quality of health services. *Annu. Rev. Public Health*, 26:513–559.
- Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, 1(1):39–60.

- Vera-Hernandez, M. (2003). Structural estimation of a principal-agent model: moral hazard in medical insurance. *RAND Journal of Economics*, pages 670–693.
- Wolinsky, A. (1983). Prices as signals of product quality. *The review of economic studies*, 50(4):647–658.
- Zhang, X., Jhanji, V., Leung, C., Li, E., and C, Z. (2014). Barriers for poor cataract surgery uptake among patients with operable cataract in a program of outreach screening and low-cost surgery in rural china. *Ophthalmic Epidemiology*, 21(3):153–160.

A Additional Tables & Figures

Figure A: Wait Time by Price

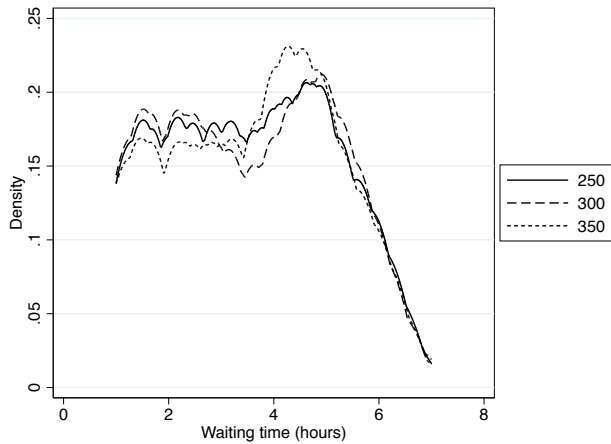
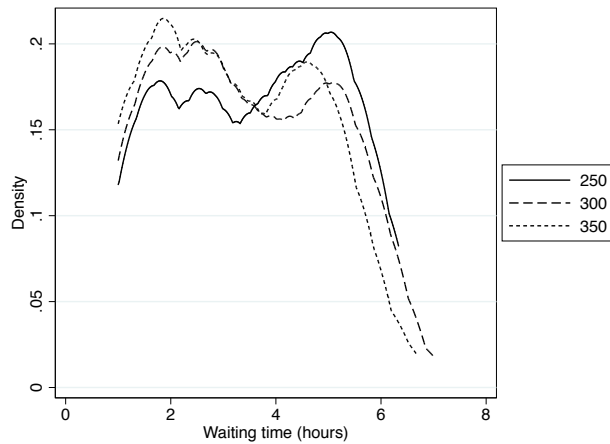


Figure B: Wait Time by Price (Cataracts)



Note: Waiting time is estimated in hours before the first available time slot for basic consultation. It is announced to the patient upon arrival at the clinic. Randomization is at individual level. Figure A presents the wait time for the full sample across the three group defined by the randomized prices of 250, 300 and 350 and Figure B presents the wait time across the three for the sample of patients diagnosed with cataracts.

Figure C: Age by Price

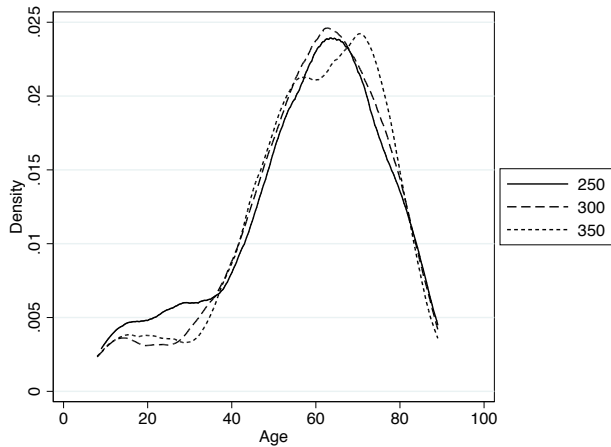
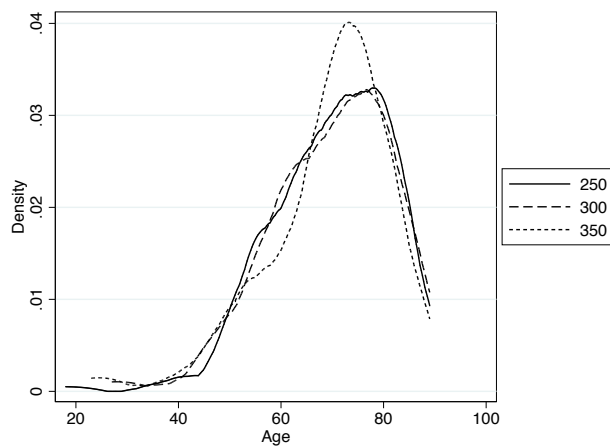


Figure D: Age by Price (Cataracts)



Note: Figure C presents the age for the full sample across the three groups defined by the randomized prices of 250, 300 and 350. Figure D presents the age across the three groups for the sample of patients diagnosed with cataracts.

Table A1: Kolmogorov-Smirnov Tests Across Randomized Price

Waiting time			
	Difference	p-value	Corrected
Group 1[Price 250 and 300]	0.020	0.718	
Group 2[Price 350]	-0.035	0.364	
Combined K-S:	0.035	0.693	0.671
Age			
	Difference	p-value	Corrected
Group 1[Price 250 and 300]	0.024	0.616	
Group 2[Price 350]	-0.044	0.195	
Combined K-S:	0.044	0.387	0.363
Male			
	Difference	p-value	Corrected
Group 1[Price 250 and 300]	0.000	1.000	
Group 2[Price 350]	-0.004	0.988	
Combined K-S:	0.004	1.000	1.000

Note: Waiting time is the estimated waiting time in hours before the first available time slot for basic consultation. It is announced to the patient upon arrival at the clinic. Randomized Price is a price for premium consultation randomly assigned to a patient. Age refers to the age of a patient in years. Male is an indicator variable, which equals 1 if patient is male and 0 if patient is female.

Table A2: Reduced Wait Time Consultation Take-up

VARIABLES			
1[Randomized Price = 250]	-0.029 (0.014)	-0.028 (0.014)	-0.026 (0.014)
1[Randomized Price = 300]	-0.020 (0.015)	-0.019 (0.015)	-0.017 (0.015)
Waiting time (Hours)		0.023 (0.004)	0.023 (0.004)
Male			0.004 (0.011)
Age			0.0002 (0.0003)
Constant	0.083 (0.011)	0.003 (0.014)	-0.010 (0.021)
Observations	2,085	2,085	2,075
Mean of Reduced Wait Time Consultation	0.065	0.065	0.065

Note: Robust standard errors in parenthesis. Randomization is at individual level. Waiting time (hours) is defined as the estimated time before the first available time slot for basic consultation; it is announced to the patient upon arrival at the clinic. The unit for age of the patient is years. The "reduced wait time" consultation differs from the basic consultation in letting the patient skip ahead in the queue (reduced waiting time). No auxiliary services are provided during reduced wait time consultation.

B Model and Estimation

In this section, we develop a discrete choice model of consultation choice and surgery take up. The model draws on Vera-Hernandez (2003) and Einav et al. (2012) among others.

B.1 Model

Our model begins at the point when a consumer enters the clinic. We assume that individuals derive (dis)utility from having cataracts; the wait time before consultation; amenities provided; and money. They maximize expected discounted utility. Each patient has a prior probability of having a cataract, s_0 , which implies a disutility (a penalty health shock) of magnitude v_0 (similar to Vera-Hernandez, 2003). Patients arrive at the clinic and receive a randomized price p_p for the premium consultation, and fixed prices, p_w and p_b , for the reduced wait time consultation and the basic consultation, respectively.

As we mentioned before, the premium consultation provides reduced waiting time and extra amenities that *ex-ante* provide an incremental value, $u_{0,a}$. The reduced wait time consultation involves regular facilities and reduced waiting time that *ex ante* provides an incremental value, $u_{0,w}$, and the basic consultation involves regular wait time with regular facilities. Individuals thus potentially differ along four dimensions: the probability of having cataracts, s_0 , their penalty health shock (value for being unhealthy or having a cataract), v_0 , and their *ex-ante* incremental value for waiting time, $u_{0,w}$, and extra amenities, $u_{0,a}$.¹⁷

In the second period, individuals discover if they are diagnosed with a cataract, and conditional on this event, they decide whether to undergo cataract surgery or not. Let $\tilde{\mathbf{p}}_p \equiv (p_p, p_s)'$ where p_s is the price of the surgery. Thus, if the patients choose the premium consultation in period 1, and undergo cataract surgery, their utility is $u_{2|p}(\tilde{\mathbf{p}}_p, 0) \equiv u(\tilde{\mathbf{p}}_p' \cdot \mathbf{1}_{[2,1]}, 0) + u_{1,p}$, where $u(\cdot, \cdot)$ is decreasing with respect to both arguments, $u_{1,p} \equiv u_{1,a} + u_{1,w}$, and $u_{1,a}$ and $u_{1,w}$ are the updated expected utilities provided by the extra amenities and reduced waiting time, respectively. If patients do not undergo the surgery their utility is $u_{2|p}(\tilde{\mathbf{p}}_p, v_0) \equiv u(p_p, v_0)$. The analysis is similar if patients choose the reduced wait time consultation or the basic consultation in period 1.

Given a prior probability, s^* , of having a cataract, patients expected utility from the premium

¹⁷This is in addition to other characteristics like waiting time and socioeconomic variables.

consultation in period 1 depends on if they undergo cataract surgery or not, in period 2:

$$u_{1,p}(\tilde{\mathbf{p}}_p, v_0) \equiv s^* E_{u_{0,p}|s^*} [\max \{u(\tilde{\mathbf{p}}'_p \cdot \mathbf{1}_{[2,1]}, 0) + u_{0,p}, u(p_p, v_0)\}] + (1 - s^*) u(p_p, 0), \quad (6)$$

where $u_{0,p} \equiv u_{0,a} + u_{0,w}$.¹⁸ Let $\tilde{\mathbf{p}}_w \equiv (p_w, p_s)'$, if patients take the reduced wait time consultation their expected utility would be

$$u_{1,w}(\tilde{\mathbf{p}}_w, v_0) \equiv s^* E_{u_{0,w}|s^*} [\max \{u(\tilde{\mathbf{p}}'_w \cdot \mathbf{1}_{[2,1]}, 0) + u_{0,w}, u(p_w, v_0)\}] + (1 - s^*) u(p_w, 0). \quad (7)$$

Finally, let $\tilde{\mathbf{p}}_b \equiv (p_b, p_s)'$, if patients choose the basic consultation, their utility would be

$$u_{1,b}(\tilde{\mathbf{p}}_b, v_0) \equiv s^* \max \{u(\tilde{\mathbf{p}}'_b \cdot \mathbf{1}_{[2,1]}, 0), u(p_b, v_0)\} + (1 - s^*) u(p_b, 0).$$

To solve the model we work backward from the second period. Given a positive cataract diagnosis and given that a patient chose the premium consultation, in period 2, individuals undergo cataract surgery if

$$u_{2|p}(\tilde{\mathbf{p}}_p, 0) - u_{2|p}(\tilde{\mathbf{p}}_p, v_0) \geq 0. \quad (8)$$

Note that the analysis is similar if patients chose the reduced wait time consultation or the basic consultation in period 1. In period 1, individuals choose the premium consultation if

$$u_{1,p}(\tilde{\mathbf{p}}_p, v_0) \geq \max \{u_{1,w}(\tilde{\mathbf{p}}_w, v_0), u_{1,b}(\tilde{\mathbf{p}}_b, v_0)\}. \quad (9)$$

and similarly for the reduced wait time consultation and the basic consultation.

B.2 Econometric Specification: Linear Approximation

We now link the discrete choice model to the data. In the data, we observe the randomized price received by each patient, waiting time for the basic consultation, cataract diagnosis, characteristics of the patients (e.g., age, gender), and if patients undergo cataract surgery.

¹⁸Note we assume that the utility (or disutility) from a high price for the consultation, having or not having cataract, wait time, and amenities provided are additively separable in $u(\cdot, \cdot)$ and the incremental value provided by the reduced wait time and the amenities.

We make functional form assumptions that are closely related to the observed outcomes.¹⁹ In the model, the characteristics of the patients are related to observed outcomes by the consultation decision (equation 9) and the surgery take-up decision (equation 8) and by the probability of having a cataract. In particular, we assume that the utility functions are well approximated by linear relationships. We adopt this linear approximation for convenience, and we show later that it provides good fit to the observed data. That is, if patients chose the premium consultation in period 1, then the difference between undergoing cataract surgery or not in period 2 is well approximated by

$$\begin{aligned} u_{2|p}(\tilde{\mathbf{p}}_p, 0) - u_{2|p}(\tilde{\mathbf{p}}_p, v_0) \\ \approx \beta_v v_0 + u_{1,p} + \beta_p \mathbf{p}. \end{aligned} \quad (10)$$

Similarly, if patients chose the reduced wait time consultation in period 1, then in period 2

$$\begin{aligned} u_{2|w}(\tilde{\mathbf{p}}_w, 0) - u_{2|w}(\tilde{\mathbf{p}}_w, v_0) \\ \approx \beta_v v_0 + u_{1,w} + \beta_p \mathbf{p}, \end{aligned} \quad (11)$$

and if patients chose the basic consultation in period 1, then in period 2

$$\begin{aligned} u_{2|b}(\tilde{\mathbf{p}}_b, 0) - u_{2|b}(\tilde{\mathbf{p}}_b, v_0) \\ \approx \beta_v v_0 + \beta_p \mathbf{p} \end{aligned} \quad (12)$$

In period 1, we assume that the differences between the expected utility of premium consultation and that of the reduced wait time or basic consultation (denoted by k) are well approximated by

$$\begin{aligned} u_{1,p|s^*}(\tilde{\mathbf{p}}_p, v_0) - u_{1,k|s^*}(\tilde{\mathbf{p}}_k, v_0) \\ \approx \alpha_v v_0 + \alpha_a u_{0,a} + \alpha_w u_{0,w} + \alpha_p p + \alpha_s s^* \end{aligned} \quad (13)$$

for $k \neq p$, $k \in \{p, w, b\}$, where s^* is the probability of each patient of having a cataract, which we also assume is well approximated by a linear relationship.

¹⁹We follow a similar strategy as in Einav et al. (2012).

B.2.1 Covariates

First, we incorporate individual characteristics into the model. We describe a patient by a vector of characteristics, $\Xi = (x, \tilde{x}, p, \varepsilon_u, \varepsilon_w, \varepsilon_v)$ where x includes demographic characteristics (e.g., age, gender), \tilde{x} includes x plus the waiting time, and p is the price of premium consultation. The scalar characteristics $\varepsilon_u, \varepsilon_w, \varepsilon_v$ are not observed. Moreover, we assume that $(\varepsilon_u, \varepsilon_w, \varepsilon_v)$ are drawn from a multivariate normal distribution $N(0, \Sigma_0)$ independent of (\tilde{x}, p) . We parametrize type as

$$v_0 = x' \xi_v + \varepsilon_v, \quad (14)$$

$$u_{w,0} = \tilde{x}' \xi_w + \varepsilon_w, \quad (15)$$

$$u_{a,0} = \tilde{x}' \xi_a + \varepsilon_u. \quad (16)$$

Note that type is a linear combination of the observed and unobserved characteristics. We combine our parametric assumptions to obtain

$$\begin{aligned} & u_{2|p}(\tilde{\mathbf{p}}_p, 0) - u_{2|p}(\tilde{\mathbf{p}}_p, v_0) \\ & \approx x'(\beta_v \xi_v) + u_{1,p} + \beta_p p + \beta_v \varepsilon_v, \end{aligned} \quad (17)$$

if patients chose the premium consultation in period 1 and

$$\begin{aligned} & u_{2|w}(\tilde{\mathbf{p}}_w, 0) - u_{2|w}(\tilde{\mathbf{p}}_w, v_0) \\ & \approx x'(\beta_v \xi_v) + u_{1,w} + \beta_p p + \beta_v \varepsilon_v, \end{aligned} \quad (18)$$

if patients chose the reduced wait time consultation in period 1.²⁰ Finally, if patients chose the basic consultation in period 1,

$$\begin{aligned} & u_{2|b}(\tilde{\mathbf{p}}_b, 0) - \bar{u}_{2|b}(\tilde{\mathbf{p}}_b, v_0) \\ & \approx x'(\beta_v \xi_v) + \beta_p p + \beta_v \varepsilon_v. \end{aligned} \quad (19)$$

Analogous to the functional forms assumed for period 2, we assume that the utility in period 1 is

²⁰Remember that $u_{1,p} \equiv u_{1,a} + u_{1,w}$.

well approximated by

$$u_{1,p|s^*}(\tilde{\mathbf{p}}_p, v_0) - u_{1,k|s^*}(\tilde{\mathbf{p}}_k, v_0) \quad (20)$$

$$\approx x'(\alpha_v \xi_v + \alpha_w \xi_w + \alpha_a \xi_a) + \alpha_w wt + \alpha_p p + \alpha_s s^* + (\alpha_v \varepsilon_v + \alpha_w \varepsilon_w + \alpha_a \varepsilon_a). \quad (21)$$

As we mentioned earlier, individuals arrive to the clinic and have a prior of having a cataract. We assume this is well approximated by a linear relationship:

$$s^* \approx x' \gamma + \varepsilon_s. \quad (22)$$

where ε_s is normally distributed, $N(0, \sigma_s^2)$.²¹

We can define new parameters and random variables as:

$$\alpha_x \equiv \alpha_v \xi_v + \alpha_w \xi_w + \alpha_a \xi_a, \quad \varepsilon_u \equiv \alpha_v \varepsilon_v + \alpha_w \varepsilon_w + \alpha_a \varepsilon_a,$$

$$\beta_x \equiv \beta_v \xi_v, \quad \text{and} \quad \varepsilon_q \equiv \beta_v \varepsilon_v.$$

B.3 Likelihood Function

In this section we present the likelihood function used to estimate the parameters of the model. The model can be thought of as a system of three equations: (i) a probit cataract equation, (ii) an ordered probit consultation equation, and (iii) a probit undergo surgery equation. The model's three equations are

$$s_i^* \equiv x_i' \gamma + \varepsilon_{si}, \quad (23)$$

$$u_{1i|s^*}^* \equiv x_i' \alpha_x + \alpha_w wt_i + \alpha_p p_i + \alpha_s s_i^* + \epsilon_{ui}, \quad (24)$$

$$u_{2i|k,s^*}^* \equiv x_i' \beta_x + u_{1i,k} + \beta_p p_i + \varepsilon_{qi}. \quad (25)$$

The system's endogenous variables are the prior probability of individual i of having cataract, s_i^* , the latent purchase utility of consultation $k \in \{p, w, b\}$, $u_{1i|s^*}^*$, and the latent utility of undergo cataract surgery conditional on being diagnosed with cataract. The system's exogenous variables are the waiting time, wt_i , the randomize price, p_i , and a vector of characteristics of individual i , including age and

²¹This assumption is not crucial to our conclusions.

gender. Note that s_i^* , $u_{1i|s^*}^*$ and $u_{2i|k,s^*}^*$ are not observed for all patients. Thus, we follow a similar strategy as in Einav et al. (2012).

From our earlier assumptions, $(\varepsilon_u, \varepsilon_w, \varepsilon_v)$ are drawn from a multivariate normal distribution $N(0, \Sigma_0)$, then it follows that $(\varepsilon_s, \varepsilon_u, \varepsilon_q) \sim N(0, \Sigma)$ where

$$\Sigma = \begin{pmatrix} \sigma_s^2 & \rho_{su}\sigma_s\sigma_u & \rho_{sq}\sigma_s\sigma_q \\ \rho_{su}\sigma_s\sigma_u & \sigma_u^2 & \rho_{uq}\sigma_q\sigma_u \\ \rho_{sq}\sigma_s\sigma_q & \rho_{uq}\sigma_q\sigma_u & \sigma_q^2 \end{pmatrix},$$

which allow us to express the unconditional density of $(\varepsilon_s, \varepsilon_u, \varepsilon_q)$ as a function of

$$f_{\varepsilon_s, \varepsilon_u, \varepsilon_q}(s, u, q) = f_{\varepsilon_q|\varepsilon_s, \varepsilon_u}(q|s, u) f_{\varepsilon_u|\varepsilon_s}(u|s) f_{\varepsilon_s}(s). \quad (26)$$

Thus, the joint density of $(s_i^*, u_{1i|s^*}^*, u_{2i|k,s^*}^*)$ can be expressed as

$$\begin{aligned} f_{\varepsilon_s, \varepsilon_u, \varepsilon_q}(s_i^*, u_{1i|s^*}^*, u_{2i|k,s^*}^* | x_i, wt_i, p_i) = & \quad (27) \\ & f_{\varepsilon_q|\varepsilon_s, \varepsilon_u}(u_{2i|k,s^*}^* - x_i'\beta_x - u_{1i|k} - \beta_p p_i | x_i, wt_i, p_i, s_i^*, u_{1i|s^*}^*) \\ & \times f_{\varepsilon_u|\varepsilon_s}(u_{1i|s^*}^* - x_i'\alpha_x - \alpha_w wt_i - \alpha_p p_i - \alpha_s s_i^* | x_i, wt_i, p_i, s_i^*) \\ & \times f_{\varepsilon_s}(s_i^* - x_i'\gamma | x_i). \end{aligned}$$

Next, we rewrite expression (27) in terms of the observable endogenous variables $(s_i, u_{1i|s}, u_{2i|k,s})$. First, we derive the likelihood of being diagnosed with cataract. The probability of observing individual i diagnosed with cataract is

$$p_{s_i} := \mathbb{P}(x_i'\gamma + \varepsilon_{s_i} \geq 0) = \Phi(x_i'\gamma) \quad (28)$$

where $\Phi(\cdot)$ denotes the standard normal distribution function.

Second, conditional on being diagnosed with cataract, we can derive the likelihood of observing a patient chosen consultation type k . If we set

$$\begin{aligned} u_p &= \mu_p - x_i'\alpha_x - \alpha_w wt_i - \alpha_p p_i - \alpha_s s_i^* \\ u_b &= \mu_b - x_i'\alpha_x - \alpha_w wt_i - \alpha_p p_i - \alpha_s s_i^* \end{aligned} \quad (29)$$

The likelihood of premium consultation conditional on having cataract can be computed from the

covariance matrix Σ and the properties of the multivariate distribution as

$$\begin{aligned} p_{u_{1i}=p|s_i=1} &:= \mathbb{P}(x'_i\alpha_x + \alpha_w wt_i + \alpha_p p_i + \alpha_s s_i^* + \varepsilon_{ui} > \mu_p \mid x'_i\gamma + \varepsilon_{si} \geq 0) \\ &= \frac{1}{\Phi(x'_i\gamma)} \int_{-x'_i\gamma}^{\infty} F_{\varepsilon_u|\varepsilon_s=s}(2\rho_{su}s - u_p) f_{\varepsilon_s}(s) ds, \end{aligned}$$

recalling that $\varepsilon_u|\varepsilon_s = s \sim N(\rho_{su}s, 1 - \rho_{su}^2)$. For the reduced wait time consultation is

$$\begin{aligned} p_{u_{1i}=w|s_i=1} &:= \mathbb{P}(\mu_b < x'_i\alpha_x + \alpha_w wt_i + \alpha_p p_i + \alpha_s s_i^* + \varepsilon_{ui} < \mu_p \mid x'_i\gamma + \varepsilon_{si} \geq 0) \\ &= \frac{1}{\Phi(x'_i\gamma)} \int_{-x'_i\gamma}^{\infty} [F_{\varepsilon_u|\varepsilon_s=s}(u_p) - F_{\varepsilon_u|\varepsilon_s=s}(u_b)] f_{\varepsilon_s}(s) ds, \end{aligned}$$

and for the basic consultation is

$$\begin{aligned} p_{u_{1i}=b|s_i=1} &:= \mathbb{P}(x'_i\alpha_x + \alpha_w wt_i + \alpha_p p_i + \alpha_s s_i^* + \varepsilon_{ui} < \mu_b \mid x'_i\gamma + \varepsilon_{si} \geq 0) \\ &= \frac{1}{\Phi(x'_i\gamma)} \int_{-x'_i\gamma}^{\infty} F_{\varepsilon_u|\varepsilon_s=s}(u_b) f_{\varepsilon_s}(s) ds. \end{aligned}$$

We can derive analogously the likelihood for premium, reduced wait time and basic consultation conditional on not having cataract.

Third, we derive the likelihood of observing a patient's decision to undergo cataract surgery. Let

$$u_{2p} = -x'_i\beta_x - u_{1,p} - \beta_p p_i, \quad u_{2b} = -x'_i\beta_x - \beta_p p_i.$$

Conditional on being diagnosed with a cataract, the likelihood that an individual who chose premium consultation would undergo cataract surgery is

$$\begin{aligned} p_{u_{2i}=1|s_i=1, u_{1i}=p} &:= \\ &\mathbb{P}(x'_i\beta_x + u_{1,p} + \beta_p p_i + \varepsilon_{qi} \geq 0 \mid \varepsilon_{ui} > \mu_p - x'_i\alpha_x - \alpha_w wt_i - \alpha_p p_i - \alpha_s s_i^* \text{ and } \varepsilon_{si} \geq -x'_i\gamma) \quad (30) \\ &= \frac{1}{\Phi(x'_i\gamma) p_{u_{1i}=p|s_i=1}} \int_{u_p}^{\infty} \int_{-x'_i\gamma}^{\infty} F_{\varepsilon_q|\varepsilon_s=s, \varepsilon_u=u}(2\mathbb{E}[\varepsilon_q|\varepsilon_s = s, \varepsilon_u = u] - u_{2p}) f_{\varepsilon_u, \varepsilon_s}(u, s) ds du. \end{aligned}$$

Similarly, conditional on being diagnosed with a cataract, the likelihood of an individual who chose

the basic consultation would undergo cataract surgery is

$$\begin{aligned}
& p_{u_{2i}=1|s_i=1, u_{1i}=b} := \\
& \mathbb{P} \left(x'_i \beta_x + \beta_p p_i + \varepsilon_{qi} \geq 0 \mid \varepsilon_{ui} < \mu_b - x'_i \alpha_x - \alpha_w w t_i - \alpha_p p_i - \alpha_s s_i^* \text{ and } \varepsilon_{si} \geq -x'_i \gamma \right) \\
& = \frac{1}{\Phi(x'_i \gamma) p_{u_{1i}=b|s_i=1}} \int_{-\infty}^{u_b} \int_{-x'_i \gamma}^{\infty} F_{\varepsilon_q|\varepsilon_s=s, \varepsilon_u=u} (2\mathbb{E}[\varepsilon_q|\varepsilon_s=s, \varepsilon_u=u] - u_{2b}) f_{\varepsilon_u, \varepsilon_s}(u, s) ds du.
\end{aligned} \tag{31}$$

Analogously, we can derive the likelihood of an individual who chose the basic consultation would undergo cataract surgery conditional on being diagnosed with a cataract. Note that conditional on not being diagnosed with a cataract, the likelihood that an individual who chose premium, reduced wait time and basic consultation would undergo cataract surgery is 0, for all three cases.

Finally, we combine the probit cataract, ordered probit consultation, and the probit surgery equation, into a full likelihood function, $\mathcal{L}(s_i, u_{1i}, u_{2i}|x_i, w t_i, p_i)$. Before writing the likelihood function, we define the possible outcomes observed in the data as:

- I_1 : No cataracts and *premium consultation*.
- I_2 : No cataracts and *reduced wait time consultation*.
- I_3 : No cataracts and *basic consultation*.
- I_4 : Cataracts, *premium consultation*, surgery.
- I_5 : Cataracts, *reduced wait time consultation*, surgery.
- I_6 : Cataracts, *basic consultation*, surgery.
- I_7 : Cataracts, *premium consultation*, no surgery.
- I_8 : Cataracts, *reduced wait time consultation*, no surgery.
- I_9 : Cataracts, *basic consultation*, no surgery.

Then, the full likelihood is

$$\begin{aligned}
\log \mathcal{L} = & \sum_i \log(p_{s_i}) + \\
& \sum_{i \in I_1} \{\log(p_{u_{1i}=p|s_i=0})\} + \sum_{i \in I_2} \{\log(p_{u_{1i}=w|s_i=0})\} + \sum_{i \in I_3} \{\log(p_{u_{1i}=b|s_i=0})\} +
\end{aligned}$$

$$\begin{aligned}
& \sum_{i \in I_4} \{ \log (p_{u_{1i}=p|s_i=1}) + \log (p_{u_{2i}=1|s_i=1, u_{1i}=p}) \} + \\
& \sum_{i \in I_5} \{ \log (p_{u_{1i}=w|s_i=1}) + \log (p_{u_{2i}=1|s_i=1, u_{1i}=w}) \} + \\
& \sum_{i \in I_6} \{ \log (p_{u_{1i}=b|s_i=1}) + \log (p_{u_{2i}=1|s_i=1, u_{1i}=b}) \} + \\
& \sum_{i \in I_7} \{ \log (p_{u_{1i}=p|s_i=1}) + \log (p_{u_{2i}=0|s_i=1, u_{1i}=p}) \} + \\
& \sum_{i \in I_8} \{ \log (p_{u_{1i}=w|s_i=1}) + \log (p_{u_{2i}=0|s_i=1, u_{1i}=w}) \} + \\
& \sum_{i \in I_9} \{ \log (p_{u_{1i}=b|s_i=1}) + \log (p_{u_{2i}=0|s_i=1, u_{1i}=b}) \} +
\end{aligned}$$

B.4 Initial Values and Estimation

To compute the initial values we estimate (i) a probit cataract equation, (ii) an ordered probit consultation equation, and (iii) and a biprobit model to account for the probability of a patient chosen premium consultation and undergo surgery equation, conditional on having cataract.

Our estimates of the parameters $\gamma, \alpha_x, \alpha_w, \alpha_p, \alpha_s, \mu_p, \mu_b, \beta_x, u_{1,p}, u_{1,w}, \beta_w, \beta_p$, and Σ maximize this log-likelihood function. The maximizations of these three equations are standard but cumbersome since we need to integrate over unobservables. Instead of computing the integrals of the conditional probabilities in the likelihood function by simulation, we expressed the likelihood function in terms of the joint probabilities to get an exact expression of the function. To maximize the likelihood function we compute the gradient using automatic differentiation (see e.g., section 6 in Bücker et al., 2006). Given that we have 16 terms in $\log \mathcal{L}$ and we want to estimate 19 parameters, symbolic differentiation is very inefficient.

We followed an object oriented programming approach: We split the likelihood function into a composite of smaller and simpler sub-functions, assigning to each new sub-function a class that computes the derivative of such sub-function. Inside every class we define specific methods that recognize basic algebraic operations (from sum to exponentiation).