Sources of limited consideration and market power in e-commerce: the case of contact lenses*

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Abstract

The internet has allowed consumers to easily learn about competing retailers' product offerings, and it has allowed firms to enter retail industries without establishing physical stores. Despite these conditions, which could plausibly induce high levels of consumer search effort and cut-throat price competition in retail, consumers exhibit severely limited consideration in online markets and often pay prices significantly above the minimum available one for a particular product. In this paper, I develop a model of sequential consumer search and retailer price competition to assess the roles of search costs and seller differentiation in explaining limited consideration and market power in contact lens e-commerce. My empirical framework exploits the panel nature of my data to estimate the extent of state dependence and the nature of consumers' persistent unobserved tastes for sellers; it also features a novel approach for computing probabilities of sequential search outcomes. I find that various forms of seller differentiation are primarily responsible for limited consideration and market power in contact lens e-commerce.

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1 Introduction

The internet has allowed consumers to easily learn about competing retailers' product offerings from the comfort of their homes. It has also given potential retailers a way to sell products without incurring the costs of establishing physical stores. Why has the internet, then, failed to initiate an age of expansive consumer knowledge about purchasing opportunities and of cut-throat price competition in retail? This outcome is a leading theoretical possibility in retail industries in which stores compete in sales of minimally differentiated products such as particular book titles or boxes of contact lenses. Indeed, if search were truly costless on the internet and if sellers' product offerings were truly undifferentiated, then consumers would compare a product's prices across all available retailers before selecting a particular retailer from whom to purchase that product, and these industries would feature Bertrand price competition with prices depressed to the level of the lowest marginal cost among potential retailers.

Yet, in practice, online retail markets for minimally differentiated products often feature consumers who undertake little search effort and sellers whose prices exhibit substantial dispersion. These facts could reflect that search frictions remain significant on the internet, or that sellers' product offerings are somehow differentiated. Much of the empirical literature on consumer search online has emphasized the role of search costs in generating price dispersion in homogeneous product markets. When consumers find it costly to search across e-commerce sites, online retailers can maintain a positive market share while charging prices markedly above those of their competitors. This is because these search-averse consumers are willing to purchase from one of the first sites that they find rather than continuing to search for lower prices.[1]

In this paper, I emphasize the contribution of seller differentiation to limited consideration and price dispersion in online retail. Even when the characteristics of the physical product that arrives on a consumer's doorstep do not depend on which online vendor the consumer selects, a consumer may differentially value retailers for non-price reasons because of, e.g., these retailers' shipping and logistical efficiency, their reputations, their user interfaces, and their customer service operations. Stores may be both vertically and horizontally differentiated along these dimensions. A consumer may also be more likely to buy from stores from which that consumer has previously made a purchase because of habit formation, store loyalty, or switching costs. If the consumer has limited knowledge about a seller, but the consumer's knowledge is enough for her to know it is unlikely that she would want to buy from that seller upon visiting its site, then the consumer may not visit the seller even when search costs are negligible.

In this paper, I empirically investigate potential sources of limited consideration and market power in the online direct-to-consumer market for soft contact lenses in the United States. In particular, I assess the contribution of various features of the market to the extent of consumer search and equilibrium markups in contact lens e-commerce. Contact lens e-commerce features a small number of online retailers that market contact lenses purchased from a common set of manufacturers to consumers. It also features consumers who often purchase products above their minimum available online prices; prices for many boxes of contact lenses significantly vary across across the retailers on which I focus in this study. Absent large differences in retailers' costs of providing consumers with a specific box of

[1] As noted later, Hortaçsu and Syverson (2004) and Hong and Shum (2006) were early papers in the empirical search literature that considered search frictions as an explanation for price dispersion in product markets with little product differentiation.

contact lenses, this significant price dispersion is evidence of significant markups in the industry that vary across retailers.

My motivation for studying contact lenses is two-fold. This setting is well suited for the study of consumer search because consumers require a *brand-specific* prescription to buy contact lenses. A consumer prescribed Acuvue Oasys lenses, for instance, cannot substitute the prescription to buy Acuvue 2 lenses or Freshlook lenses. This allows me to credibly assume that all search occurs across stores for a physically homogeneous product rather than across products and stores simultaneously. Several studies of consumer search online analyze product categories in which it is likely that consumers search both across physical products and across retailers; a consumer searching for books, for example, may visit different stores in pursuit of a particular book title, visit different books' pages at a particular online bookstore, or search across both book titles and bookstores. Thus, in the books setting that has been popular in the empirical search literature, the assumption of search exclusively occurring across stores within a product seems implausible. Another favourable aspect of the contact lens setting is that the major contact lens retailers only sell contact lenses and contact lens accessories. Thus, modelling the supply side of the industry does not require accounting for the interdependencies between retailers' operations across different product categories.

I study contact lens e-commerce using a consumer panel dataset that records each of its panelist's web browsing and online transactions histories. Unlike almost all existing studies of consumer search online, I incorporate a dataset's panel dimension to learn about state dependence and consumers' persistent heterogeneous preferences for stores, which are forms of seller differentiation that I consider to be important potential drivers of limited consideration and market power in e-commerce. Throughout this paper, I use the term state dependence to refer to effect of a previous purchase on a consumer's contemporaneous choice probabilities, whether this effect is explained by habit formation, store loyalty, switching costs, or some other phenomena.

Understanding why consumers exhibit limited consideration of available sellers (i.e., why they do not visit the websites of many sellers before making a purchase) and how online retailers are able to charge substantial markups despite competing in sales of undifferentiated contact lens products is important for understanding competition in e-commerce markets. Understanding competition in e-commerce is in turn important for understanding the efficacy of policies intended to remedy market power in the industry. To illustrate, if search frictions were the primary source of market power in e-commerce, then a policy designed to increase consumer information may make e-commerce markets more competitive. If search costs were trifling and switching costs were instead primarily responsible for market power online, then this remedy would be ineffective; a policy that helped consumers switch between online retailers could be appropriate instead.

My first analyses provide various descriptive facts about the e-commerce market for contact lenses in the United States. This analysis reveals that consumer consideration is indeed severely limited in the market for contact lenses even though prices vary significantly across online sellers, which suggests possible gains from search. In 83% of the search efforts for contact lenses in my sample, the consumer visits only one contact lens retailer. Also, the average transaction price for contact lenses is 16% above the minimum price available among the three major retailers for the brand the consumer ultimately purchases.

I answer this paper's research questions using a model of sequential consumer search and of retailer price competition. In particular, I use this model to determine how search behaviour and equilibrium markups change when consumer preferences counterfactually change. This analysis indicates which aspects of consumer preferences give rise to limited consideration and market power in contact lens e-commerce. In estimating my model, I exploit a one-to-one mapping between search effort outcomes and chains of inequalities relating consumers' preferences for sellers. This mapping is implied by the optimal sequential search strategy of Weitzman (1979). To make the use of this mapping in estimation and simulation computationally practical, I deploy a novel parametric assumption on consumers' search costs. Additionally, whereas almost all empirical search models have used cross-sectional data variation, I develop techniques for analyzing panel data in the context of a search model. These techniques address an initial conditions problem and an endogeneity problem, both of which generally introduce difficulties in the analysis of nonlinear dynamic panel models. As noted above, panel data is especially valuable in my setting because patterns in consumers' search activity across time are informative about state dependence and persistent preferences for specific retailers, which are potential explanations for limited consumer consideration and market power online.

Although the contact lens setting is suitable for studying search, the applicability of my study's conclusions to other e-commerce settings is somewhat limited due to differences between contact lens e-commerce and other online retail industries. The fact that consumers must enter their prescriptions when they initially buy contact lenses from a particular retailer, for instance, may make state dependence higher in contact lens e-commerce than in other e-commerce product categories. Contact lens retailers, whether online or offline, resemble pharmacies in that they require consumers to present prescriptions from medical professionals before purchasing products and in that their product offerings are limited to a specific product category (e.g., contact lenses or prescription drugs). My findings, then, may have implications for competition between pharmacies. Last, my methodological framework for studying contact lens e-commerce may be straightforwardly applied to other e-commerce industries, although the assumption that consumer search for a fixed product across stores seems less plausible than in the contact lens setting.

Before beginning the paper in earnest, I summarize its conclusions and provide a brief review of related literature. My first main finding is that the low levels of consumer search observed in my data are primarily justified by state dependence and store differentiation in spite of low estimated search costs. When I eliminate state dependence, the share of consumer search efforts involving a visit to more than one store when searching for contact lenses rises by over 25 percentage points, whereas eliminating persistent unobserved heterogeneity in consumers' tastes for stores increases this share by about 15 percentage points. Cutting the median search cost in half only increases this share by seven percentage points. Note that my estimate of the median search cost is 60 cents, which is much lower than estimates appearing in the empirical consumer search literature of the cost of searching online for books. Additionally, state dependence and consumers' persistent unobserved tastes for stores give rise to market power (i.e., equilibrium markups) whereas search costs do not significantly contribute to markups at their estimated magnitudes. Indeed, removing state dependence reduces equilibrium markups for one popular brand of contact lenses by over 30% at the two leading online contact lens retailers, and removing persistent unobserved heterogeneity in consumers' tastes for stores reduces equilibrium markups at these retailers by over 70%. Lowering the median search cost by half, meanwhile, barely changes markups. This suggests that seller differentiation, not search costs, explains limited consideration and market power in contact lens e-commerce.

1.1 Related literature

My paper situates in the empirical consumer search literature, much of which analyzes search on the internet.[2] One early paper in this literature is Hong and Shum (2006), who analyze consumer search for textbooks across online retailers. Hong and Shum (2006) interpret price dispersion across sellers for the homogeneous products that they study as evidence of search frictions. Indeed, search costs are one reason why a seller charging a price higher than those of its competitors can gain a positive market share in a homogeneous product market. Hortaçsu and Syverson (2004) similarly propose search frictions as an explanation for price dispersion among financially homogeneous S&P 500 index funds. Note that Hortaçsu and Syverson (2004) allow for vertical differentiation between product offerings whereas Hong and Shum (2006) do not. Neither study, however, allows for horizontal differentiation between product offerings. As I emphasize in my study, heterogeneous tastes for retailers of a homogeneous product also justify consumers' decisions to purchase from retailers charging different prices for physically identical products. Furthermore, horizontal differentiation between sellers is important to model in an analysis of market power because it typically softens price competition in differentiated product markets.

Both Hong and Shum (2006) and Hortaçsu and Syverson (2004) analyze search using market-level data as opposed to microdata on individual consumers' search efforts and purchase decisions. These papers make inferences about search frictions from market-level data using firms' profit-maximization conditions. Several recent papers in the empirical search literature have instead used microdata to make inferences about consumers' search costs and other aspects of consumer preferences directly from consumer choices. One such study is De Los Santos et al. (2012), which analyzes models of consumer search using data on consumers' browsing and transactions on book-retailing websites. Another is Morozov et al. (Forthcoming), whose authors emphasize the relationship between preference heterogeneity and search frictions in determining consumer purchasing behaviour. They argue that ignoring search costs leads the researcher to overstate the importance of unobserved preference heterogeneity, which—together with search costs—is a driver of repeat purchasing. Their study, like my own, exploits panel data to learn about the nature of preference heterogeneity. Morozov et al. (Forthcoming), however, consider purchases on an online cosmetics stores. This setting differs from mine in that it involves search across products within a store as opposed to search across stores.

Last, my paper analyzes state dependence, unobserved heterogeneity, and inertia in consumer choice. Both state dependence—that is, the effect of an agent's previous choice on that agent's contemporaneous choice probabilities—and persistent unobserved heterogeneity in consumers' tastes give rise to *inertia*, which refers to repeat purchasing across shopping occasions. In their empirical analysis of these phenomena, Dubé et al. (2010) emphasize that state dependence and persistent unobserved heterogeneity have different implications for patterns of how consumers switch between alternatives. I make a similar argument to justify my disentanglement of state dependence and persistent preferences. Other studies of consumer search that model features of preferences inducing inertia are Honka (2014) and Morozov et al. (Forthcoming). Honka (2014) does not attempt to separate the contributions of state dependence and persistent unobserved tastes to inertia, and instead includes the consumer's previous decision as an exogenous utility shifter. Thus, Honka (2014)'s model features state dependence but not persistent unobserved heterogeneity. Morozov et al. (Forthcoming) make the alternative choice of modelling persistent preference heterogeneity but not state dependence. One of my paper's contributions, then, is its incorporation of both state dependence

[2] For a more detailed characterization of the empirical consumer search literature, see Honka et al. (2019).

and persistent unobserved heterogeneity in a panel-data study of consumer search.

1.2 Roadmap

This paper proceeds as follows. Section 2 discusses this study's industrial setting and its data source; Section 3 then conducts descriptive analyses of these data. Sections 4 and 5 present my model of sequential consumer search and my model of retailer price competition, respectively. Section 6 outlines my estimation procedure and informally discusses the identification of my search model. Section 7 reports my parameter estimates and Section 8 describes the counterfactual analyses that I conduct using these estimates. Section 9 concludes.

2 Setting and data

This study's primary data source is the Comscore Web Behavior Panel for the years 2007 and 2008. This dataset includes the online browsing and transactions activities for a large panel of US households.[3] As noted by De Los Santos et al. (2012), the Comscore Web Behavior Panel is representative of online consumers in the United States on various observable demographic variables. The browsing data include a record for each web domain visited by a panelist, and each of these records includes the identifier of the panelist who visited the domain, the visit's time, the visit's duration, and whether the visit is associated with a transaction. The data do not include the list of webpages visited by a panelist within a web domain; for example, when we see that a panelist visited `amazon.com`, we do not see which product pages that the consumer visited while browsing Amazon's website. For each transaction in the data, I observe the panelist who conducted the transaction, the name of the purchased product, the unit price of the product, the quantity of the product purchased, the total price of the consumer's shopping basket, the time of the transaction, and the web domain on which the transaction took place.

The transactions analyzed in this paper occur at the three major contact lens retailers in the data, which collectively account for about 95% of observed contact lens transactions in the Comscore data. These retailers are 1-800 Contacts (1800), Vision Direct (VD), and Walmart (WM). As is clear from Table 1, the retailers specializing in contact lens sales—1800 and VD—have much higher sales volumes than WM. Both 1800 and VD almost exclusively sold contact lenses in the sample period; their other offerings were contact lens solutions and other contact lens accessories.

For each online retailer and each brand of contact lens in the data, I construct a daily time series of the retailer's prices for that brand. My construction of price time series is facilitated by the assumption that prices remain constant between observed transactions. Thus, if I observed a transaction for Acuvue 2 at 1800 on July 7, 2007 for $20.00 and an observation for the same brand at 1800 on July 10, 2007 for $21.00, I would assume that the price on July 8 and July 9 of 2007 was $20.00 and that the price from July 10 until the date of the next observed transaction of Acuvue 2 at 1800 was $21.00. Although this procedure introduces some measurement error into my price variables, the magnitude of the error is likely to be small because my sample size is reasonably large and there is little intertemporal variation in brands' prices for a particular store relative to variation in prices across brands and across stores; see Appendix Table 16 for a description of the price variation in my transactions data.

[3] About 92 000 households are included in the 2007 panel, and about 58 000 are included in the 2008 panel.

The prices in my data do not include shipping fees, although 1800 and VD both offered free delivery for sufficiently large purchases during the period that I study. Additionally, contact lens manufacturers often offered rebates for contact lens purchases; consumers could receive rebates by sending information on their purchased boxes to the manufacturer, who would then send funds to the consumer. Since these rebates were offered by manufacturers of contact lenses and not their retailers, they should not affect the appeal of buying from one retailer compared to another.

The data that I ultimately analyze take the form of a panel of search efforts; each search effort is an ordered sequence of visits to stores and an associated purchase decision, where the available alternatives for the purchase decision are the visited stores and the outside option of purchasing from none of the online stores (which includes the possibility of purchasing contact lenses from an offline retailer). Figure 1 illustrates a panel of two search efforts that a consumer in my analysis sample could possibly conduct. I construct the search effort for each contact lens transaction in my data by determining all contact lens retailers that the consumer visited in the days prior to making the transaction. In particular, I include all visits to 1800 or VM in the fourteen days prior to the transaction and all visits to WM in the two days prior to the transaction. The reason for using a shorter time window for WM is that consumers may visit Walmart for purposes that are not related to search for contact lenses (e.g., to search for other products sold by Walmart), and setting a shorter time window for Walmart is likely to exclude visits unrelated to contact lenses without dropping many visits that genuinely belong to the consumer's search effort. I also construct a search effort for each visit to 1800 or VM that does not result in a transaction. In doing so, I search for visits to other contact lens retailers within seven days (1800 and VM) or two days (WM) of this visit, and I associate these nearby visits with the same search effort as the initial visit. I proceed to add visits that are within seven (1800 and VM) or two (WM) days of visits that have already been added to the search effort, and I continue to iteratively add visits to a search effort until no more visits are added in an iteration. The reason for using a different time window for Walmart is the same as that discussed above for the case in which a search effort includes an online transaction. In both the case in which the search effort involves a transaction and in which it does not, I identify the chronologically first, second, and third visits in the search effort, and I use this ordering in my empirical analysis.

In the United States, optometrists and ophthalmologists prescribe contact lenses to their patients after administering eye exams and contact lens fittings for these patients. A contact lens prescription specifies the prescribed brand of contact lenses, various parameters of the prescription (e.g., diameter and power), and an expiration date. Prescriptions are typically valid for one to two years, and there is no limit on the quantity of contact lens boxes that a consumer can purchase with a particular prescription if the consumer makes these purchases before the prescription expires. I infer the prescription of consumers in my sample based on the brand of contact lens that these consumers buy. When I see a consumer buy a different brand than the consumer purchased in his previous search effort, I assume that the consumer's prescription has changed to this newly purchased brand and the consumer holds this prescription alone (not in addition to his previous one) until his next purchase.

My empirical analysis relies on the panel structure of my data to study the role of store loyalty in guiding search and purchase behaviour. To facilitate the treatment of consumers' previous purchases as observable variables, I drop from my estimation sample each consumer's search efforts made before and including the search effort in which the consumer first made a purchase. Note that all consumers in the remaining sample have made a purchase, and thus I am able to infer the prescription of each consumer in this sample.

Figure 1: Illustration of search efforts

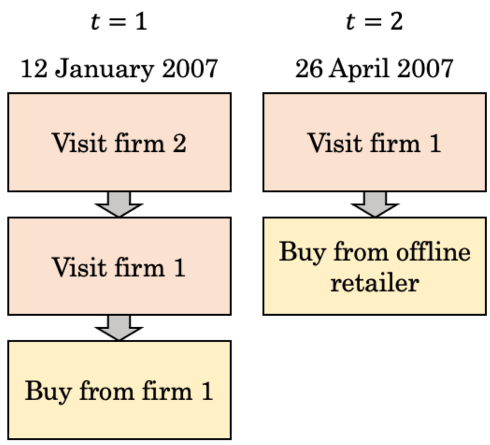


Table 1: Sales and prices by store (2007–2008)

Store	Transactions	Average relative price
1800contacts.com	849	1
visiondirect.com	416	0.85
walmart.com	70	0.94

Note: the average relative price column reports the average ratio of the store's price to 1800's price across transactions in the 2007–2008 sample.

The fact that the major online contact lens retailers almost exclusively sell contact lenses helps in analyzing the outside option of not buying contact lenses from any online retailer (but perhaps buying them from an offline retailer). This is because I can identify visits to online contact lens retailers that do not result in a purchase as search efforts in which the consumer chooses the outside option. If I studied search for books, for example, I could not reasonably conclude that a consumer's visit to Amazon represented a search effort for books if the consumer did not buy any product from Amazon and I did not know which product pages the consumer viewed on Amazon.

3 Descriptive analysis

3.1 Overview of data

This section describes descriptive analyses that provide an overview of my data. To begin, Table 1 provides the number of transactions at each of the three retailers studied in this paper as well as their average transaction prices relative to the price at 1800. Note that 1800 and VD sell many more contact lenses than WM, and that 1800 has the highest sales despite having the highest average prices.

Table 2 describes the transactions in my sample. First, Panel A reports the number of observed transactions for the brands with the most transactions. Note that there are 42 distinct contact lens brands in my sample. Panel B provides several quantiles of prices and transaction quantities in my sample. The interquartile range of transaction prices is \$19.99 to \$38.99. The median number of boxes purchased in a transaction is two, which is

Table 2: Description of transactions in contact lens data

Panel A: Transactions by brand

Brand	# Transactions
Acuvue 2	188
Acuvue Advance	145
Acuvue Oasys	129
Acuvue Advance for Astigmatism	95
Biomedics	57
Freshlook Colorblends	56
Acuvue 2 Colors	51
Soflens 66 Toric	48
Focus Night & Day	46
O2 Optix	46
Other brands	474
Total	1335

Panel B: Quantiles of transaction prices and quantities

Price quantile: 0.10	16.99
Price quantile: 0.25	19.99
Price quantile: 0.50	29.95
Price quantile: 0.75	38.99
Price quantile: 0.90	49.99
Quantity quantile: 0.25	1
Quantity quantile: 0.50	2
Quantity quantile: 0.75	4

Table 3: Description of consumers in contact lens data

	Mean	Quantiles			
		0.25	0.5	0.75	0.95
N. search efforts	2.47	1	2	3	6
N. transactions	1.65	1	1	2	4
# consumers = 793					

not surprising given that someone prescribed contact lenses will generally have a different prescription strength for each eye and will therefore need to purchase a distinct box for each eye.

Table 3 reports how often consumers in my sample search for and purchase contact lenses. Contact lens consumers make, on average, two and a half search efforts and less than two transactions, with some consumers making many more search efforts and transactions.

Table 4 displays the share of search efforts involving one, two, and three store visits. It reveals that consumer consideration of available sellers in my sample is severely limited; a full 83% of search sessions involve a visit to only one store. Consumers visit few stores despite the possibility of spending less on contact lenses by visiting and purchasing from other stores. Indeed, Table 5 shows that 70% of transactions involve purchasing a brand of contact lenses from a store that sells that brand above the minimum price offered among the three major retailers. The magnitude of spending in excess of these minimum prices is

Table 4: Share of search efforts by consideration set size

Number of visited stores	Share of sessions
1	0.83
2	0.16
3	0.01

Table 5: Transactions above minimum available price

	Value
Share of transactions above min price	0.70
Average payment over min price ($)	4.31
Average payment over min price (%)	16.3

significant – consumers pay, on average, 16.3% above the minimum available price for their brand.

Table 6 characterizes the persistence of consumer search and purchase decisions. In particular, it shows the share of consumers who choose to visit the same store first in consecutive search efforts. The table also reports the share of consumers making the same purchase decision (i.e., the decision to buy from a particular store or to not buy from any online store) in consecutive search efforts. Last, Table 6 reports the share of transactions that are from the same online retailer as the consumer's previous online transaction from an online retailer. Table 6 shows that search and purchasing behaviour exhibits a high degree of inertia in my sample, with most consumers choosing the same online store for their first visit across search efforts. Additionally, an overwhelming majority of consecutive online purchases take place at the same retailer.

3.2 Prices, browsing, and purchasing

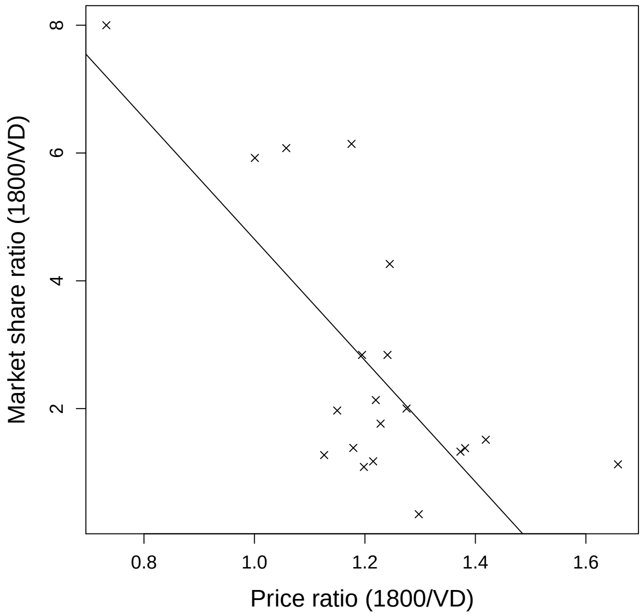
I now turn to the role of prices in directing consumers' browsing and purchasing behaviour. As Table 1 shows, 1800 boasts the highest sales despite charging the highest average prices. The positive relationship between quantities and prices suggested by this fact reflects the standard price endogeneity problem encountered in empirical industrial organization. This problem is a consequence of the fact that the empirical relationship between sales and prices reflects both consumers' distaste for paying higher prices as well as the influence of consumers' tastes for stores on pricing decisions. In my setting, the consumer considers buying physically identical products from different retailers. But retailers may offer differential quality to their consumers in dimensions unrelated to either price or their physical products. These dimensions include shipping efficiency, website user interfaces, and customer service

Table 6: Share of search efforts with the same choice as in the previous search effort

	First visit	Purchase choice	Online purchase
Share	0.85	0.49	0.98
N	1163	1163	441

Notes: The "Online purchase" column excludes search efforts in which the outside option is selected.

Figure 2: Prices and intrabrand market shares at 1800 and VD



Note: Each marker represents a brand of contact lenses in my sample. “Market share ratio (1800/VD)” provides the number of transactions at 1800 for a particular brand divided by the number of transactions at VD for that brand. “Price ratio (1800/VD)” provides the average price of a particular brand at 1800 across days in my sample divided by the analogous quantity for VD.

operations. If 1800 offers higher quality along these dimensions than its competitors, then consumers may be more willing to pay for its lenses. This would in turn lead 1800 to charge higher prices. The fact that consumers’ tastes for a store contributes positively to both that store’s sales and its prices is the source of price endogeneity in my setting.

My solution to the price endogeneity probem involves exploiting cross-brand differences in stores’ relative prices. The idea is that, if stores’ quality differences exist to the same extent in their sales of all brands, then the extent to which a store’s relatively expensive brands sell relatively fewer units will identify consumers’ sensitivity to price. Figure 2 shows that, even though 1800 sells the most contact lenses as the most expensive store, the brands for which 1800 charges high prices relative to its primary competitor VD have the lowest sales at 1800 relative to VD.

To exploit between-brand variation in prices and quantities to estimate consumers’ price sensitivity, I use store fixed effects in my specification of consumers’ indirect utilities. I assess the suitability of this approach by running descriptive multinomial logit regressions of consumers’ purchasing and browsing decisions on the major online retailers’ prices with and without store fixed effects. An additional purpose of these regressions is the determination of whether prices guide consumer search. The finding that prices predict which stores consumers visit would suggest that consumers have some knowledge of stores’ prices prior to conducting search.

The estimating equation for the multinomial logit regressions is

$$u_{ift} = q_{ft} - \alpha p_{ift} + \varepsilon_{ift} \qquad f \in \{1800, \mathrm{WM}, \mathrm{VD}\}, \tag{1}$$

where $y_{it} = \arg\max_f u_{ift}$ is, depending on the regression, either the store from which the consumer purchases contact lenses or or the store that the consumer visits first in a search effort. In equation (1), i indexes consumers, t indexes search efforts, and p_{ft} is the price charged by retailer f for i's prescribed brand at time period t. Additionally, ε_{ift} is an unobservable type 1 extreme value random variable taken to be independently distributed across i, f, and t. When I do not include store fixed effects, I impose $q_{ft} = \bar{q}$ and estimate the $\bar{q}$ parameter. When I do include store fixed effects, I set $q_{ft} = q_{f\tau}$, where τ indicates the half-year (e.g. first half of 2007, second half of 2008, etc.) in which search effort t takes place. I estimate the regressions in which the outcome y_{it} is consumer i's purchase decision on a dataset of all search efforts that end in a transaction. I use a disjoint dataset for the regressions in which the outcome y_{it} is consumer i's first-visited store in search effort t: this is the dataset of all search efforts that do not end in a transaction.

Table 7: Descriptive multinomial regression estimates

Specification 1: $q_{ft} = \bar{q} \quad \forall f, t$

	Purchase	First visit
α	-0.033	-0.067
	(0.005)	(0.011)
Implied elasticity	-1.11	-2.25
	(0.18)	(0.36)

Specification 2: seller/half-year fixed effects

	Purchase	First visit
α	0.023	0.025
	(0.004)	(0.015)
Implied elasticity	0.78	0.83
	(0.13)	(0.49)

Notes: Standard errors are reported in parentheses. The "Implied elasticity" is the average own-price elasticity at 1-800 Contacts, where the average is taken across transactions.

Table 7 provides the results of the descriptive logit regressions. Note that, when we do not use seller/half-year fixed effects, we do not obtain the expected positive sign for our estimate of price sensitivity. That is, we estimate that consumers become more likely to purchase from a seller when it charges a higher price. This problem is resolved by the introduction of seller/half-year fixed effects. Additionally, the consumer's choice of which store to visit first responds to stores' prices in a similar way as the consumer's purchase choice. This suggests that consumers have some knowledge of stores' prices before conducting search.

The Specification 2 estimates in Table 7 could reflect consumers' responses to cross-brand price differences (i.e., consumers are less likely to buy from a store with a relatively high price for their brand on average across time) or intertemporal price variation (i.e., consumers become less likely to buy from a store when the relative price of their brand at that store increases). To assess the relative contributions of cross-brand and intertemporal price variation to the price coefficient estimates in Table 7, I run between and within (fixed-effects) regressions of consumers' purchase decisions on prices. The cross-sectional units of my panel are brands, and the time units are transactions ordered by time. The estimating equation upon which my regressions are based is

$$\mathbb{1}\{t \text{ results in purchase from 1800}\} = \beta_0 + \beta_p \log\left(\frac{p_{j,1800,t}}{\bar{p}_{jt}}\right) + \varepsilon_t, \tag{2}$$

where j is the prescribed brand of the consumer making transaction t, $p_{j,1800,t}$ is 1800's price for this brand at the time of transaction t, and $\bar{p}_{jt}$ is the average price of brand j across retailers at the time of transaction t.

Table 8 provides estimates of (2) obtained via ordinary least squares (OLS), the between estimator, and the within/fixed-effects estimator. The between estimator is computed by regressing each brand's cross-transaction average of the outcome variable on that brand's cross-transaction average of the regressor. The between price-sensitivity estimate is larger in

Table 8: Between- and within- price sensitivity

	β_p		
	OLS	Between	Within
Estimate	-0.31	-0.48	-0.40
Std. Error	0.13	0.20	0.22

absolute value and is more statistically significant than the within estimate, although the difference between the magnitudes of these estimates is small and the within estimate is almost statistically significant at the usual 0.05 level. This suggests that the relationship between purchase decisions and prices in my sample owe both to responses to differences in stores' relative prices across brands and to responses to stores' price changes across time.

Appendix Table 16 characterizes the variation in prices across brands, across stores, and across time. To summarize, the variation in prices across brands is greater than the variation across stores for a particular brand, and variation across time in a brand's price at a particular store is the smallest of the three types of price variation.

4 Model of consumer search

This section outlines the model of consumer search that I use in my empirical analysis. In the model, consumers search for contact lenses across F online retailers at different occasions across time. Each consumer i has a prescription for a particular brand j of contact lenses. The consumer makes search efforts $t \in \{1, \ldots, T_i\}$ at exogenously determined calendar times. In each search effort, the consumer determines which online retailers $f \in \mathcal{F} = \{1, \ldots, F\}$ to visit. Each online retailer f charges a price p_{jft} for brand j during a given search effort t. The consumer additionally chooses a store f from which to purchase under the constraint that it is only possible to purchase from visited stores. The consumer can also choose to purchase from the outside option, which I denote by $f = 0$ and which represents the possibility of purchasing contact lenses offline or not purchasing contact lenses at all.

Search is costly for the consumer, who incurs a search cost of κ_{ift} for visiting store f in search effort t. In each search effort, the consumer conducts directed sequential search according to the optimal strategy characterized by Weitzman (1979). Consumer i's utility from purchasing from store f at time t is

$$\text{(Online)} \quad u_{ijft} = q_f - \alpha p_{jft} + \phi h_{ift} + \gamma_{if} + \varepsilon_{ift} \tag{3}$$

$$\text{(Offline)} \quad u_{ij0t} = -\alpha_{\text{out}} p_{j0t} + \varepsilon_{i0t}, \tag{4}$$

where q_f is the quality of store f; γ_{if} is persistent component of consumer i's idiosyncratic taste for f; ε_{ift} is the time-varying component of consumer i's idiosyncratic taste for f. Additionally, h_{ift} is an indicator for whether f was the online store from which i most recently purchased contact lenses. In my empirical analysis, I exclude each consumer's search efforts until and including the search effort in which the consumer first purchases from an online retailer. Thus, I assume from here on that each consumer has previously purchased from one of the F online retailers in the model. I will refer to $h_{it} = \{h_{ift}\}_{f \in \mathcal{F}}$ as consumer i's *state* at t throughout this paper. Both α and ϕ are model parameters; the former governs consumers' price sensitivity and the latter governs the extent of state dependence, which I call store loyalty in the case in which $\phi > 0$.

Although I mostly use the term "store loyalty" to refer to a positive effect of previously purchasing from store f on a consumer's probability of ordering from store f, there are several interpretations of this effect that are not best described as loyalty. The effect, for instance, could be explained by habit formation or switching costs. In my setting, I expect state dependence to owe in some part to the fact that consumers must send their prescriptions to online retailers before purchasing contact lenses. Once the consumer has sent a recent prescription to an online retailer as a part of a purchase, then that consumer can make future purchases from the retailer without the effort of sending in a prescription again. Similarly, a consumer who has uploaded billing and delivery information to an online retailer can make future purchases without incurring the effort of uploading this information again. Both of these features of contact lens e-commerce suggest that $\phi > 0$.

Whereas equation (3) provides the consumer's indirect utilities for contact lenses purchased online, equation (4) provides the consumer's indirect utility for purchasing contact lenses offline. The price p_{j0t} is the offline price of brand j during search effort t. Because the price coefficient α_{out} appearing in (4) may differ from the coefficient α in (3), the consumer may be differentially sensitive to offline and online prices. In the remainder of the paper, I will often suppress the brand subscript j appearing in (3) and (4).[4]

I assume that the consumer knows everything about his preferences for each store $f \in \mathcal{F}$ except ε_{ift}, which I will call i's *match value* with t, before visiting store f. Additinally, I assume that the consumer knows u_{i0t} before beginning search. My assumption implies that the consumer knows each store's price before visiting that store. Section 4.1 justifies this assumption in my setting. I also assume that consumeres are myopic in that they do not anticipate the effects of their choices in a given search effort on their payoffs in future search efforts. Future payoffs depend on current choices in my setting because the ϕh_{ift} term in (3) gives rise to state dependence.

The optimal sequential search strategy of Weitzman (1979) involves sorting alternatives in descending order by an index called *reservation utility* and then searching the stores in this order until obtaining an indirect utility higher than the maximum reservation utility among unsearched alternatives. Consumer i's reservation utility r_{ift} for store f in search effort t, is defined by

$$\kappa_{ift} = \int_{r_{ift}}^{\infty} (u - r_{ift}) dF_{ift}(u), \tag{5}$$

where F_{ift} is the distribution of u_{ift} conditional on everything except ε_{ift}. Note that r_{ift} is the quantity that makes the consumer indifferent between (i) enjoying a payoff of r_{ift} without further search and (ii) visiting store f before enjoying a payoff equal to whichever of u_{ift} and r_{ift} is greater.

In my model, the reservation utilities can be written as

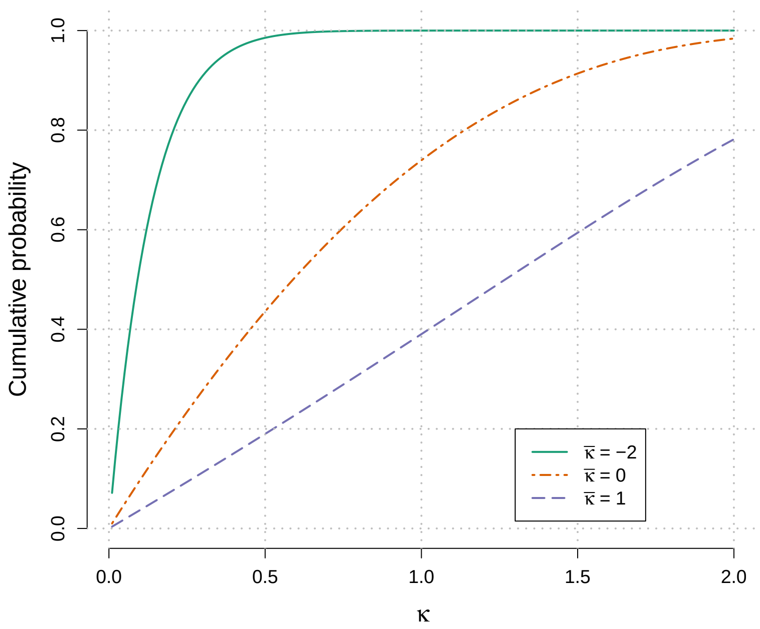
$$r_{ift} = q_f + \gamma_{if} - \alpha p_{ft} + \phi h_{ift} + \Gamma_0^{-1}(\kappa_{ift}), \tag{6}$$

for

$$\Gamma_0(\kappa) = \int_{\kappa}^{\infty} (u - \kappa) dF_0(u),$$

[4] Although there is no good reason for consumers to differentially value a dollar spent offline versus a dollar spent online, I allow for $\alpha > \alpha_{\text{out}}$ to account for the fact that the outside option includes the possibility of not buying any contact lenses. Thus, the indirect utility from purchasing offline can be interpreted as the inclusive value of all available offline stores and of not buying contact lenses at all (and perhaps wearing eyeglasses instead). If all online sellers' prices and the offline sellers' prices increased dramatically, we would expect the outside option's market share to increase since the outside option includes the option of not purchasing any contact lenses. This would not occur if $\alpha = \alpha_{\text{out}}$, but it would occur if $\alpha > \alpha_{\text{out}}$. Hence why I allow for these two parameters to take on different values.

Figure 3: Illustration of the search cost distribution function



where F_0 is the distribution of the ε_{ift} match values; this is the type 1 extreme value distribution in my empirical analysis. Note that Γ_0 (and its inverse) are strictly decreasing functions, which means that a store's reservation utility is decreasing in the search cost associated with a visit to that store. Kim et al. (2010) and Moraga-González et al. (2018) similarly invert equations defining reservation utilities to obtain expressions resembling my equation (5) that express reservation utilities as a sum of the parts of the indirect utilities known prior to search and of a decreasing function of the search cost.

There is a convenient parametric form of distribution of search costs κ_{ift} that yields tractable choice probabilities for consumers' entire ordered sequences of store visits and purchases. Suppose that $\kappa_{ift} \sim F_\kappa(\cdot; \bar{\kappa})$ independently of all else, where

$$F_\kappa(\kappa; \bar{\kappa}) = 1 - \exp\left\{ - \exp\left\{ -\Gamma_0^{-1}(\kappa) - \bar{\kappa} \right\} \right\}. \tag{7}$$

Then, we can express equation (6) as

$$r_{ift} = q_f + \gamma_{if} - \alpha p_{ft} + \phi h_{ift} - \bar{\kappa} + \eta_{ift},$$

where the η_{ift} are mutually independent (across i, f, and t) random variables following a type 1 extreme value distribution. Note that the $\bar{\kappa}$ parameter has a positive relationship with both the mean and variance of the search cost distribution. Figure 3 plots F_κ for various values of $\bar{\kappa}$.

The search cost distribution proposed above is one of two features of my model that gives rise to tractable choice probabilities. The other is a collection of inequalities implied by Weitzman (1979)'s optimal sequential search strategy. This strategy provides a bijective mapping between (i) inequalities relating reservation utilities r_{ift} and indirect utilities u_{ift} and (ii) outcomes of consumer search efforts (i.e., search and purchase decisions). Given my distributional assumptions on ε_{ift} and κ_{ift}, these inequalities yield rank-ordered logit probabilities of outcomes. To illustrate, suppose that a consumer visits a store f and f' before buying from store f. This sequence of visits implies that the consumer's highest reservation utility is that for store f. It also implies that the reservation utility for store f' exceeds the indirect utility for store f; otherwise, the consumer would have terminated search after visiting f to buy from that store. We similarly know that the reservation utility for store f' exceeds the reservation utility for the outside option. Since the consumer purchases from store f, we know that the indirect utility of store f exceeds the indirect utilities of store f' and of the outside option in addition to the reservation utilities of all stores other than f and f'. The reasoning above is summarized by the following chain of inequalities (in which I suppress the search effort subscript t):[5]

$$r_{if} \geq r_{if'} \geq u_{if} \geq u_{i0} \vee u_{if'} \vee \max_{g \in \mathcal{F} \setminus \{f,f'\}} r_{ig}.$$

Given my distributional assumptions, the probability of the consumer's search outcome is

$$\frac{e^{\bar{r}_{if}}}{\sum_{g=1}^{F} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}} \times \frac{e^{\bar{r}_{if'}}}{\sum_{g \neq f} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}} \times \frac{e^{\bar{u}_{if}}}{\sum_{g \notin \{f,f'\}} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}}, \tag{8}$$

where $\bar{u}_{ig} = u_{ig} - \varepsilon_{ig}$ and $\bar{r}_{ig} = r_{ig} - \eta_{ig}$. Appendix B provides the chains of inequalities and choice probabilities corresponding to other search effort outcomes.

The choice probabilities in (8) are straightforward to compute, which facilitates the estimation of the model and counterfactual analysis using the model. Without using either the search cost distribution (7) or the chains of inequalities implied by the Weitzman (1979) strategy, computing choice probabilities would require, for a given draw of unobservables κ_{ift} and u_{ift}, the inversion of a function defined by an integral (i.e., Γ_0) to compute reservation utilities. It would then require the sequential solution of the consumer's search problem by comparing reservation utilities and indirect utilities revealed by search at each step in the consumer's search effort. We would then need to integrate over κ_{ift} and u_{ift} in order to obtain the probabilities of the various search effort outcomes. By contrast, my choice probabilities have a convenient closed form. Note that the mapping between chains of inequalities involving reservation and indirect utilities and search effort oucomes reduces the burden of computing choice probabilities without a parametric assumption on the search cost distribution F_κ or even an assumption that the search costs are identically and independently distributed. Other empirical papers that have exploited inequalities involving indirect and reservation utilities in estimating and analyzing a sequential search model include Moraga-González et al. (2018) and Morozov et al. (Forthcoming). But the one-to-one mapping between search effort outcomes and the specific chains of inequalities relating reservation utilities and indirect utilities described above (which gives rise to a rank-ordered logit model under particular parametric assumptions) is a novel contribution of this paper.

The search cost distributions used in the empirical consumer search literature are not typically chosen to achieve tractable chioce probabilities in the same way that I have chosen my search cost distribution. Several papers use a log-normal distribution for search costs, e.g., Kim et al. (2010) and Morozov et al. (Forthcoming). The paper whose approach most closely relates to my own is Moraga-González et al. (2018), whose authors derive a search cost distribution that ensures a random variable determining their choice probabilities has a type 1 extreme value distribution. This considerably simplifies computation in their context.

[5] Note that $\vee$ is the maximum operator, i.e. $a \vee b = \max\{a, b\}$.

4.1 Justification of assuming search over match value

The assumption of known prices and search over match values is common in the literature on consumer search; see, e.g., Kim et al. (2010) and Moraga-González et al. (2018). The assumption is justified in my context for several reasons. First, the descriptive multinomial logit regressions from Section 3.2 suggest that consumers respond to prices in choosing which stores to visit even when they do not make purchases. This is compatible with the consumer choosing which store to visit based on the consumer's knowledge of the prices that each store charges for that consumer's prescribed brand of contact lenses. A question that naturally arises is whether there is any reason for consumers to know stores' prices for their contact lens brand before search. Recall also that prices exhibit relatively little intertemporal variation (see Appendix Table 16) and that I drop consumers' first search efforts from my estimation sample. This means that all consumers in my sample have previous search experience. One explanation for consumer knowledge of prices is that consumers obtained information about stores' prices from previous search efforts.

Another justification of my assumption that consumers search over match values ε_{ijft} is that there are several sources of non-price variation in stores' contact lens offerings that the consumer must conduct search to reveal. Contact lenses vary not only by brand but by other parameters of the consumer's prescription; these include base curve, power, sphere, diameter, cylinder, axis, and addition. Importantly, contact lens' prices vary by brand but not by these other parameters. Whether or not a particular retailer has the consumer's exact specification in stock for that consumer's prescribed brand determines the store's shipping time for the consumer's order and hence the consumer's valuation of ordering from that store. Additionally, online contact lens retailers frequently update their websites to highlight different brands, and this level of variation in brand/site-specific promotion may induce idiosyncratic variation in consumers' valuation of sites across search efforts.

The alternative assumption that consumers conduct search to learn stores' prices faces several problems relating to the specification of consumers' beliefs about prices. One common approach in the empirical search literature is to select a parametric distribution for prices, to estimate this distribution using observed prices, and then to assume that consumers' beliefs follow this estimated price distribution.[6] My setting features relatively little intertemporal price variation for paricular brand/store pairs, which means that each estimated brand/store-specific price distributions will be concentrated around the store's mean price for a given brand. In practice, the assumption that these distributions represent consumers' beliefs will therefore be similar to assuming that consumers believe that the mean price (which is similar to the price at any given point in time) is the current price. Thus, I do not expect the approach of estimating price distributions to substantially differ from my approach in terms of its implications for consumer knowledge of prices. Unless I developed a novel framework in which consumers searched over both match value and price, using an approach with search over price instead of one with search over match value would involve ruling out non-price variation in consumers' valuations of sites's contact lens offerings, which—as argued above—are relevant in my setting.

[6] See Mehta et al. (2003), Hong and Shum (2006), Moraga-González and Wildenbeest (2008), and Honka (2014).

4.2 Probabilities of sequences of search efforts

Consumers in my model make search efforts at different calendar times, with their choice probabilities between search efforts related by state dependence and persistent store tastes. In this section, I provide an expression for the probability of a consumer's entire sequence of search efforts across time. I begin by introducing some notation used in this expression. Let $y_i = \{y_{it}\}_{t=1}^{T_i}$, where y_{it} denotes consumer i's search/purchase choices in search effort t. Similarly let $p_i = \{p_{it}\}_{t=1}^{T_i}$, where p_{it} denotes the prices of consumer i's brand at search effort t across all stores f. Next, let h_{i1} denote consumer i's initial state. I will also use θ to denote an arbitrary model parameter vector belonging to the parameter space Θ, and I will use θ_0 to denote the true parameter vector under which we assume the estimation sample was generated.

The model outlined in the preceding sections provides conditional probabilities of search effort outcomes under given model parameters θ; I will denote these probabilities by

$$P(y_{it}|p_{it}, h_{it}, \gamma_i; \theta).$$

Then, the overall conditional probability of consumer i's sequence of search efforts is

$$\Pr(y_i|p_i, h_{i1}, \gamma_i; \theta) = \prod_{t=1}^{T_i} P(y_{it}|p_{it}, h_{it}, \gamma_i; \theta).$$

Note that this probability is taken conditional on the unobservable γ_i. To obtain a probability that is taken conditional only on observables, we need to integrate out γ_i against its distribution conditional on the observables x_i and h_{i1}:

$$\Pr(y_i \mid p_i, h_{i1}; \theta) = \int P(y_i|p_i, h_{i1}, \gamma_i; \theta) dG(\gamma_i|p_i, h_{i1}; \theta).$$

Here, G is the distribution of γ_i conditional on p_i and h_{i1}.

Integrating over the conditional distribution of γ_i raises two econometric problems. The first is the standard initial condition problem: the distribution of γ_i conditional on p_i and h_{i1} will depend on h_{i1} because h_{i1} reflects consumers' past choices, which depended on γ_i. Thus, we cannot drop h_{i1} from the conditioning set.

The second problem, which I call the endogeneity problem, relates to the dependence of γ_i and prices p_i conditional on h_{i1}. To understand this dependence, suppose that store f sold two brands of contact lenses and that its price for the first brand was high relative to other stores whereas its price for the second brand was relatively low. In that case, consumers with a prescription for the first brand who buy at f will tend to have favourable tastes for the store (i.e., high γ_{if} values) in order to justify buying from f despite its high price for their brand. Similarly, consumers with prescriptions for the second brand who buy from f will tend to have low tastes for the brand because some consumers will buy from f despite their distaste for the store to take advantage of its low price. My model generally implies that, conditional on the initial state, the prices that prevailed when the consumer made her initial purchase and that consumer's persistent unobserved tastes for stores will be correlated. Given that prices are highly persistent across time, I expect the same correlation to hold for the prices that the consumer faces in later search efforts. Thus, the random-effects assumption that γ_i is independent of p_i conditional on h_{i1} is not plausible. Appendix A presents empirical evidence that consumers who have previously purchased contact lenses from a seller who charges a relatively high price for that consumer's prescribed brand have especially strong tastes for that seller.

The two problems above prevent me from making the simplifying assumption that $G(\gamma_i|p_i, h_{i1}; \theta)$ depends neither on the initial state nor on prices. Instead, I model the dependence of G on p_i and h_{i1} by making the parametric assumption that

$$\gamma_{if} \mid (p_i, h_{i1}) \sim \begin{cases} N\left(\lambda \tilde{p}_{jf}, \sigma_\gamma^2\right), & h_{if1} = 1 \\ N\left(\Gamma_{fg}, \sigma_\gamma^2\right), & h_{ig1} = 1 \end{cases}$$

where j is consumer i's prescribed brand; λ, Γ_{fg}, and σ_γ^2 are parameters; and $\tilde{p}_{jf}$ is the relative price of j at f at i's first observed purchase:

$$\tilde{p}_{jf} = \frac{p_{jf1} - \frac{1}{F}\sum_{g=1}^F p_{jg1}}{\frac{1}{F}\sum_{g=1}^F p_{jg1}}.$$

The parameter λ governs the extent to which consumers who initially buy from f despite f charging a high price for their brand have more favourable tastes for f. The parameter Γ_{fg} governs the tastes for store f of consumers who initially buy from store g. Last, the parameter σ_γ^2 governs variability in consumers' persistent idiosyncratic tastes for sellers.

My approach to modelling the conditional distribution of γ_i is based on commonly used approaches to the initial condition problem and endogeneity problems in panel data settings. First, my assignment of a parametric distribution to unobserved heterogeneity γ_i conditional on the initial state h_{i1} follows Wooldridge (2005). As discussed by Wooldridge (2005), the primary alternative to this approach is to specify the distribution of the initial state conditional on the unobserved heterogeneity. One could obtain this distribution by computing the steady-state distribution of the initial state for a consumer with a particular value of γ_i after selecting an assumption on the transition of stores' prices (e.g., that they follow a Markov chain). This approach is far more computationally burdensome than the Wooldridge (2005)-based approach that I use. Second, my modelling of γ_i's dependence on prices conditional on the initial state follows the correlated random effects (CRE) approach commonly used to account for endogeneity in panel data models. CRE approaches involve explicitly modelling the dependence of an individual i's persistent unobserved heterogeneity on the regressors observed for that individual across time. In the widely used CRE model of Chamberlain (1980), the conditional expectation of the unobserved heterogeneity is a linear function of the explanatory variables for each time period.[7] Like Chamberlain (1980), I specify a parametric form for the expectation of unobserved heterogeneity conditional on explanatory variables. My approach differs from Chamberlain (1980)'s in that I use a *nonlinear* function of the explanatory variables that captures the influence of prices on the consumer's decision at the time the initial state is determined.

Morozov et al. (Forthcoming) similarly assume a normal distribution for persistent unobserved heterogeneity in their panel model of consumer search online. The difference between my approach and theirs is that I model conditional distributions of persistent unobserved heterogeneity whereas they model the unconditional distribution of persistent unobserved heterogeneity. The unconditional distribution is enough in their setting because they do not face the initial conditions and endogeneity problems that I face on account of the fact that their model does not feature state dependence.

[7] Mundlak (1978) proposes a closely related approach that is also widely used. Wooldridge (2010) uses the term "correlated random effects" to refer to both Chamberlain (1980)'s and Mundlak (1978)'s approaches.

5 Models of price competition

One of my paper's primary goals is the determination of how various features of the contact lens e-commerce industry—in particular, search costs, state dependence, and various forms of vertical/horizontal differentiation—affect markups in the industry. To make this determination, I use the concept of Bertrand-Nash pricing equilibrium. This is a static notion of pricing equilibrium under which each firm's prices maximize that firm's profits. The challenge in defining a Bertrand-Nash equilibrium in my case is specifying a static demand system given that state dependence adds a dynamic aspect to consumer choice.

I specify two different demand systems based on different assumptions about firm behaviour. The first demand system, which I call *short-run demand*, is based on the assumption that a firm sets its price for a brand of contact lenses to maximize its expected profits from a consumer who makes a search effort for a specific brand of contact lens given the current joint distribution of states h_{it} and persistent unobserved heterogeneity γ_i. The second demand system, which I call *long-run demand*, is based on the assumption that a firm sets its prices to maximize expected profits once the joint distribution of consumer states and unobserved heterogeneity has fully responded to the prevailing prices. The remainder of this section defines and discusses these two notions of demand. In what follows, I focus on pricing competition among retailers within a particular brand of contact lenses without explicitly reflecting this in the notation.

Short-run demand reflects consumer choices conditional on a particular distribution of consumer states. In my empirical analysis, the distribution of consumer states that I consider is the brand-specific distribution of initial states in my sample. Consider a type-γ_i consumer with state $h_{igt} = 1$. Let $\sigma_{fg}(p, \gamma_i)$ denote this consumer's probability of buying from store f given prices p. The short-run market share for store f is defined as

$$\sigma_f^S(p) := \int \int \sigma_{fg}(p, \gamma_i) dG(\gamma_i \mid h_{i1}) d\Psi(h_{i1}),$$

where Ψ is a distribution of states. That is, σ_f^S is the expected probability of a search effort resulting in purchase from f, where the expectation is taken over the distribution of states and the distribution of unobserved heterogeneity γ_i conditional on the state. In practice, I use the estimated distribution of γ_i conditional on h_{i1} and the prices p_{i1} at the beginning of the sample period as $G(\gamma_i \mid h_{i1})$ when computing short-run demand.

Whereas short-run demand reflects consumer choice holding fixed the distribution of consumers across states when prices change, long-run demand represents consumer choice under the long-run stationary distribution of states corresponding to a particular vector of prices. Consider consumer i's search and purchase behaviour across search efforts under prices p. I define the *long-run state probabilities* $\{\rho_f(p, \gamma_i)\}_{f=1}^F$ as the solutions of the system of linear equations

$$\rho_f(p, \gamma_i) = \sum_g \left[\frac{\sigma_{fg}(p, \gamma_i)}{1 - \sigma_{0g}(p, \gamma_i)} \right] \rho_g(p, \gamma_i) \qquad \forall f. \tag{9}$$

Note that the right-hand side of (9) is the overall probability of a consumer belonging to state f after a search effort when the probability that consumer belongs to state g prior to the search effort is $\rho_g(p, \gamma_i)$. Thus, the condition (9) imposes that a type-γ_i consumer's probability of belonging to state f does not change after an additional search effort. The long-run market share for store f is then

$$\sigma_f^L(p) := \int \sum_g \rho_g(p, \gamma_i) \sigma_{fg}(p, \gamma_i) dH(\gamma_i)$$

where H is the unconditional distribution of γ_i.

In my subsequent analysis, I present estimates of both short- and long-run demand elasticities. In my counterfactuals involving the computation of new pricing equilibria, however, I exclusively focus on results using the long-run demand concept because (i) I estimate state dependence to be important in contact lens e-commerce and (ii) more of my estimated long-run own-price elasticities are consistent with stores' profit maximization than my estimated short-run own-price elasticities.

6 Estimation

There are several ways to estimate my model's true parameters θ_0 based on the expressions for search-effort outcomes $P(y_i|p_i, h_{i1}; \theta)$ provided in Section 4.2. I ultimately choose to estimate the model using an indirect inference (I-I) estimator of the sort detailed by Gouriéroux et al. (1993).[8] This approach involves (i) computing statistics $\hat{\beta}_n$ on my estimation sample; (ii) simulating outcomes y_i conditional on (p_i, h_{i1}) and a trial parameter value θ using my search model; and (iii) computing the same statistics on the simulated data as I initially computed on the estimation sample, letting $\tilde{\beta}_n(\theta)$ denote the statistics computed on the simulated data. The I-I estimator is a value $\hat{\theta}$ that minimizes a measure of the distance between $\hat{\beta}_n$ and $\tilde{\beta}_n(\hat{\theta})$.

To be precise, my I-I estimator is defined by

$$\hat{\theta}_n = \arg\min_{\theta \in \Theta} (\hat{\beta}_n - \tilde{\beta}_n^H(\theta))' \hat{\Omega}_n (\hat{\beta}_n - \tilde{\beta}_n^H(\theta))$$

where $\hat{\beta}_n$ are ordinary least squares (OLS) estimators computed on my estimation sample and $\tilde{\beta}_n^H(\theta)$ are the same OLS estimators computed on a dataset of outcomes simulated under θ conditional on the x_i and h_{i1} values of observations in my estimation sample, outcomes simulated H times for each (p_i, h_{i1}) in my estimation sample.[9] Additionally, Θ is the parameter space and $\hat{\Omega}_n$ is a weighting matrix selected so that $\hat{\Omega}_n$ converges in probability to a positive definite weighting matrix Ω as n grows large. Appendix C provides additional details on the I-I estimator that I deploy and the regressions used in computing the I-I criterion function. It also discusses the form of the asymptotically optimal weighting matrix and my procedure for estimating this matrix, which involves a preliminary consistent estimator of θ_0 obtained by setting the weighting matrix $\hat{\Omega}_n$ to the the identity matrix.

I now enumerate the regression coefficients included in $\hat{\beta}_n$ and the structural parameters that they are included to target. Many of these coefficients are simple sample averages obtained by regressing a variable on a vector of ones.

[8]The primary reason that I use an I-I estimator instead of a maximum likelihood estimator (MLE) is that MLEs tend to exhibit poor finite-sample performance in discrete-choice settings with many low probability potential outcomes. This is because the likelihood function highly penalizes observations to which the model assigns a near-zero probability of occurrence, which makes the MLE highly sensitive to low probability observations. If my model under a particular parameter vector, for instance, assigned a probability near zero to a particular search outcome that was observed in my data with a probability of 1%, then the likelihood for this parameter vector would be highly negative. The MLE estimate would be selected in large part to justify low probability observations in the data, and thus it would be very sensitive to which low probability observations are realized. Other papers that similarly justify the use of I-I or moment-based estimators include Krasnokutskaya and Seim (2011), Pakes et al. (2007), and Collard-Wexler (2013).

[9]Thus, the sample size of the dataset on which I run the regressions yielding $\tilde{\beta}_n^H$ is H times the sample size of the dataset on which I run the regressions yielding $\hat{\beta}_n$.

(i) *Stores' visit shares*: For each store f, I compute the mean across search efforts of an indicator for whether the consumer visited store f in search effort t. These statistics are intended to target the estimation of stores' qualities q_f and the search cost parameter $\bar{\kappa}$.

(ii) *Consideration set size*: I compute the mean across search efforts of an indicator for whether the consumer visited all available stores in search effort t. This statistic is intended to target the estimation of the search cost parameter $\bar{\kappa}$.

(iii) *Visit inertia*: I compute the mean across search efforts of an indicator for the consumer's first-visited store in search effort t being the same as the consumer's first-visited store in the consumer's previous search effort $t-1$. This statistic is intended to target the estimation of the state dependence parameter ϕ and the parameters governing the distribution of consumers' persistent tastes γ_i.

(iv) *Choice inertia*: I compute the mean across search efforts of an indicator for whether the search effort ended with the consumer making the same purchase decision (i.e., the store from which the consumer purchased or the offline option) as in the consumer's previous search effort. This statistic is intended to target the estimation of the state dependence parameter ϕ and the parameters governing the distribution of consumers' persistent store tastes γ_i.

(v) *State inertia*: I compute the mean across search efforts of an indicator for a consumer purchasing from the store f for which $h_{ift} = 1$. This regression differs from the "choice inertia" regression because the consumer's previous purchase may have been from the outside option, which does not change the consumer's state. This statistic is intended to target the estimation of the state dependence parameter ϕ and the parameters governing the distribution of consumers' persistent store tastes γ_i.

(vi) *Role of lagged price*: I regress an indicator for whether a search effort t ended in a transaction at 1800 on the price of the consumer's brand at 1800 during search effort t and the price of that brand at 1800 during the consumer's previous search effort $t-1$. This statistic is intended to target the estimation of the state dependence parameter ϕ and the parameters governing the distribution of consumers' persistent store tastes γ_i.

(vii) *Price sensitivity*: I regress an indicator for whether a search effort t ended in a transaction at store f on store indicators and the price of the consumer's brand at store f. The dataset used for running this regression includes three observations for each search effort, one corresponding to each of the stores. This statistic is intended to target the estimation of the price sensitivity parameter α and the store qualities q_f.

(viii) *Outside share*: I regress an indicator for whether a search effort t did not end in an online transaction on the average price of the consumer's brand across the major three online stores. This statistic is intended to target the estimation of the offline price sensitivity parameter α_{out}.

(ix) *Cross-visits*: For each pair of distinct stores (f, g), I compute the mean across search efforts t in which the consumer's state is given by $h_{igt} = 1$ of an indicator for whether the search effort involved a visit to store f. This statistic is intended to target the estimation of the parameters Γ_{fg}, which govern the mean tastes of consumers for each store conditional on each initial state.

(x) *Dependence of tastes and prices conditional on initial state*: I regress an indicator for whether consumer i visited store g in search effort t on the ratio of the price of the consumer's brand at the store f for which $h_{if1} = 1$ to the average price of the consumer's brand across the three major stores. In doing so, I use the prices from the time at which the consumer made his first observed purchase. I use each store $g \neq f$ in the regressions. This statistic is intended to target the estimation of λ.

Appendix Table 17 presents these statistics' values in my estimation sample.

6.1 Identification

I now informally discuss the identification of my model's parameters. First, as noted in Section 3.2, my general approach to the problem of price endogeneity is to use cross-brand variation in stores' relative prices to learn about consumers' price sensitivity. In my model, this means assuming that that store quality q_f varies by store *but not* by brand in order to identify the α parameter. This assumption could be partially relaxed; we could allow store qualities to vary in additional dimensions, e.g., time period, manufacturer, whether the lenses are spherical versus toric or transparent versus coloured, etc. What is essential is that there remains residual variation in price within the units for which we use fixed effects.

Second, we may worry that state dependence (i.e., store loyalty) and persistent unobserved tastes are not separately identified as explanations for inertia in consumer choice. These explanations for inertia, though, imply different patterns of switching behaviour; Dubé et al. (2010) make this point in their study of inertia in consumers' grocery store purchasing. Consider, for instance, a consumer who is initially observed making a transaction from a store f. Suppose that the next time the consumer makes a search effort, store f raises its price and the consumer responds by purchasing from store g instead. Last, suppose that the third and final time that we observe the consumer make a transaction, store f's price returns to its original level. If there is a high degree of store loyalty, the consumer is likely to purchase from store g again because this was the store she most recently purchased from. If the consumer's initial purchase from f stemmed from her favourable, persistent tastes for store f, then we would expect her to instead purchase from store f in her final search effort as long as store loyalty is not too strong. Thus, store loyalty and persistent idiosyncratic tastes for stores imply different predictions concerning the nature of consumer switching. Note also that switching patterns in both purchases *and* visits respond differently to state dependence and persistent unobserved states, which suggests that variation in purchasing and in visiting behaviour will be useful in estimating the parameters of my model governing these two explanations for inertia in consumer choices.

7 Parameter estimates

This section presents and discusses the parameter estimates yielded by the indirect inference estimator outlined in the preceding section. In addition to estimating the full model with all of the parameters discussed in preceding sections, I estimate a model without state dependence (i.e., in which ϕ is constrained to zero) and without persistent unobserved tastes for stores (i.e., in which γ_{if} is constrained to zero for all consumers i and all stores f). The purpose of estimating this constrained model is to understand how failing to account for aspects of preference heterogeneity about which panel data are informative affects inference about the extent of search cost.

Table 9 presents estimates of all parameters except the Γ_{fg} parameters governing the distribution of γ_i. Table 10 presents estimates of the Γ_{fg} parameters. The "Baseline" columns of Table 9 provide estimates for the full model whereas the "Constrained" columns provide estimates for the model without state dependence and persistent unobserved store tastes. To make the estimates of the search-cost distribution parameter $\bar{\kappa}$ more readily interpretable, I include the median search cost implied by these estimates in both utils and dollars in the bottom two rows of Table 9. A comparison of the "Baseline" columns with the "Constrained" columns suggests that ruling out state dependence and persistent unobserved store tastes across consumers leads to a large overstatement of search costs relative to the estimates from specifications accounting for these aspects of consumer preferences. This occurs because store loyalty and persistent unobserved tastes for stores tend to limit consumer consideration by exaggerating utility differences between stores relative to the variability of the match value uncovered by search. When the match value is a relatively unimportant part of a consumer's payoff from purchasing from a store, then the consumer may choose not to visit a store that is unappealing at the outset of search even when the cost of visiting that store is negligible. The estimates in the "Baseline" columns of Table 9 suggest that state dependence is particularly important; having previously purchased from a store increases a consumer's valuation of the store by over \$12. Recall that the median transaction price in my sample is about \$30.

Somewhat surprisingly, 1800's quality parameter is estimated to be below that of VD. That 1800 sells more contact lenses than its competitors despite its higher average prices and lower quality is explained by the facts that (i) 1800 began the sample period with a leading market share, which helped it maintain a high level of sales given the importance of state dependence, and (ii) consumers of 1800 tend to have negative idiosyncratic tastes for the other contact lens retailers, as is indicated by the highly negative estimates of Γ_{21} and Γ_{31} in Table 10. In fact, the estimated mean value of γ_{if} across consumers is -0.208 for 1800, -2.20 for WM, and -2.41 for VD. Therefore, in terms of the measure $q_f + \mathbb{E}[\gamma_{if}]$—which I call f's *mean store taste*—1800 is the superior store. See Table 11 for all stores' estimated mean store tastes.

My search cost estimates fall substantially below some others in the empirical literature on consumer search. Hong and Shum (2006), for instance, find median search costs for textbooks between \$2.32 and \$29.40. De Los Santos et al. (2012), who use the Comscore Web Behavior Database to analyze search for books, find average search costs of \$4.14. Note that these studies' estimated search costs are of the same order of magnitude as my estimated search costs from my specification without state dependence or persistent unobserved store tastes, features that are not accounted for by either Hong and Shum (2006) or De Los Santos et al. (2012). Although this comparison is somewhat limited by the fact that my contact lens setting differs from the book setting, my results suggest that high estimated search costs in the empirical search literature may reflect a failure to account for forms of seller differentiation that limit consumer consideration.

Table 12 reports estimates of own- and cross-price elasticities for the 1-Day Acuvue brand computed using each of the notions of demand described by Section 5. In particular, each entry corresponds to the elasticity of demand for 1-Day Acuvue at the store indicated by the entry's row with respect to the price indicated by the entry's column. For the two leading stores, 1800 and VD, demand is more elastic in the long run than in the short run. This is to be expected given that an increase in a store's price will eventually lead fewer consumers to belong to that store's state, which amplifies the short-run effect of the price increase on quantity sold under the presence of store loyalty. Also, the cross-elasticities for these stores are substantially larger in the long run.

Figure 4 plots the cross-brand distribution of the absolute values of each store's estimated own-price elasticities. Vertical lines appear at 1, which is the theoretical lower bound on the

Table 9: Parameter estimates

	Baseline		Constrained	
Parameter	Estimate	SE	Estimate	SE
q_{1800}	-1.639	0.739	3.933	0.386
q_{WM}	-0.922	0.376	0.747	0.411
q_{VD}	-0.754	0.527	0.029	0.184
ϕ	2.502	0.525	-	-
α	0.191	0.014	0.533	0.033
$\bar{\kappa}$	-1.779	0.301	0.885	2.586
σ_{γ}^2	0.049	0.078	-	-
α_{out}	0.165	0.013	0.201	0.047
λ	9.747	2.769	-	-
Median search cost (utils)	0.114	0.036	1.173	1.809
Median search cost ($)	0.596	0.199	2.199	3.677

Note: The "Estimate" columns provide point estimates obtained from the indirect inference estimator outlined in 6 whereas the "SE" columns report the estimates' standard errors.

Table 10: Baseline estimates of γ_i distribution parameters

Parameter	Estimate	SE
Γ_{12}	2.000	2.514
Γ_{13}	-2.778	3.480
Γ_{21}	-2.685	0.701
Γ_{23}	-1.464	0.443
Γ_{31}	-3.251	0.551
Γ_{32}	0.652	0.467

Note: Γ_{fg} is the mean value of γ_i among consumers with initial state h_{i1} given by $h_{ig1} = 1$. The "Estimate" columns provide point estimates obtained from the indirect inference estimator outlined in 6 whereas the "SE" columns report the estimates' standard errors.

Table 11: Estimates of mean store tastes

Store f	Mean taste for store f $q_f + \mathbb{E}\gamma_{if}$
1800	-1.85
WM	-3.12
VD	-3.17

Table 12: Elasticity estimates for 1-Day Acuvue

Panel A: Point estimates

Short-run demand

	Price		
Share	1800	WM	VD
1800	-1.62	0.01	0.01
WM	0.10	-7.72	4.16
VD	0.00	0.09	-1.55

Long-run demand

	Price		
Share	1800	WM	VD
1800	-2.52	0.19	0.19
WM	1.38	-8.23	4.90
VD	0.28	0.97	-2.12

Panel B: Standard errors

Short-run demand

	Price		
Share	1800	WM	VD
1800	0.86	0.03	0.49
WM	1.77	0.89	0.94
VD	1.24	0.10	0.72

Long-run demand

	Price		
Share	1800	WM	VD
1800	1.58	1.39	0.62
WM	1.36	1.90	1.64
VD	1.63	1.33	1.25

Note: standard errors computed using the parametric bootstrap with 100 bootstrap replicates.

elasticity under the assumption that each firm sets its prices to maximize its static profits with respect to its residual (short- or long-run) demand curve under non-negative marginal costs. Almost all the long-run own-price elasticities exceed this lower bound, whereas numerous short-run own-price elasticities fall short of one. This constitutes evidence that contact lens retailers take state dependence into account when pricing their products, i.e., that they maximize prices with respect to long-run demand rather than short-run demand.

8 Counterfactuals

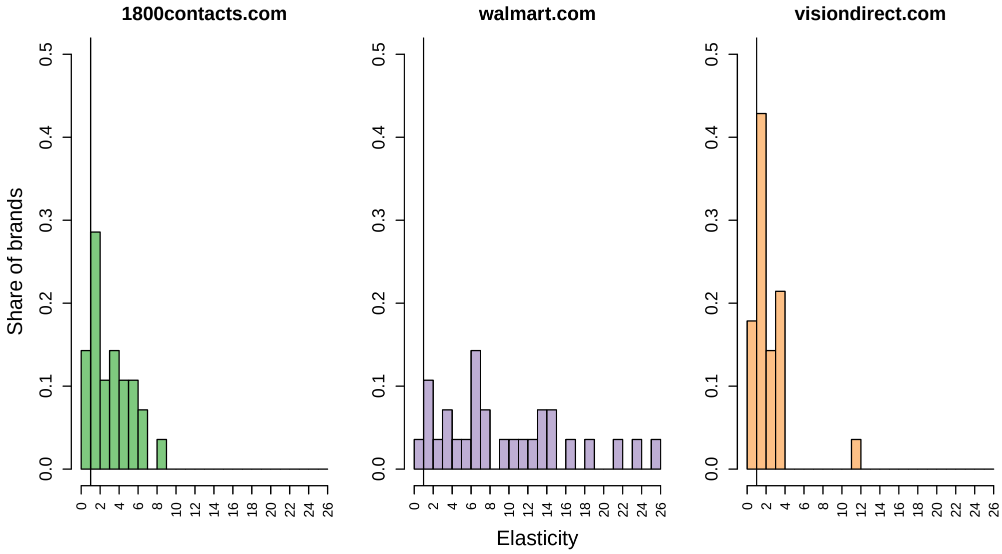
In this section, I conduct counterfactual analyses intended to assess the sources of limited consideration and market power in contact lens e-commerce.

8.1 Sources of limited consideration

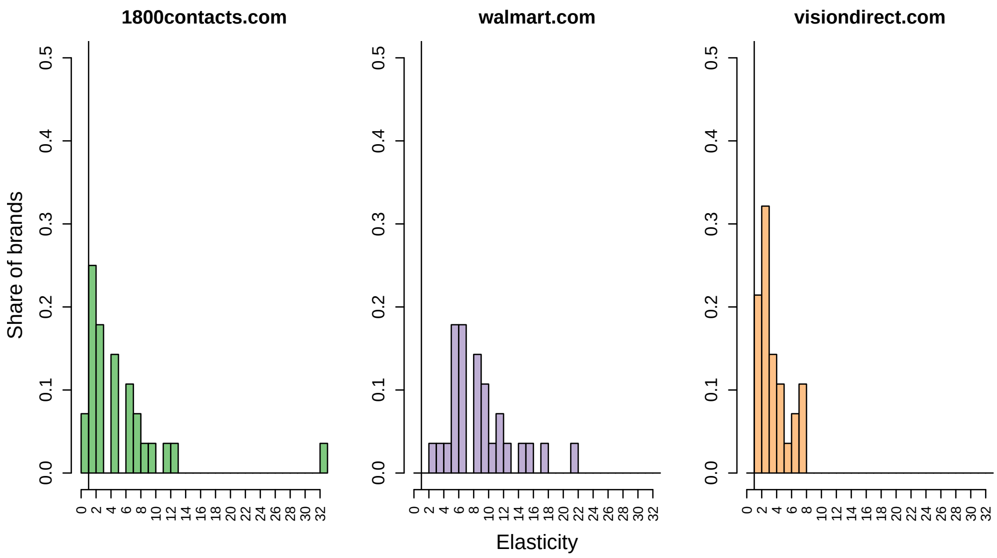
My assessment of the sources of limited consideration in online search for contact lenses involves simulating search efforts under counterfactual preference parameters. I consider an aspect of consumer preferences to be a driver of limited consideration if it exerts significant influence on the extent of consumer consideration (i.e., on how many stores a consumer visits). Note, though, that the exercise considered by this section involves simulating search efforts conditional on observed prices rather than simulating search efforts in a pricing equilibrium

Figure 4: Cross-brand distributions of own-price elasticities

Panel A: Short-run demand



Panel B: Long-run demand



computed under counterfactual model parameters. Thus, the exercise addresses the question of why consumers exhibit limited consideration in response to the prices they face in the data rather than the question of why consideration is limited in a pricing equilibrium. To produce the simulated datasets discussed throughout this section, I simulate each consumer's history of search efforts 50 times; in each simulation, I draw outcomes conditional on that consumer's prescribed brand, the prices faced by that consumer, and the consumer's initial state. In order to condition on the initial state, I drop all search efforts before and including that in which I first observe the consumer make an online purchase.

The counterfactual consumer preferences that I consider are

(i) Low search costs: reduce $\bar{\kappa}$ so that the median search cost equals one half of the median search cost under the estimated value of $\bar{\kappa}$;

(ii) No loyalty: set $\phi = 0$;

(iii) No vertical differentiation: set $q_f + \mathbb{E}[\gamma_{if}] = 0$ for each store f to eliminate mean quality differences between stores;[10]

(iv) No persistent unobserved store tastes: set $\gamma_{if} = 0$ for all consumers i and online retailers f; and

(v) Logit only: eliminate search costs, state dependence, and persistent unobserved store tastes. Under these counterfactual consumer preferences, only prices and the ε_{ijft} unobservable differentiate retailers from the consumer's perspective.

Counterfactually altering a consumer's preferences changes that consumer's inclusive value of the online stores considered together, and therefore changes the probability that a consumer buys from any of the online stores. Store loyalty, for example, is a major driver of a consumer's decision to purchase from any online store. Removing store loyalty therefore substantially decreases the volume of online transactions. Thus, the effects of the counterfactual preference changes described above would reflect both a qualitative change in consumer preferences and a change in the magnitude of consumers' tastes for online retail. To focus on the effect of various qualitative changes in consumer preferences, I make an additional adjustment to consumers' preferences in each counterfactual. In particular, I add a compensating constant $q^\dagger$ to each consumer's indirect utility for every online store to ensure that the outside good's share is constant across the counterfactuals. The value of $q^\dagger$ differs across counterfactuals. Appendix Table 18 provides results for counterfactual preference changes in which this compensating factor is not included.

[10] I compute $\mathbb{E}[\gamma_{if}]$ by first integrating over each consumer i's estimated distribution of γ_{if} conditional on consumer i's initial state and the prices of that consumer i faces while searching, and then integrating over the distribution of consumers in my sample.

Table 13: Model fit and counterfactual search patterns

Specification	Share visiting one store only	Mean # of visits	Share buying from... any	1800	VD	Visit order	Share paying $>$ min. price	Mean over-payment ($)
Observed	0.820	1.193	0.597	0.337	0.236	0.414	0.633	3.74
Baseline	0.918	1.087	0.668	0.381	0.267	0.653	0.633	3.47
Low search costs (comp.)	0.850	1.164	0.668	0.367	0.282	0.699	0.616	3.37
No loyalty (comp.)	0.650	1.409	0.667	0.192	0.420	0.535	0.421	1.82
No vertical diff. (comp.)	0.885	1.121	0.668	0.224	0.414	0.654	0.464	2.24
No persistent unobs. (comp.)	0.753	1.284	0.667	0.056	0.504	0.453	0.261	0.63
Logit only (comp.)	0.000	3.000	0.668	0.131	0.346	1.000	0.439	1.51

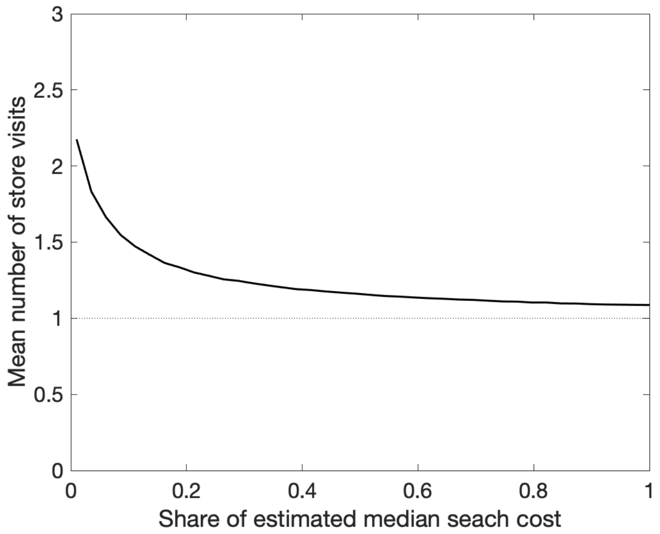
Table 13 characterizes consumer search in the estimation sample, in search efforts simulated under the parameter estimates, and in search efforts simulated under counterfactual parameters. For a version of the table with additional counterfactual preferences and with standard errors, see Appendix Table 18. The "comp." label appearing in parentheses for some of the specifications indicates that the value of buying from each of the stores has been adjusted by a compensating factor $q^{\dagger}$ as described in the preceding paragraph. The "Share visiting one store only" column provides the share of search efforts involving a visit to only one of the three online stores; the "Mean # of visits" column provides the average number of visits in a search effort; and the "Share buying from" columns report the shares of search efforts resolving in a purchase from either any store or from one of the two leading stores, 1800 and VD. Next, the "Visit order" column reports the share of search efforts involving a visit to each of 1800 and VD in which 1800 is visited first. The final two columns characterize the extent to which consumers pay above the minimum available price for contact lenses: "Share paying over min. price" provides the share of search efforts involving the purchase of a contact lens brand at a price above the minimum price available among the three retailers. Last, "Mean overpayment ($)" reports the mean difference between the price at which the consumer purchased contact lenses and the minimum available price for the consumer's brand across search efforts ending in online transactions.

A comparison of the first two rows provides an evaluation of model fit. Note that the model underpredicts the extent of consumer search, although it closely fits the share of consumers purchasing from 1800 and VD. A comparison of the second row with the remaining rows characterizes the sources of limited consideration under the model. Of the aspects of consumer preferences that I consider, state dependence plays the largest role in explaining why consumers exhibit limited consideration; the share of search efforts involving a visit to more than one store rises from about 8% to 35% upon the elimination of state dependence. Additionally, the extent to which consumers overpay for contact lenses decreases in this counterfactual. These results together suggest that the consumer's preference for purchasing from the store from which the consumer most recently made a purchase explains why the consumer avoids visiting other stores even when they offer lower prices.

Eliminating vertical differentiation only modestly expands the extent of consumer consideration. This is because it leads some consumers who previously visited only 1800 to also consider VD. Given that 1800 is estimated to be the vertically superior store in terms of mean store tastes $q_f + \mathbb{E}[\gamma_{if}]$, the elimination of 1800's mean quality advantage over its less expensive competitor VD leads more consumers to consider and ultimately purchase from VD. This decreases the average overpayment. Therefore, we can conclude that consumers' overpayment for contact lenses partially reflects superior quality offered by more expensive stores that justifies the overpayment, and thus that overpayment for contact lenses does not necessarily reflect consumer inattention.

Search costs play a much smaller role in limiting consumer search, and reducing search cost has little influence on the extent that consumers overpay for contact lenses. Figure 5 shows how the number of stores that consumers visit changes as search costs are reduced. In particular, it shows the relationship between the mean number of visits in a search effort and the median search cost as a fraction of its estimated level. The median search cost must fall below roughly 10% of its estimated level for the average number of visits in a search effort to exceed one and a half.

Figure 5: Role of search costs in limiting consumer search



8.2 Sources of market power

I assess the sources of market power in online contact lens retail by recomputing pricing equilibria for a particular brand of contact lenses after changing consumer preferences and then computing the change in equilibrium markups from the baseline equilibria to the counterfactual equilibria. The pricing equilibrium concept that I use is static Bertrand-Nash equilibrium under long-run demand. That is, I assume that each store f's equilibrium prices p_f maximize its long-run profits

$$\Pi_f(p) = (p_f - mc_f)\sigma_f^L(p)$$

given the equilibrium prices of f's competitors. Two elements of the Π_f function are unknowns: the long-run demand function σ_f^L and the marginal costs mc_f. In order to compute firm profits in practice, I use the estimate of σ_f^L derived from my search model estimates, and estimates of marginal costs mc_f obtained by solving firms' first-order conditions for profit maximizations under the observed prices and my demand estimates σ_f^L. Throughout this section, I focus on price competition within a single brand of contact lenses. The brand for which I present my counterfactual results is 1-Day Acuvue, which is one of the most popular brands in my sample.

The changes in consumer preferences that I consider are similar to those considered in Section 8.1. They are:

(i) Low search costs: reduce $\bar{\kappa}$ so that the median search cost equals one half of the median search cost under the estimated value of $\bar{\kappa}$;

(ii) No loyalty: set $\phi = 0$; and

(iii) No persistent unobserved store tastes: set $\gamma_{if} = \mathbb{E}\gamma_{if}$ for each consumer i and each store f.

Table 14 provides the results of the analysis for 1-Day Acuvue at 1800 and VD, the dominant retailers in my sample. Reducing search costs does little to change equilibrium markups, implying that price dispersion for physically identical goods sold online is not a consequence

Table 14: Counterfactual changes in markups for 1-Day Acuvue

Panel A: Point estimates

Store	Low search costs	No loyalty	No persistent . unobs.
1800	-0.02	-0.43	-0.74
VD	-0.01	-0.30	-0.72

Panel B: Standard errors

Store	Low search costs	No loyalty	No persistent . unobs.
1800	0.01	0.20	0.23
VD	0.02	0.22	0.10

of search frictions providing sellers with market power. Instead, Table 14 suggests that the sources of market power online are store loyalty and store differentiation.

8.3 Policy implications

My results have implications for business practices that make switching between stores difficult. As discussed earlier, there are several interpretations of state dependence in my setting. These include habit formation, switching costs, and the convenience of not having to re-enter prescription, billing, and delivery information. Given that eliminating state dependence would decrease payment above the minimum available price and decrease equilibrium markups, it may benefit consumers to reduce the extent of state dependence. An example of a policy that would accomplish this is the introduction of an intermediary service to which the user uploads prescription, billing, and delivery information. This service could then share the user's information with any online retailer with which the consumer seeks to make a transaction without the user having to separately input this information for each online retailer. This proposed service resembles e-commerce platforms like Amazon and eBay that provide an interface through which a consumer can deal with many retailers.

Search costs in contact lens e-commerce are small and do not meaningfully contribute either to limited consideration or market power in the industry. Given that searching across contact lens retail sites is qualitatively similar to searching across sites operating in other product categories, I expect the same conclusion to hold for e-commerce more broadly. Additionally, searching within a site for products seems less difficult than searching across sites since it does not require navigating to sites via search engines or URL entry. Thus, I expect that the costs of searching within Amazon or eBay, for example, are lower than the search costs that I estimate in this paper. As such, remedies to market power in the industry that aim to make search easier, e.g., by introducing comparison tools or by increasing retailers' transparency about their product offerings, are unlikely to meaningfully lower prices or otherwise improve the consumer experience in online retail.

9 Conclusion

This paper applied a model of consumer search to a panel dataset describing consumers' browsing and purchasing behaviour in contact lens e-commerce. The paper's first primary contribution is its development of a tractable empirical framework for studying sequential search models. This framework exploits a property of the Weitzman (1979) search strategy and, optionally, a convenient set of parametric assumptions to simplify the computation of probabilities of particular search outcomes. Additionally, my framework can be used to learn about state dependence and persistent unobserved heterogeneity in a search setting from panel data; these are aspects of consumer preferences that have not been simultaneously accounted for in previous empirical studies of consumer search. The paper's other primary contribution is in drawing substantial conclusions about limited consideration and market power in e-commerce. My analysis suggests that various forms of seller differentiation play a much larger role than search frictions in accounting for these phenomenon.

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Appendices

A Conditional dependence of store tastes and prices

In Section 4, I note that the prices that a consumer encounters and that consumer's tastes for stores will be correlated conditional on the consumer's initial state. The reason is that, conditional on the consumer having previously purchased from store f, higher prices at store f for the consumer's brand of contact lenses will be associated with stronger tastes for store f. This is because strong tastes for f are required to justify the consumer's history of purchasing from f despite its high prices.

I now consider empirical evidence for the conditional correlation described in the preceding paragraph. In particular, I consider the regression of an indicator for whether a consumer visits stores other than the store f of corresponding to the consumer's initial state on the relative price of f at the time that the consumer made the purchase that determined his initial state. To be clear, the regression equation is

$$\mathbb{1}\{i \text{ visits store other than } f \text{ in } t\} = \lambda_0 + \lambda_1 \left({p_{jf1}}/{\bar{p}_{j1}}\right) + \epsilon_{it}$$

where j is consumer i's prescribed brand; p_{jf1} is f's price when i first purchased contact lenses in my sample; and $\bar{p}_{j1}$ is the mean price of j across 1800, WM, and VD at the time i first purchased contact lenses in my sample. I run the ordinary least squares regression on a dataset including all search efforts observed after their consumers' first purchases. I expect my estimate of λ_1 to be positive, as this would indicate that consumers with a history of purchasing from a relatively expensive store are less likely to even consider purchasing from other stores; this indicates that these consumers have strong preferences for the store from which they have historically bought contact lenses.

Appendix Table 15 provides the regression results. As expected, the estimate of λ_1 is positive. I take this as evidence of a positive correlation between store f's price and consumer i's tastes for store f conditional on the consumer having previously purchased from store f.

Table 15: Results for regression assessing conditional dependence of prices and store tastes

Parameter	Estimate	SE
Intercept	0.434	0.112
Slope	-0.227	0.109

Notes: "SE" column provides asymptotic standard errors.

B Expressions for search effort outcome probabilities

This appendix provides chains of inequalities relating indiret and reservation utilities for every possible search effort outcome in my model. As explained in Section 4, I use these inequalities in computing conditional choice probabilities. Throughout this appendix, I suppress the brand j and search effort t subscripts.

First, consider the case in which consumer i visits only store f and then chooses the outside option. This corresponds to one of the following chains of inequalities:

$$\begin{aligned} r_{if} \geq u_{i0} &\geq u_{if} \vee \max_g r_{ig} \\ u_{i0} \geq r_{if} &\geq u_{if} \vee \max_g r_{ig} \\ u_{i0} \geq u_{if} &\geq r_{if} \vee \max_g r_{ig}. \end{aligned} \tag{10}$$

It is possible for the consumer to visit store f when the outside option's indirect utility exceeds f's reservation utility because, by assumption, the consumer must visit at least one store in a search effort. Under the distributional assumptions outlined in Section 4, the probability of the first chain of inequalities is

$$\frac{e^{\bar{r}_{if}}}{e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + \sum_{g=1}^{F} e^{\bar{r}_{ig}}} \times \frac{e^{\bar{u}_{i0}}}{e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + \sum_{g \notin \{0,f\}}^{F} e^{\bar{r}_{ig}}} \tag{11}$$

for $\bar{u}_{ig} = u_{ig} - \varepsilon_{ig}$ and $\bar{r}_{ig} = r_{ig} - \eta_{ig}$. The probability of the search effort outcome described above is the sum of the probabilities of the chains of inequalities in (10). I will not explicitly state any more choice probabilities, however, since they follow the same rank-order logit form as (11).

Now consider the case in which i buys from f after visiting f alone. The inequalities inducing this outcome are

$$\begin{aligned} r_{if} \geq u_{if} &\geq u_{i0} \vee \max_g r_{ig} \\ u_{if} \geq r_{if} &\geq u_{i0} \vee \max_g r_{ig} \\ u_{if} \geq u_{i0} &\geq r_{if} \vee \max_g r_{ig}. \end{aligned}$$

Now consider the case in which i visits f_1 and f_2 in that order, but does not buy from either firm. The inequality leading to this outcome is

$$r_{if_1} \geq r_{if_2} \geq u_{i0} \geq u_{i1} \vee u_{i2} \vee \max_{g \notin \{f_1, f_2\}} r_{ig}.$$

Now consider the case in which i visits f_1 and f_2 before buying from f_1. The inequality leading to this outcome is

$$r_{if_1} \geq r_{if_2} \geq u_{if_1} \geq u_{i0} \vee u_{if_2} \vee \max_{g \notin \{f_1, f_2\}} r_{ig}$$

Now consider the case in which i visits f_1 and f_2 before buying from f_2. The inequalities leading to this outcome are

$$r_{if_1} \geq r_{if_2} \geq u_{if_2} \geq u_{i0} \vee u_{if_1} \vee \max_{g \notin \{f_1, f_2\}} r_{ig}$$

$$r_{if_1} \geq u_{if_2} \geq r_{if_2} \geq u_{i0} \vee u_{if_1} \vee \max_{g \notin \{f_1, f_2\}} r_{ig}$$

$$u_{if_2} \geq r_{if_1} \geq r_{if_2} \geq u_{i0} \vee u_{if_1} \vee \max_{g \notin \{f_1, f_2\}} r_{ig}.$$

Now consider the case in which i visits f_1, f_2, and f_3 (in that order) but does not buy from any seller. The inequality leading to this outcome is

$$r_{if_1} \geq r_{if_2} \geq r_{if_3} \geq u_{i0} \geq \max_{1 \leq j \leq 3} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}.$$

Now consider the case in which i visits f_1, f_2, and f_3 (in that order) and buys from firm f_1. The inequalities leading to this outcome are

$$r_{if_1} \geq r_{if_2} \geq r_{if_3} \geq u_{if_1} \geq u_{i0} \vee \max_{2 \leq j \leq 3} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}.$$

Now consider the case in which i visits f_1, f_2, and f_3 (in that order) and buys from firm f_2. The inequalities leading to this outcome are

$$r_{if_1} \geq r_{if_2} \geq r_{if_3} \geq u_{if_2} \geq u_{i0} \vee \max_{j \in \{1,3\}} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}.$$

Now consider the case in which i visits f_1, f_2, and f_3 (in that order) and buys from firm f_3. The inequalities leading to this outcome are

$$r_{if_1} \geq r_{if_2} \geq r_{if_3} \geq u_{if_3} \geq u_{i0} \vee \max_{j \in \{1,2\}} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}$$

$$r_{if_1} \geq r_{if_2} \geq u_{if_3} \geq r_{if_3} \geq u_{i0} \vee \max_{j \in \{1,2\}} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}$$

$$r_{if_1} \geq u_{if_3} \geq r_{if_2} \geq r_{if_3} \geq u_{i0} \vee \max_{j \in \{1,2\}} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}$$

$$u_{if_3} \geq r_{if_1} \geq r_{if_2} \geq r_{if_3} \geq u_{i0} \vee \max_{j \in \{1,2\}} u_{if_j} \vee \max_{g \notin \{f_1, f_2, f_3\}} r_{ig}.$$

C Details of indirect-inference estimation

C.1 Structure of regressions underlying the I-I estimator

Let $Y_n = \{y_{it}\}_{i=1}^n$ denote the collection of search effort outcomes in the estimation sample, where $y_i = \{y_{it}\}_{t=1}^{T_i}$ and y_{it} is a vector of search outcomes for consumer i in search effort t (i.e., the sequence of stores that consumer i visited in search effort t and consumer i's purchase decision in search effort t). Next, let $X_n = \{x_i\}_{i=1}^n$ denote the collection of explanatory variables in the estimation sample, where $x_i = \{x_{it}\}_{t=1}^{T_i}$ and x_{it} is a vector including the prices for consumer i's prescribed brand of contact lenses during search effort t as well as the consumer's state during search effort t.[11] The statistic $\hat{\beta}_n$ is the value of β minimizing the criterion function

$$Q_n(Y_n, X_n, \beta) = \frac{1}{n}\sum_{i=1}^{n} g(y_i, x_i, \beta).$$

where

$$g(y_i, x_i, \beta) = \sum_{j=1}^{J}\sum_{t=1}^{T_i} w_{ijt}(y_{it,j} - x'_{it,j}\beta_k)^2.$$

Under this form of the g function, the value of β minimizing the auxiliary criterion function is the vector obtained by stacking J weighted least squares estimators, each computed on a dataset of search efforts. Each j corresponds to a distinct regression, and each $y_{it,j}$ is some scalar-valued transformation of y_{it} that is used as the dependent variable in the jth regression. Similarly, each $x_{it,j}$ is some vector-valued transformation of x_{it} that is used as the regressor vector in the jth regression. The weights w_{ijt} will generally depend on the data (y_i, x_i).

Consider, for the sake of illustration, the regression j corresponding to the share of search efforts in which a consumer in state $h_{ift} = 1$ visits store g. In this case, $y_{it,j}$ is an indicator for whether consumer i visited store g in search effort f, $x_{it,j} = 1$, and w_{ijt} is an indicator for whether consumer i's state at search effort t was $h_{ift} = 1$.

The auxiliary model statistics computed on data that are simulated under structural model parameter θ are defined by

$$\tilde{\beta}_n^H(\theta) = \arg\min_{\beta\in B} Q_{nH}(\tilde{Y}_n^H(\theta), \tilde{X}_n^H, \beta).$$

Here, H is the number of simulates, $\tilde{Y}_n^H(\theta)$ are outcome variables simulated under θ conditional on $\tilde{X}_n^H$, and $\tilde{X}_n^H$ is constructed by repeating X_n H times.

C.2 Optimal weighting matrix

The asymptotic normality of the I-I estimator is ensured by conditions that are standard in the I-I literature.[12] Recall that the I-I estimator is defined by

$$\hat{\theta}_n^H(\Omega) = \arg\min_{\theta\in\Theta}(\hat{\beta} - \tilde{\beta}_n^H(\theta))'\hat{\Omega}_n(\hat{\beta} - \tilde{\beta}_n^H(\theta)).$$

The asymptotic normality result for the I-I estimator is

$$\sqrt{n}(\hat{\theta}_n^H(\Omega) - \theta_0) \to_d N\left(0, V_{\hat{\theta}_n^H}(\Omega)\right)$$

where

$$V_{\hat{\theta}_n^H}(\Omega) = (B_0'\Omega B_0)^{-1}B_0'\Omega\Gamma_0^{-1}V_{\hat{\beta}}\Gamma_0^{-1}\Omega B_0(B_0'\Omega B_0)^{-1}$$

[11] This is a minor abuse of notation, since I use y_i and x_i to signify subtly different random elements in the main structural model and in the auxiliary model. The x_i appearing in my exposition of the structural model, for instance, excludes the consumer's state.

[12] See Gouriéroux et al. (1993) for details.

for

$$
\begin{aligned}
V_{\hat{\beta}} &= \mathrm{Var}\left(s_{i0} - \frac{1}{H}\sum_{h=1}^{H} s_{ih}\right) \\
s_{ih} &= \begin{cases} \frac{\partial g}{\partial \beta}(y_i, x_i, \beta_0), & h = 0, \\ \frac{\partial g}{\partial \beta}(\tilde{y}_i^h(\theta_0), x_i, \beta_0), & h \in \{1, \dots, H\} \end{cases} \\
\Gamma_0 &= \frac{\partial^2 Q}{\partial \beta \partial \beta}(\beta_0; \theta_0) \\
B_0 &= \frac{\partial b}{\partial \theta}(\theta_0).
\end{aligned}
$$

In the definitions above, $\tilde{y}_i^h(\theta_0)$ are search effort outcomes simulated under model parameters θ_0 and $Q(\beta; \theta)$ is the population criterion function, i.e., the uniform probability limit of $Q_n(Y_n, X_n, \beta)$ as $n \to \infty$ when (Y_n, X_n) are generated under the model with structural parameter θ. Also, the binding function

$$
b(\theta) = \arg\min_{\beta \in} Q(\beta; \theta)
$$

is the probability limit of the $\hat{\beta}$ parameters under a given vector of structural parameters θ. Last, $\beta_0 = b(\theta_0)$.

The optimal weighting matrix Ω^* is

$$
\Omega^* = \Gamma_0 V_{\hat{\beta}}^{-1} \Gamma_0,
$$

which yields

$$
V_{\hat{\theta}_n^H}(\Omega^*) = \left(B_0' \Gamma_0 V_{\hat{\beta}}^{-1} \Gamma_0 B_0\right)^{-1}.
$$

I estimate the optimal weighting matrix and asymptotic variance of my estimator by replacing population objects appearing in expressions above with their sample analogues. Additionally, as is standard in the estimation of optimal weighting matrices in generalized method of moments and I-I estimators, I replace the true value of the structural parameter θ_0 with $\hat{\theta}_n^H(I)$ in the expression for the optimal weighting matrix when estimating this weighting matrix; here, I is the identity matrix.

D Supplemental tables

Table 16: Decomposition of price variation

Type of variation	Std. dev
Interbrand	12.26
Interstore	3.91
Intertemporal	1.15

Notes: "Interbrand" provides the cross-brand standard deviation of brands' average transaction prices. "Interstore" provides the average standard deviation of a brand's price across stores, where the average is taken over transactions in the sample. "Intertemporal" provides the average standard deviation of a particular brand's price at a particular store, where the average is taken across both brands and stores.

Table 17: Auxiliary model statistics computed on estimation sample

Statistic	Value	SE
Share visiting 1800	0.688	0.014
Share visiting WM	0.145	0.010
Share visiting VD	0.360	0.014
Share visiting every store	0.013	0.003
Visit inertia	0.846	0.011
Choice inertia	0.486	0.015
State inertia	0.988	0.003
Role of lagged price: slope for current price	-0.351	0.252
Role of lagged price: slope for lagged price	0.023	0.240
Price sensitivity: slope	-0.155	0.070
Outside share: slope	0.037	0.120
Dep. of tastes and prices cond. on initial state: slope	-0.302	0.098

Notes: See Section 6 for a description of the various auxiliary model statistics. The "SE" column reports asymptotic standard errors.

Table 18: Model fit and counterfactual search patterns: full results

Spec.	Share visiting one store only	Mean # of visits	Share buying from... any	1800	VD	Visit order	Share paying > > min. price	Mean over-payment ($)
Observed	0.820	1.193	0.597	0.337	0.236	0.414	0.633	3.74
	-	-	-	-	-	-	-	-
Baseline	0.918	1.087	0.668	0.381	0.267	0.653	0.633	3.47
	(0.038)	(0.040)	(0.057)	(0.058)	(0.094)	(0.088)	(0.091)	(0.66)
Low search costs	0.851	1.163	0.649	0.375	0.254	0.713	0.644	3.53
	(0.056)	(0.062)	(0.057)	(0.063)	(0.100)	(0.103)	(0.100)	(0.72)
Low search costs (comp.)	0.850	1.164	0.668	0.367	0.282	0.699	0.616	3.37
	(0.056)	(0.062)	(0.057)	(0.064)	(0.102)	(0.102)	(0.100)	(0.72)
No loyalty	0.884	1.127	0.224	0.086	0.122	0.528	0.480	2.43
	(0.039)	(0.047)	(0.076)	(0.047)	(0.080)	(0.070)	(0.144)	(0.97)
No loyalty (comp.)	0.650	1.409	0.667	0.192	0.420	0.535	0.421	1.82
	(0.099)	(0.134)	(0.057)	(0.097)	(0.144)	(0.078)	(0.141)	(0.97)
No vertical diff.	0.825	1.195	0.958	0.337	0.569	0.728	0.476	2.24
	(0.070)	(0.084)	(0.041)	(0.172)	(0.124)	(0.124)	(0.113)	(0.94)
No vertical diff. (comp.)	0.885	1.121	0.668	0.224	0.414	0.654	0.464	2.24
	(0.051)	(0.057)	(0.057)	(0.127)	(0.081)	(0.126)	(0.131)	(1.04)
No persistent unobs.	0.841	1.174	0.428	0.032	0.335	0.448	0.241	0.62
	(0.037)	(0.044)	(0.073)	(0.013)	(0.099)	(0.037)	(0.105)	(0.37)
No persistent unobs. (comp.)	0.753	1.284	0.667	0.056	0.504	0.453	0.261	0.63
	(0.060)	(0.076)	(0.058)	(0.018)	(0.120)	(0.046)	(0.104)	(0.39)
No search	0.000	3.000	0.631	0.366	0.237	1.000	0.651	3.69
	(0.000)	(0.000)	(0.037)	(0.064)	(0.046)	(0.000)	(0.056)	(0.47)
Logit only (comp.)	0.000	3.000	0.668	0.131	0.346	1.000	0.439	1.51
	(0.000)	(0.000)	(0.057)	(0.013)	(0.028)	(0.000)	(0.012)	(0.08)

Notes: This table expands upon Table 13 by adding rows corresponding to additional counterfactual parameters and also by including standard errors obtained by a parametric bootstrap with 100 replicates. The rows “Low search costs,” “No loyalty,” and “No persistent unobs.” all report results for the counterfactual discussed in Section 8 with the exception that no adjustment is made to the value of the outside option to ensure that the share purchasing from any store is held fixed in the counterfactual. The “No search” row reports results for a counterfactual in which consumer i knows each ε_{ijft} without searching and is able to purchase from any store without having visited that store.