Sources of limited consideration and market power in e-commerce*

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Abstract

This article develops techniques for the empirical analysis of repeated sequential search over unordered alternatives using data on consumer search processes. I use these techniques to assess why consumers conduct little search in e-commerce and often pay significantly above the minimum available price for a product. Search costs could explain these facts, as could pre-search seller differentiation: consumers with low search costs may not visit stores they dislike based on information known before search. I find that seller differentiation is primarily responsible for limited consideration and market power.

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1 Introduction

This article develops techniques for the empirical analysis of directed sequential search. These techniques apply to the setting in which a consumer sequentially searches unordered alternatives and the search process (i.e., the identities and ordering of searched alternatives) is observed by the researcher. The starting point of the analysis is the Weitzman (1979) optimal sequential search strategy. I show that this strategy implies a one-to-one mapping between search effort outcomes and chains of inequalities relating consumer utilities for an arbitrary number of alternatives. This mapping facilitates model analysis even without parametric restrictions on search costs. However, the mapping is especially useful under a particular search cost distribution proposed in the article and inspired by the approach of Moraga-González et al. (2023). The combination of this distribution and the mapping between search effort outcomes and utility inequalities yields closed-form expressions for joint search *and* purchase outcomes. This is the case even when the distribution of search costs varies across retailers. One advantage of the model is that it permits analysis of the relative roles of awareness and quality differentials in explaining retailers' market shares.

The article applies its techniques to study a fundamental question in the economics of e-commerce: what drives limited search and retailer market power in online markets for minimally differentiated products? Although the internet facilitates consumer learning about retailers' product offerings, consumers actively consider few sellers in online markets. Additionally, online markets for undifferentiated goods often feature considerable price dispersion, which suggests the presence of market power.[1] If internet search were costless and both sellers and their product offerings were undifferentiated, consumers would compare prices across all retailers and purchase from the

[1]See, e.g., Clay et al. (2001), Clemons et al. (2002), Moraga-González and Wildenbeest (2008), Koulayev (2014), and Jolivet and Turon (2019).

lowest-price seller. That consumers conduct little search and often buy from higher-price sellers of undifferentiated products could reflect that search frictions remain significant online — consumers may buy at high prices to avoid further search. Much of the empirical online search literature emphasizes this explanation.[2] Seller differentiation can also explain limited consideration. Even when the product that arrives on a consumer's doorstep does not vary across retailers, a consumer may differentially value retailers due to vertical differences in shipping efficiency or customer service. Retailers may also be horizontally differentiated by their user interfaces and marketing strategies. Additionally, consumers may prefer to buy from stores that they have previously patronized due to habit formation, store loyalty, or switching costs. If the consumer knows before searching that they are unlikely to buy from a seller, then the consumer may not visit the seller even when search costs are negligible.

I empirically investigate sources of limited search and market power in US contact lens e-commerce. This setting is attractive for the study of across-retailer search because consumers require *brand-specific* prescriptions to buy lenses, which allows me to credibly assume that search occurs across stores and not across products. With that said, the article's framework is readily adapted to the analysis of search across products when the researcher possesses data on such search. The analysis draws upon panel data of US web browsing and transactions in 2007–2008. I first document that consumer consideration is severely limited: in 83% of search efforts for contact lenses, the consumer visits only one retailer. Also, the mean transaction price for lenses is 16% above the minimum price available among major retailers for the consumer's brand. I also analyze books, PS3 consoles, iPods, and DVDs and reach similar conclusions as for contact lenses.

[2] See Hortaçsu and Syverson (2004), Hong and Shum (2006), Moraga-González and Wildenbeest (2008), and Jolivet and Turon (2019).

To understand limited search and overpayment for contact lenses, I develop a model of sequential search for contact lenses across retailers. The article's methodological innovations facilitate estimation and analysis of this model. The availability of data on both store visits and on purchases permits a quantification of the distinct roles of awareness and quality differences in determining retailers' sales. One challenge in identifying parameters affecting purchase utility is price endogeneity, which owes to the dependence of unobserved retailer quality and prices. My solution to this problem exploits within-retailer, across-brand variation in relative prices and relative market shares. Under this solution, the extent to which a retailer has a relatively low market share in sales of a brand that it sells for a relatively high price identifies price sensitivity. Separate identification of state dependence and unobserved heterogeneity follows from standard arguments concerning their distinct implications for choice dynamics.

Indirect-inference estimates of the model imply median search costs of under $1.25 for all retailers. Removing various forms of seller differentiation from the model raises estimated search costs dramatically — eliminating factors that limit search requires search costs to play a larger role in justifying limited consideration. This finding suggests that flexible modelling of retailer differentiation is essential in reliably estimating search costs.

Both search frictions and store differentiation play a role in limiting search. Eliminating vertical differentiation—i.e., differences in mean consumer tastes for retailers—raises the mean number of store visits from 1.20 to 1.30 by inducing consumers who prefer the vertically superior retailer to consider other stores. Eliminating horizontal differentiation—i.e., cross-consumer dispersion in tastes for stores—similarly boosts search intensity by leading consumers to look beyond their favoured store. Although reducing search costs raises search intensity, it does not meaningfully affect the extent to which consumers pay above the minimum available price for contacts. I instead find that consumers pay above the minimum available price largely because they value the superior quality of higher-price retailers, which could reflect superior shipping times, customer service, or return policies. I additionally assess sources of markups in contact lens e-commerce. The results suggest that seller differentiation shapes equilibrium markups whereas search costs do not. For one popular brand, eliminating horizontal differentiation reduces markups by 55% on average. Additionally, eliminating the upscale retailer's vertical advantage reduces its markups by 20%. Prices at rival retailers rise absent vertical differentiation, thus reducing price dispersion. Results for other brands are similar. Together, the results suggest that retailer differentiation is responsible for market power and price dispersion in e-commerce.

The model also permits an analysis of the roles of awareness and quality differences in explaining firms' market shares. The largest contact lens retailer, 1-800 Contacts, outsold its rivals at higher prices. Notably, 1-800 Contacts was also known for its superior service quality and extensive advertising, which is reflected in a higher estimate of quality and a lower estimate of search costs for 1-800 than for its rivals. I show that 1-800's quality advantage rather than its awareness advantage underlies its market dominance: equalizing the quality of 1-800 Contacts and Vision Direct, its main rival, reduces the ratio of the former's sales to the latter's from 1.71 to 0.38, whereas equalizing these retailers' search cost distributions reduces the ratio only to 1.67.

Since 2007–2008, e-commerce has witnessed entry of many new sellers, including those that primarily sell within e-commerce platforms, and changes in the nature of advertising. The article's framework is well suited for the study of contemporary e-commerce markets. The model is easily adapted to the case of consumer search across products or third-party sellers on an e-commerce platform. Furthermore, the fact that article's characterization of the probabilities of joint search and purchase outcomes holds for any arbitrary number of retailers makes its methods useful in settings with many retailers. The model also permits heterogeneity in the magnitude of search costs across retailers and variance in consumer/retailer-specific search costs; this allows it to capture both (i) differences in the intensity of informative advertising across retailers and (ii) personalized advertisements, both features of contemporary e-commerce. The article's framework is also generally fit for use in analyzing non-contact-lens markets in which consumers search sequentially over sellers, products, or both. With that said, the analysis of more complex patterns of consumer search using the article's framework requires more detailed data.

1.1 Related literature

The article's primary contribution is the development of techniques for estimating a sequential search model using data on consumer search processes, namely the establishment of (i) a one-to-one mapping between search outcomes and utility inequalities and (ii) a parametric specification that operationalizes this mapping. These techniques draw on Weitzman (1979) and Moraga-González et al. (2023). The article extends the analysis of Moraga-González et al. (2023), which provides expressions for probabilities of purchase outcomes, by providing expressions for probabilities of both search and purchase outcomes. These expressions are useful in drawing upon the identifying power of datasets that describe not only purchase decisions but also search processes. Absent the techniques in this article, complexities arise in the analysis of sequential consumer search with data on consumer search processes. Honka and Chintagunta (2017) provide a foundational study in the estimation of the sequential search model with data on consumers' search sequences. In a setting similar to my own, they pool together distinct sets of inequalities that characterize search effort outcomes and approximate the probabilities implied by these inequalities via simulation. I build upon their contribution by developing techniques that yield closed-form probabilities from comprehensive chains of inequalities characterizing search and purchase outcomes.

I also develop econometric techniques for the analysis of search data with a panel dimension. Whereas recent studies have considered persistent unobserved heterogeneity (Morozov et al. 2021) and state dependence (Honka 2014) separately, my article considers both phenomena simultaneously, proposing solutions based on the panel econometrics literature to an endogeneity problem and an initial conditions problem that arise.

This article's applied contribution is its explanation of limited search and market power in e-commerce. Brynjolfsson and Smith (2000) studied price dispersion in early e-commerce, concluding that seller heterogeneity remained significant on the internet. Early articles in the empirical consumer search literature—namely Hong and Shum (2006), Hortaçsu and Syverson (2004), and Moraga-González and Wildenbeest (2008)—demonstrated that search frictions could explain price dispersion in homogeneous goods markets.[3] Several recent studies account for other factors that limit search and generate market power both within and outside of e-commerce (e.g., Honka 2014, Morozov et al. 2021, Brown et al. 2023).

My article's methods are specialized to the setting in which a consumer sequentially considers unordered alternatives and the consumer search process is observed. Much of the empirical search literature focuses on dissimilar settings.[4] First, De Los Santos et al. (2012) develop methods for estimating a fixed sample size search model whereas I develop methods for estimating

[3] Although Hortaçsu and Syverson (2004) allow for vertical (but not horizontal) differentiation between product offerings, Hong and Shum (2006) and Moraga-González and Wildenbeest (2008) use a model without seller differentiation.

[4] See Honka et al. (2019) for an overview of the empirical consumer search literature.

a sequential search model. Furthermore, although they analyze the same Comscore data that my article studies, they do not incorporate the panel dimension of these data in their analysis (they analyze books, which unlike contact lenses are typically purchased once). My article and De Los Santos et al. (2012) are complementary in that they provide empirical techniques for distinct sorts of search models that are differentially applicable to different settings. Another sort of non-sequential model in the literature is that of Allen et al. (2014), who develop a search model in which exerting search effort at a cost allows consumers to raise their chances of obtaining additional mortgage quotes. Turning to sequential search models, Koulayev (2014) models a consumer clicking through pages of hotel listings on a booking platform. This model is tailored to a context in which alternatives are ordered, whereas my approach applies to contexts with an unordered set of retailers. Ursu (2018) similarly studies search of ordered hotel listings. Jolivet and Turon (2019) study sequential search for products within an e-commerce platform, although their empirical approach is tailored to the case in which the consumer search process is not observed.

Three other literatures are relevant to my work. First, it relates to a literature that studies sources of limited consideration and market power in brick-and-mortar retail; see Sorensen (2000) for analysis of pharmacies and Dubois and Perrone (2015) for analysis of supermarkets. Second, it relates to a literature on inertia in consumer choice (including, e.g., Heckman 1981 and Kasahara and Shimotsu 2009), especially Dubé et al. (2009) and Dubé et al. (2010). Last, this article relates to a literature on platform design in e-commerce, including Dinerstein et al. (2018), who study search within eBay, and Lee and Musolff (2021) who study the interaction of seller differentiation and platform design on Amazon's Marketplace platform.

2 Setting and data

This study's primary data source is the Comscore Web Behavior Panel for 2007–2008 (Comscore 2007–2008). This dataset includes online browsing and transactions activities for a panel of US households.[5] As noted by De Los Santos et al. (2012) and Saruya and Sullivan (2023), the Comscore panel is representative of online US consumers. The browsing data include a record of each web domain visited by a panelist; each record includes a panelist identifier and transactions associated with the visit.[6] For each transaction, I observe the price and quantity of each purchased product.

The contact lens transactions analyzed in this article occur at three retailers that collectively account for about 95% of contact lens transactions in the data: 1-800 Contacts (1800), Vision Direct (VD), and Walmart (WM). The specialty retailers 1800 and VD in turn account for about 95% of sales among these three retailers. The former, 1800, launched in 1995 and was the market leader during 2007—2008 with a market share of about two-thirds. Vision Direct launched later, in 2004. Contact lens e-commerce was sizeable by 2007; 1800 made net sales of $125 million in the first half of 2007. Although many new retailers have entered contact lens e-commerce since 2008, 1800 has remained the market leader, boasting well over half of all sales.[7]

For each retailer and each brand of lenses, I construct a daily price time series. In doing so, I assume that the brand's price remains fixed at its most

[5] The 2007 and 2008 panels include about 92 000 and 58 000 households, respectively.

[6] The data do not include the list of pages visited by a panelist within a web domain; for example, a record of a panelist visiting `amazon.com` does not reveal the visited product pages within Amazon.

[7] A response by 1800 to a Federal Trade Commission complaint (FTC Matter 141 0200, docket no. 9372, "Respondent 1-800 Contacts, Inc.'s Proposed Findings of Fact and Conclusions of Law") in 2017 stated that 1800 accounted for about 10% of total US contact lens sales whereas all purely online contact lens retailers accounted for about 17% of sales, implying that 1800's market share among online contact lens retailers was about 60%. More recently, a report by the market research firm Earnest Research found that the share of eyewear sales accounted for by 1800 did not change from Q1 2017 to Q3 2021; see `https://www.earnestanalytics.com/insights/retail/eyeing-warby-parkers-s-1/`.

recent observed transaction price until the time of the subsequent observed transaction. This procedure introduces some measurement error, but the error is likely to be small because prices are updated often: the mean gap between transactions for top brands is generally under two weeks (see Table 1). The prices in the time series do not include shipping fees, although 1800 and VD both waived shipping fees for sufficiently large purchases.[8] Additionally, the price time series do not account for the rebates that manufacturers offered consumers who purchased a sufficient number of contact lens boxes in a single transaction. That these rebates often varied across retailers complicates analysis of contact lens e-commerce. I ignore rebates on the basis that most consumers were ineligible for rebates based on their purchase quantities: in October 2007, rebates were only available to 1800 consumers who purchased at least eight boxes for eight of the ten most popular brands, but only 7.6% of transactions included eight or more boxes.

I focus on contact lenses but also analyze books, iPods, Playstation 3 (PS3) consoles, and DVDs. Like contact lenses, these categories contain products with many observed purchases. Online Appendix O.1 describes these categories' data.

The dataset used in the article's analysis is a panel of search efforts, each of which is a sequence of store visits and a purchase decision. The purchasing alternatives here are visited stores and the outside option of not buying online. I construct the search effort for a transaction by determining all visits to retailers nearby in time to the transaction. Appendix A details the procedure. For online retailers that exclusively sell contact lenses and associated products, there is little danger of incorrectly assuming that a consumer's visit to the retailer involved searching for contact lenses rather than some other product. For other retailers and product categories, this is a real risk: a consumer's visit to Amazon prior to buying a book from Barnes & No-

[8] 1800, for example, offered free shipping on orders over $50.

ble, e.g., could represent search for products other than books. Incorrectly assuming that visits to multi-category retailers like Amazon prior to a purchase constitute search associated with the purchase may lead the researcher to overstate the extent of consumer consideration: if, e.g., the consumer in the example above did not search for books on Amazon, then they would not be aware of Amazon's book offerings relative to those of Barnes & Noble. I choose to focus on contact lenses in part because the leading two online contact lens retailers sold contact lenses almost exclusively, which reduces the risk of incorrectly overstating consumer consideration in this category.[9] The researcher can reduce this risk in the analysis of across-retailer search in other product categories by obtaining data on within-website consumer search.

In the United States, optometrists and ophthalmologists prescribe contact lenses to their patients after administering exams and fittings. A prescription specifies a brand, parameters (e.g., diameter and power), and an expiration date (typically one or two years in the future). I infer consumers' prescription based on the brand of lenses that they buy. When a consumer buys a different brand than that previously purchased, I assume the consumer's prescription has changed and that the consumer holds the new prescription alone until the next purchase. About 15% of consumers in the sample switch brands.[10]

Tables 1, 2, and 3 describe brands, retailers, and consumers in the data,

[9] Walmart, however, sold many other products online. Consequently, I use a more restrictive rule for including visits to Walmart in the sample (see Appendix A) and assess the robustness of model estimates to the treatment of Walmart (i.e., to dropping Walmart or treating it in the same way as the other retailers in constructing search efforts). The parameter estimates are largely robust to the treatment of Walmart; see Online Appendix O.12.

[10] Tables O.17 and O.18 in the Online Appendix provide analysis of these switchers. One finding of these analyses is that household size does not predict whether a consumer switches, which suggests that switching does not reflect distinct household members ordering different brands. In addition, the difference in mean prices faced by a consumer before and after switching is small and not statistically significant. One explanation of this finding is that switches are not driven by price considerations.

respectively. Table 1 reports the number of transactions for the best-selling brands in the sample. There are 42 brands altogether, and sales are dispersed across brands; the best selling brand accounts for 14% of sales, and brands outside the top 10 best sellers account for 36% of sales. Table 2 reports the number of transactions at each retailer and each retailer's average relative price, defined as the across-transaction mean ratio of the retailer's price to 1800's price for the transacted brand at the time of the transaction. The table shows that 1800 had a market share of about two-thirds while charging higher prices than its rivals. VD had a market share of about 30% and offered contacts at 85% of 1800's prices, on average. Table 3 describes consumers in the sample. The median price paid for a box of lenses was about $30 and the median number of boxes of lenses purchased was two (one for each eye). Consumers make 2.5 search efforts on average, yet some consumers make many more search efforts. The median time between transactions is 14 weeks. Additionally, consumer search exhibits inertia: in 85% of cases, the first store that the consumer visits in a search effort is the same as the first store visited in the consumer's previous effort.

3 Descriptive analysis

This section first provides evidence that consumers conduct little search online and often pay above the minimum available price in online markets for undifferentiated products. It then characterizes the influence of prices on consumer browsing and purchasing decisions.

3.1 Limited consideration

Active consideration of online retailers is severely limited in contact lens e-commerce. Table 4 displays the share of contact lens search efforts involving one, two, and three store visits. The "Baseline" column provides results for search efforts constructed from visits to 1800 or VD up to 14 days before a purchase as described in Appendix A. The "2 days before" column only

Table 1: Description of transactions in contact lens data

Brand	# trans.	Weeks b/w trans. Mean	Median
Acuvue 2	188	0.56	0.0
Acuvue Advance	145	0.72	1.0
Acuvue Oasys	129	0.81	1.0
Acuvue Advance for Astigmatism	95	1.05	1.0
Biomedics	57	1.79	2.0
Freshlook Colorblends	56	1.89	1.0
Acuvue 2 Colors	51	1.90	1.5
Soflens 66 Toric	48	1.91	1.0
Focus Night & Day	46	2.29	1.0
O2 Optix	46	2.22	2.0
Other brands	474		
Total	1335		

Notes: "# trans." reports the number of transactions for each brand. The "Weeks b/w trans." columns describe the duration of time between observed transactions of each brand.

Table 2: Sales and prices by store (contact lenses, 2007–2008)

Store	Transactions	Average relative price
1800contacts.com	849	1.00
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.

Table 3: Description of search efforts and transactions

	Mean	Quantiles 0.25	0.5	0.75	0.95
Transaction price	31.05	19.99	28.95	38.95	54.99
Transaction quantity	2.83	1.00	2.00	4.00	8.00
N. search efforts	2.47	1.00	2.00	3.00	6.00
N. transactions	1.65	1.00	1.00	2.00	4.00
N. consumers = 793					
N. search efforts (total) = 1956					
N. transactions (total) = 1310					

includes visits made up to two days before a purchase or another visit. Under the baseline data construction, 83% of search efforts involve a visit to only one store. Table 4 also shows that search efforts are insensitive to the time-window used in constructing search efforts. Online Appendix Table O.10 provides results for other categories using a five-days-before definition of a search effort. For all categories except PS3s, over 75% of search efforts involve a visit to only one or two stores.

Consumers visit few stores despite the possibility of saving on lenses by visiting and purchasing from other stores. Table 5 shows that 70% of transactions occur at a store that sells the purchased brand above the minimum price offered among the three major retailers. The magnitude of spending in excess of these minimum prices is significant — consumers pay, on average, 16.3% above the minimum available price. Additionally, in 43% of search efforts with multiple visits, the consumer does not choose the store with the lowest price among visited sites. On average, the consumer pays 7.1% over the minimum available price among visited sites. Table O.11 reports analogous results for other categories. In all categories except PS3s, most consumers pay above the minimum available price. Search frictions provide one explanation for purchasing above the minimum available price. An alternative explanation is that some retailers offer superior customer service or shipping, and some consumers prefer to purchase from these retailers over lower-price rivals. The fact that 1800 outsells VD despite charging higher prices—see Table 2—suggests that 1800 is more appealing to consumers in non-price dimensions. Alternatively, consumer awareness of 1800 could be higher than that of VD. The availability of both search and purchase data will allow me to distinguish between these explanations.

3.2 Prices, browsing, and purchasing

I now turn to the role of prices in directing consumer behaviour. That 1800 boasted the highest sales despite charging the highest average prices could reflect that consumers generally prefer 1800, which could lead 1800 to charge

Table 4: Share of search efforts by number of visited stores

# of visits	Share of sessions Baseline	2 days before
1	0.83	0.84
2	0.16	0.15
3	0.01	0.01

Notes: see Online Appendix Table O.10 for results for other product categories.

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

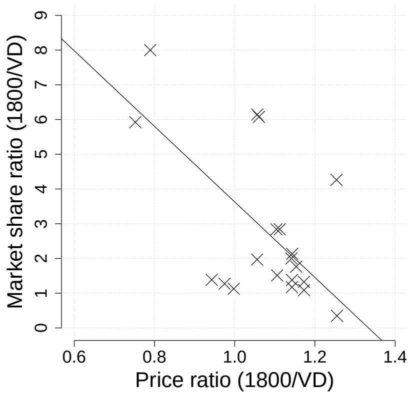
Notes: this table reports the (i) share of transactions made above the minimum available price (MAP); (ii) the average difference of paid price and the MAP, and (iii) the average relative difference of the transaction price over the MAP.

higher prices. My solution to this price endogeneity problem in demand estimation is to exploit cross-brand differences in stores' relative prices. If stores' quality differences equally affect their sales of all brands, then the extent to which a store has relatively lower sales for brands that it sells for relatively higher prices is informative about consumer price sensitivity. Figure 1, which plots 1800's sales relative to VD's against its price relative to VD's for the 20 best-selling brands, illustrates this idea: the brands for which 1800 charges especially high prices relative to VD's are those for which 1800's sales are relatively low.

To exploit between-brand variation to estimate price sensitivity, I specify store fixed effects in consumer utilities. I assess the suitability of this approach with descriptive multinomial logit regressions with and without fixed effects. An additional purpose of these regressions is to determine whether prices guide search, which would suggest that consumers have some knowledge of prices prior to search. The estimating equation is

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

Figure 1: Prices and intrabrand market shares at 1800 and VD



Note: Each point represents a brand. "Market share ratio (1800/VD)" provides the ratio of transactions at 1800 to those at VD. "Price ratio (1800/VD)" provides the average daily price of a brand at 1800 divided by the analogous quantity for VD. The plot includes the 20 best-selling brands and displays a least-squares line of best fit.

where $y_{it} = \arg\max_f u_{ift}$ is either the store from which the consumer purchases or the first-visited store in a search effort, i indexes consumers, t indexes search efforts, and p_{ift} is retailer f's price for i's brand. Additionally, ε_{ift} is an unobservable iid type 1 extreme value (T1EV) shock. I estimate a specification without fixed effects in which $q_{ft} = \bar{q}$ for all f and t and one with fixed effects in which $q_{ft} = q_{f\tau}$, where τ indicates the half-year (e.g. first half of 2007). I estimate the regressions with the purchase decision as the outcome on a dataset of all search efforts that end in a transaction. I use a disjoint dataset of all search efforts that do not end in a transaction for the regressions with first-visited store as the outcome.

Table 6 reports results. Without fixed effects, I estimate that consumers are more likely to purchase from sellers charging higher prices. This relationship is reversed upon the introduction of fixed effects.[11] Additionally, the first-visited store responds to prices in a similar way as purchases. This suggests

[11] Online Appendix O.6 evaluates the extent to which the positive α estimate reflects cross-brand price differences (i.e., consumers prescribed a brand for which a store charges a relatively high price are less likely to buy from that store on average across time) versus intertemporal price variation, concluding that both sources of variation are relevant.

Table 6: Descriptive multinomial logit regressions (contact lenses)

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

	Purchase	First visit
α	-0.006	-0.056
	(0.003)	(0.010)
Average elasticity	-0.072	-0.692
	(0.045)	(0.086)

Specification 2: seller/half-year fixed effects

	Purchase	First visit
α	0.035	0.025
	(0.004)	(0.014)
Average elasticity	0.449	0.455
	(0.049)	(0.111)

Notes: The table reports maximum likelihood estimates of (1) for the contact lenses category. Standard errors are reported in parentheses. The "Average elasticity" is the average own-price elasticity taken across transactions.

that consumers have some knowledge of prices before search.

4 Model of consumer search

This section outlines the search model. Consumers search for lenses across F online retailers at different occasions in time. Each consumer i has a prescription for a brand j of lenses. The consumer makes search efforts $t \in \{1, \ldots, T_i\}$ at exogenously determined times. In each effort, the consumer determines which retailers $f \in \mathcal{F} = \{1, \ldots, F\}$ to visit (by, e.g., entering their URLs or making a search-engine query). Retailer f charges a price p_{ift} for consumer i's brand during a search effort t. The consumer additionally chooses a store f among visited stores from which to purchase, or not to buy lenses online (denote $f = 0$). The consumer incurs a search cost κ_{ift} for visiting store f in search effort t. Search costs here capture costs of learning about store f and navigating to the webpage on which it lists the consumer's brand for sale; these costs may be influenced by display, search-engine, or other advertisements. Consumers conduct sequential search according to the optimal strategy of Weitzman (1979). Consumer i's utility from purchasing from store f during search effort t is

$$\text{(Online)} \quad u_{ijft} = q_f - \alpha_i p_{ift} + \phi h_{ift} + \gamma_{if} + \varepsilon_{ift} \tag{2}$$

$$\text{(Offline)} \quad u_{ij0t} = \varepsilon_{i0t}, \tag{3}$$

where q_f governs the quality of store f; γ_{if} is consumer i's persistent taste for f; ε_{ift} is consumer i's t-specific match value with f. Store quality here captures shipping speed, customer service, returns policies, and persuasive effects of advertising. Additionally, h_{ift} is an indicator for whether the consumer purchased from f in search effort $t-1$. I refer to $h_{it} = \{h_{ift}\}_{f\in\mathcal{F}}$ as consumer i's *state*. Price sensitivity depends on $\alpha_i = \alpha_0 + \alpha_1 I_i$, where I_i is an indicator for consumer i's household income exceeding $75,000. Additionally, ϕ governs state dependence, which may arise from habit formation, switching costs, or store loyalty.

Before search, the consumer knows all but the ε_{ift} match values. Section 4.2 justifies this assumption. I also assume that consumers are myopic in not anticipating the effects of their choices on future payoffs, a common assumption in the state dependence literature (e.g., Dubé et al. 2010).

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

$$\kappa_{ift} = \int_{r_{ift}}^{\infty} (u - r_{ift}) dF_{ift}(u), \tag{4}$$

where κ_{ift} is the search cost that consumer i incurs for visiting store f in search effort t and $u_{ift} \sim F_{ift}$ conditional on all but 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 the maximum of u_{ift} and r_{ift}. Reservation utilities can be written as

$$r_{ift} = q_f - \alpha_i p_{ift} + \phi h_{ift} + \gamma_{if} + \Gamma_0^{-1}(\kappa_{ift}), \tag{5}$$

for $\Gamma_0(\kappa) = \int_{\kappa}^{\infty} (u - \kappa) dF_0(u)$, where F_0 is the distribution of the ε_{ift} match values, assumed T1EV. Because Γ_0 and its inverse are strictly decreasing functions, a store's reservation utility is decreasing in its search cost. Kim et al. (2010) and Moraga-González et al. (2023) similarly invert equations defining reservation utilities to obtain expressions resembling (5).

There is a convenient parametric distribution of the search costs κ_{ift} that yields tractable choice probabilities for search effort outcomes. Suppose that $\kappa_{ift} \sim F_\kappa(\cdot; \bar{\kappa}_f)$ independently of all else (including search costs for other search efforts $t' \neq t$ or other consumers i), where

$$F_\kappa(\kappa; \bar{\kappa}_f) = 1 - \exp\left\{-\exp\left\{-\Gamma_0^{-1}(\kappa) - \bar{\kappa}_f\right\}\right\}. \tag{6}$$

The $\bar{\kappa}_f$ parameter positively relates with both the mean and variance of the distribution of search costs for store f. Differences in this parameter across retailers f reflects differences in awareness of retailers and in ease of navigating to and within retailers' websites. Figure 2 plots $F_\kappa(\cdot; \bar{\kappa})$. Under this distribution, we can express equation (5) as

$$r_{ift} = q_f + \gamma_{if} - \alpha_i p_{ft} + \phi h_{ift} - \bar{\kappa}_f + \eta_{ift}, \tag{7}$$

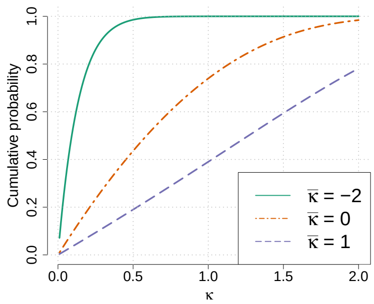
where the η_{ift} are mutually independent (across i, f, and t) T1EV random variables. To see why, note that

$$\begin{aligned} \Pr(\Gamma_0^{-1}(\kappa_{ift}) \leq x) &= \Pr(\kappa_{ift} \geq \Gamma_0(x)) \\ &= 1 - F_\kappa(\Gamma_0(x), \bar{\kappa}_f) \\ &= \exp\left\{-\exp\left\{-\Gamma_0^{-1}(\Gamma_0(x)) - \bar{\kappa}_f\right\}\right\} \\ &= \exp\left\{-\exp\left\{-(x + \bar{\kappa}_f)\right\}\right\}, \end{aligned} \tag{8}$$

which is the distribution function of a T1EV random variable with location parameter $-\bar{\kappa}_f$. The inequality within the probability operator flips in the first equality because Γ_0^{-1} is a decreasing function. Thus, $\Gamma_0^{-1}(\kappa_{ift}) + \bar{\kappa}_f \sim \eta_{ift}$, where η_{ift} is a standard T1EV random variable. Substituting $\Gamma_0^{-1}(\kappa_{ift})$ for $-\bar{\kappa}_f + \eta_{ift}$ in (5) yields (7).

The distribution above is one of the two model features that give rise to tractable choice probabilities. The other is a bijective mapping between (i)

Figure 2: Illustration of the search cost distribution function



inequalities relating reservation and indirect utilities and (ii) outcomes of search efforts. Given the distributional assumptions, these inequalities yield closed-form outcome probabilities. To illustrate, suppose that a consumer visits stores f and f' before buying from f. This sequence of visits implies that the highest reservation utility is that for f and that the reservation utility for f' exceeds the indirect utility for store f. Otherwise, the consumer would have terminated search after visiting f to buy from that store. Analogous reasoning establishes that the reservation utility for f' exceeds u_{i0}. Because the consumer purchases from f, the indirect utility of f must exceed the indirect utilities of f' and of the outside option in addition to all other reservation utilities. This reasoning is summarized by the following chain of inequalities (wherein I suppress the t subscript):[12]

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

The probability that r_{if} exceeds $r_{if'}, u_{if}, u_{i0}, u_{if'}$, and $\max_{g \in \mathcal{F} \setminus \{f,f'\}} r_{ig}$ takes the standard logit form:

$$\frac{e^{\bar{r}_{if}}}{\sum_{g=1}^{F} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}},$$

where $\bar{u}_{ig} = u_{ig} - \varepsilon_{ig}$ and $\bar{r}_{ig} = r_{ig} - \eta_{ig}$. Similarly, the probability that $r_{if'}$ exceeds u_{if}, u_{i0}, $u_{if'}$, and $\max_{g \in \mathcal{F} \setminus \{f,f'\}} r_{ig}$ also has a standard logit form,

$$\frac{e^{\bar{r}_{if'}}}{\sum_{g \neq f} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}},$$

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

as does the probability that u_{if} exceeds u_{i0}, $u_{if'}$, and $\max_{g\in\mathcal{F}\setminus\{f,f'\}} r_{ig}$:

$$\frac{e^{\bar{u}_{if}}}{\sum_{g\notin\{f,f'\}} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}}$$

Given the independence of irrelevant alternatives property of the logit, we then obtain the overall probability of the search outcome by multiplying together the probabilities above:

$$\begin{aligned} &\frac{e^{\bar{r}_{if}}}{\sum_{g=1}^{F} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}} \times \frac{e^{\bar{r}_{if'}}}{\sum_{g\neq f} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}} \\ &\qquad \times \frac{e^{\bar{u}_{if}}}{\sum_{g\notin\{f,f'\}} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}}. \end{aligned} \tag{9}$$

Online Appendix O.3 provides the inequalities corresponding to other outcomes under an arbitrary number of alternatives.

4.1 Discussion of results

The choice probabilities in (9) are straightforward to compute. Without using either the search cost distribution (6) 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 ε_{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 and indirect utilities at each step in search. Last, it would require integration over κ_{ift} and ε_{ift} to obtain choice probabilities.

The mapping between chains of inequalities and search effort outcomes reduces the burden of computing choice probabilities even under arbitrary dependence structures of $(\varepsilon_{ift}, \kappa_{ift})$ across consumers, time, and retailers.[13] Indeed, one could simulate search efforts by drawing a sequence $\{(\varepsilon_{ift}, \kappa_{ift})\}_{f\in F}$ of random variables from an arbitrary distribution and then determine the

[13]Other articles have exploited utility rankings in analyzing search models. Moraga-González et al. (2023) specify inequalities based on a result of Armstrong (2017) and Choi et al. (2018). Morozov et al. (2021) and Ursu (2018) pool separate inequalities for (i) visit order, (ii) stopping decision, and (iii) purchase decision.

associated outcome of search by identifying the set of inequalities satisfied by this sequence. This procedure facilitates estimation of the model using simulation-based estimators such as the indirect inference estimator used in this article (see Section 6.1). Notably, this procedure permits the relaxation of the article's somewhat restrictive assumption that search costs that are iid across time.

Although the article's parametric restrictions are not necessary for tractable analysis of the model, they simplify computation in several ways. First, they facilitate maximum likelihood estimation.[14] This is because the parametric restrictions yield exact closed-form choice probabilities. Without these exact closed forms, the researcher must approximate choice probabilities using computational methods such as simulation in order to compute model likelihoods. In addition, the parametric restrictions simplify the simulation of search efforts. When the researcher uses these parametric restrictions, it is possible to simulate search efforts by either (i) assessing which inequalities characterizing search effort outcomes hold under a given unobservable draw $\{(\varepsilon_{ift}, \kappa_{ift})\}_{f \in F}$ or (ii) drawing directly from simple closed-form choice probabilities. Option (i) involves assessing many pairwise inequalities, which makes option (ii) more convenient in general. Last, the closed-form expressions simplify computation of choice probabilities' derivatives, as the closed-form expressions for these probabilities are smooth in model parameters. Such derivatives are useful in executing derivative-based optimization procedures in model estimation and in computing demand derivatives for the purposes of analyzing retailer pricing.

Note that this article's framework is readily applied to the analysis of search across products within a retailer or e-commerce platform; this simply requires

[14] As noted in Section 6, I find that indirect-inference estimators are better behaved in my setting than maximum likelihood estimators. With that said, maximum-likelihood estimators boast greater asymptotically efficiency than indirect-inference estimators and thus may be more appropriate in other sequential search settings.

re-labelling sellers f as products. It is also possible to use the article's mapping between utility inequalities and search effort outcomes and the proposed search cost distribution to analyze a model of search over both retailers and products offered by each retailer (e.g., over both book titles and bookstores). Estimating such a model, though, would require data on both across- and within-retailer search. Upon specifying a within-retailer search problem, the researcher could enter the inclusive value of the within-retailer problem as a term in the store-level indirect utilities that the consumer considers in across-retailer search. When the search model described here is applied to both search problems, analyses of choice probabilities at each stage of consumer search would be facilitated by this article's methods.

4.2 Justification of assuming search over match value

The assumption of known prices and search over match values is common in the consumer search literature (e.g., Kim et al. 2010, Moraga-González et al. 2023). It is justified in my context for several reasons. First, regressions from Section 3.2 suggest that consumers respond to prices in choosing stores to visit even when they do not ultimately buy lenses. This is compatible with the consumer choosing visits based on knowledge of prices. Consumers may know prices based on previous search experience—recall that I drop consumers' first search efforts from the sample—or through adverts.[15] Another reason to assume search over match values is the presence of non-price retailer characteristics that consumers learn through search. These include the consumer's perception of the retailer's website usability and design; time-varying marketing materials on retailers' websites; the speed at which the retailer can verify prescriptions (which may depend on the retailer's website traffic and on the consumer's internet speed); and time-varying public reviews of retailers that consumers may differentially discover in the search

[15]This is plausible given that 1800 advertised heavily in the sample period, with advertising expenses equal to 12% of costs of goods sold in the first half of 2007.

process. Perhaps the most important source of variation in match values relates to prescription/brand-specific inventories and shipping times. Contact lenses vary not only by brand but also by other prescription parameters; these include base curve, power, sphere, etc.[16] Whether a retailer has a specification in stock determines the store's shipping time for an order. This likely explains why 1800's advertisements boasted of the firm's large inventories. Furthermore, a response by 1800 in 2017 to an FTC complaint suggests the importance of inventory in contact lens retail: it claims that a consumer could wait 4–8 weeks for a shipment from a rival online retailer if the retailer did not have the consumer's prescription in stock and that independent eye-care professionals typically had only about 40% of orders in stock.[17] Fulfilling a large share of orders from inventories is challenging for contact lens retailers due to the large number of prescription configurations: a 2020 webpage post by CooperVision, a contact lens manufacturer, claimed that four of the major contact lens retailers produced over 60,000 unique products (SKUs) collectively.[18]

An alternative approach is to assume search over prices and specify consumer beliefs over prices.[19] If consumer beliefs concentrate around the true prices on account of the common rational expectations assumption, this approach is similar to one that assumes knowledge of prices but fails to account for non-price information uncovered by search. A general difference between models of search over match values and search over prices is that, in the latter, search costs attenuate consumer responses to price. This is because consumers do not condition their choice of store to visit on price (given that they do not know stores' prices prior to search). Furthermore, they

[16] Prices do not vary by these parameters.

[17] See FTC Matter 141 0200, docket no. 9372, "Respondent 1-800 Contacts, Inc.'s Proposed Findings of Fact and Conclusions of Law."

[18] See `https://coopervision.com/practitioner/ecp-viewpoints/eyes-coopervision/contact-lens-nearly-every-wearer`.

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

may not visit other stores even upon finding a high price at a visited store on account of search costs, thus accepting higher prices than they would absent search costs. In models of search over match values, search costs do not necessarily blunt consumer price sensitivity and may in fact amplify it. Indeed, Choi et al. (2018)—who argue for the relevance of models of search over match values for e-commerce—show that search costs may lower prices in oligopolistic competition in such models. This reflects that the sensitivity of search to prices may amplify the overall response of sales to prices. The divergence between the search models above is relevant, e.g., for analysis of the effect of search costs on the mean payment over the minimum available price. In reality, consumers likely search over both price and non-price characteristics, and I choose to model search over the latter based on features of the setting under investigation as enumerated above. I leave study of the article's sensitivity to the choice of search model to future research.

4.3 Justification of sequential search model

Empirical consumer search studies tend to use either sequential or fixed-sample search models. I specify a sequential model for two reasons. First, sequential search better describes cross-store search for contacts. In fixed-sample search, the consumer (i) chooses which stores to visit and (ii) proceeds to visit all of these stores simultaneously before ending search. Due to the technology of web browsing, I expect a consumer to visit one store at a time. If so, the consumer has no reason to commit to visiting every initially selected store or to not search beyond the initially selected stores.

4.4 Probabilities of sequences of search efforts

Search efforts at different times are related by state dependence and persistent tastes. In this section, I provide an expression for the probability of a consumer's sequence of search efforts across time. 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. Next, let h_{i1} denote consumer i's initial state, let θ denote an arbitrary parameter vector, and let θ_0 denote the true parameter vector. The model provides conditional probabilities of search effort outcomes that I denote by $\Pr(y_{it}|I_i, p_{it}, h_{it}, \gamma_i; \theta)$. The overall conditional probability of consumer i's sequence of search efforts

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

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

Two econometric problems arise when integrating over γ_i. 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 require favourable tastes for the store to justify buying from it despite its high price. Similarly, consumers with prescriptions for the second brand may buy from f despite disliking the store to take advantage of its low price. Thus, the prices faced by a consumer and the consumer's tastes for stores are generally correlated conditional on the initial state. Online Appendix O.7 presents evidence that consumers who previously purchased lenses from a high-price seller especially like that seller.

The problems noted above invalidate the simplifying assumption that $G(\gamma_i|p_i, h_{i1}; \theta)$ depends neither on the initial state nor on prices. I address these problems by specifying a parametric model of γ_i's conditional distribution:

$$\gamma_{if} \mid (p_i, h_{i1}) \sim \begin{cases} N\left(\lambda \tilde{p}_{jf}, \sigma_\gamma^2\right), & h_{if1} = 1 \\ N\left(\Gamma_{fg}, \sigma_\gamma^2\right), & h_{ig1} = 1 \end{cases} \tag{10}$$

where g denotes a seller other than f; λ, Γ_{fg}, and σ_γ^2 are parameters; and $\tilde{p}_{if}$ is the relative price of consumer i's brand at f at i's first observed purchase:

$$\tilde{p}_{if} = \left(p_{if1} - \frac{1}{F}\sum_{g=1}^{F} p_{ig1}\right) / \frac{1}{F}\sum_{g=1}^{F} p_{ig1}.$$

The parameter λ governs the extent to which consumers who initially buy from f despite its high price 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, σ_γ^2 governs variability in persistent store tastes.

My approach to modelling γ_i is based on commonly used approaches in panel data settings. First, specifying a parametric distribution of γ_i conditional on the initial state follows Wooldridge (2005).[20] Second, modelling the dependence of γ_i on prices conditional on the initial state follows the correlated random effects (CRE) approach used to address endogeneity in panel data models (Chamberlain 1980, Mundlak 1978, Wooldridge 2010). CRE approaches involve modelling the dependence of unobserved heterogeneity on regressors.

5 Price competition

To analyze market power, I specify a pricing model. The model is static in that each retailer sets a time-invariant price for each brand. The model captures, however, long-run responses of consumer states to prices. An alternative approach is to study Markov perfect equilibria (MPE) of a dynamic game wherein sellers adjust prices in response to changes in payoff-relevant state variables. In my setting, these state variables are the shares of

[20] As discussed by Wooldridge (2005), the primary alternative is to specify the distribution of the initial state conditional on unobserved heterogeneity, which is far more computationally burdensome than the approach taken here.

consumers of each (γ_i, α_i) type who previously purchased from each seller. Whereas it is straightforward to find Nash equilibria of the static model, solving for MPE requires model simplifications given the infinite dimensionality of the state space. A dynamic pricing model can realistically capture effects of contemporaneous price changes on future sales; the static model, however, captures these effects by accounting for long-run responses of consumer states to prices. Online Appendix O.8 details the dynamic model, which yields results similar to those from the static model.

A challenge in modelling static pricing is accounting for state dependence in demand. I propose a *long-run demand* system that represents consumer choice under the long-run distribution of states. This system involves *long-run state probabilities* $\{\rho_f(p, \gamma_i, \alpha_i)\}_{f=1}^{F}$, defined as the solutions of

$$\rho_f(p, \gamma_i, \alpha_i) = \sum_g \sigma_{fg}(p, \gamma_i, \alpha_i)\rho_g(p, \gamma_i, \alpha_i) \qquad \forall f, \tag{11}$$

where $\sigma_{fg}(p, \gamma_i)$ is the probability with which a consumer with state $h_{igt} = 1$ buys from store f given prices p. The right-hand side of (11) 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 search is $\rho_g(p, \gamma_i, \alpha_i)$. Thus, condition (11) imposes that the share of type-(γ_i, α_i) consumers in state f is stable. Letting H denote the unconditional distribution of (γ_i, α_i), the long-run market share for store f is

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

6 Estimation

6.1 Indirect inference

I estimate the model using an indirect inference (I-I) estimator.[21] This approach involves (i) computing auxiliary statistics $\hat{\beta}_n$ on the sample; (ii) simulating outcomes under a trial parameter value θ using the model; and (iii) computing the statistics on the simulated data, letting $\tilde{\beta}_n(\theta)$ denote the statistics computed on the simulated data. The I-I estimator $\hat{\theta}$ minimizes a measure of the distance between $\hat{\beta}_n$ and $\tilde{\beta}_n(\hat{\theta})$:

$$\hat{\theta}_n = \arg\min_{\theta} \, (\hat{\beta}_n - \tilde{\beta}_n^H(\theta))' \hat{\Omega}_n (\hat{\beta}_n - \tilde{\beta}_n^H(\theta)) \tag{12}$$

where $\hat{\beta}_n$ are ordinary least squares (OLS) estimators computed on the sample and $\tilde{\beta}_n^H(\theta)$ are the same OLS estimators computed on outcomes simulated under θ conditional on $\{x_i, h_{i1}\}_i$, outcomes simulated $H = 50$ times for each panelist. I simulate outcomes for a panelist by first drawing $\{\gamma_{if}\}_f$ under θ conditional on $\{x_i, h_{i1}\}_i$ according to the conditional joint distribution (10). To simulate the outcome of the consumer's first search effort, I compute the probability of each search effort outcome using the closed-form expressions obtaining under the article's maintained parametric distributions. These probabilities allow me to draw a search effort outcome without simulating multiple random elements $\{(\varepsilon_{ift}, \kappa_{ift})\}_{f \in F}$ and then determining which the associated search effort outcome by identifying the set of utility inequalities that the simulated random elements satisfy. The simulated outcome of the search effort implies a state h_{i2} for the consumer's next search effort. I similarly simulate the consumer's following search efforts.

The $\hat{\Omega}_n$ object in (12) is a weighting matrix; I use an approximately optimal weighting matrix as discussed in Online Appendix O.5. This appendix

[21] See Gouriéroux et al. (1993). I use an I-I estimator instead of a maximum likelihood estimator (MLE) because that MLEs tend to exhibit poor finite-sample performance in discrete-choice settings with many low probability potential outcomes; see Krasnokutskaya and Seim (2011), Pakes et al. (2007), and Collard-Wexler (2013).

also provides an expression for the I-I estimator's asymptotic variance. I substitute estimates for true parameter values and empirical analogues for their population counterparts into this expression to obtain an estimator of the asymptotic variance. I in turn use the resulting asymptotic variance estimate to compute standard errors.

To facilitate the treatment of past purchases as observable variables in studying state dependence, I drop each consumer's search efforts made before and including the consumer's first purchase. This reduces the number of transactions from 1956 to 1160. Despite the reduction in the sample size, I obtain statistically significant estimates of each of the model parameters.

I describe the regression coefficients included in $\hat{\beta}_n$ and the parameters that they are included to target in Appendix B. Several of these coefficients are sample averages. To summarize the coefficients:

(i) *Stores' visit shares*: shares of search efforts with a visit to each store.

(ii) *Stores' purchase shares*: shares of search efforts with a purchase from each store.

(iii) *Consideration set size*: share of search efforts wherein the consumer visited all stores.

(iv) *Inertia share*: share of search efforts with the same first-visited store as the associated consumer's previous search effort.

(v) *Inertia regression*: regressions of indicators for whether a consumer visited a store on lagged purchases.

(vi) *Role of lagged price*: regressions of an indicator for buying from 1800 on the contemporaneous and lagged price at 1800.

(vii) *Price sensitivity*: regression of purchase decisions on prices.

(viii) *Cross-visiting*: shares of consumers in various states who visit each store.

(ix) *Dependence of tastes and prices conditional on initial state*: regressions of indicators for whether the consumer visited a particular store on the ratio of the store's price to the average price across stores.

(x) *Price sensitivity heterogeneity*: regression of transaction price relative to the minimum available price for the consumer's brand on an indicator for the consumer's household income exceeding $75,000.

Appendix B details these statistics. It also reports their values on both the estimation sample and on data simulated from the model at the baseline parameter estimates. Further, Online Appendix O.11 characterizes the sensitivity of the parameter estimates to the values $\hat{\beta}_n$ of the auxiliary statistics. The results in Online Appendix O.11 are consistent with the identification discussion in the proceeding subsection.

In estimation, I de-mean the prices that enter consumer utilities by the average price across stores conditional on brand and time. Without de-meaning prices, the model would mechanically predict a larger probability of choosing the outside option for expensive brands.

6.2 Identification

The model features three groups of parameters: those affecting search costs ($\bar{\kappa}_f$), those affecting consumers' purchasing utilities in a static fashion (q_f, α_0, and α_1), and those affecting consumers' purchasing utilities in a dynamic fashion (ϕ and the parameters governing the distribution of γ_{if}).[22] Here, I describe how parameters in each group are identified.

First consider the separate identification of parameters affecting search costs and those affecting purchasing utilities. The challenge here is that a store f's

[22]Note that the assumption that search costs are iid across time implies that search costs do not affect consumer behaviour in a dynamic manner. With that said, it appears possible to separately identify persistence in search costs from persistence in unobserved tastes for stores based on their different implications for search versus purchase behaviour. The argument in the proceeding paragraph suggests why this is the case.

low sales could owe to either high costs of visiting store f or low consumer preferences for purchasing from store f (i.e., low indirect utilities u_{ift}). These two explanations are separately identified with data on the search process. Indeed, the extent to which explanation holds is identified by the rate at which consumers who visit the store ultimately buy from the store. A store f having many visitors but few buyers indicates that it has low search costs but also low indirect utilities. Conversely, a store f having few visitors but a high rate of converting visitors into buyers indicates that it has high search costs but high indirect utilities.

Price endogeneity poses a challenge in identifying the static preference parameters. Here, price endogeneity arises from the fact that unobserved retailer quality influences retailer pricing. The first assumption that permits identification of the price coefficient parameters is that retailer quality does not vary across brands. This assumption permits the specification of retailer fixed effects that capture brand-invariant retailer quality. With these retailer fixed effects specified, the information that identifies the price coefficient is the covariance across brands between (i) stores' relative prices for a brand and (ii) stores' relative market shares for a brand. Figure 1 describes this covariance. The assumption underlying the identification argument above would fail if retailers' quality varied across brands of contact lenses in a manner that correlated with prices. Given that return policy and customer service assurances on retailers' websites did not condition on the brand purchased, this sort of violation seems unlikely.

The identification of the price coefficient parameters also relies on the assumption that consumers cannot substitute across brands of lenses. The model explains the negative covariance between relative prices and relative market shares using substitution across stores by consumers with a fixed brand.[23] Another explanation for this covariance is substitution across

[23]Given that a consumer is limited to choosing a single prescribed brand in the model,

brands. To illustrate, a consumer who enjoys 1800 may encourage their doctor to prescribe a brand that 1800 sells for a relatively low price. Such behaviour would also contribute to a negative covariance between a retailer's relative price for a brand and its relative market share in sales of that brand. By attributing the entirety of the covariance to within-brand substitution, I risk overstating price sensitivity α_i. With that said, the assumption of within-brand substitution is defensible given that consumers do not have complete control over their brands given that medical professionals ultimately prescribe brands, in part due to patients' optical needs (e.g., consumers with astigmatism require brands specific to this condition).

Last, I discuss the identification of parameters affecting choice dynamics. The primary challenge here is the separate identification of state dependence and unobserved heterogeneity γ_{if}. Although both elements of preferences promote inertia, they have different empirical implications. Conditioning on a consumer, a model with switching costs features dependence of a consumer's choice on the previous choice whereas a model without switching costs does not. Additionally, in the context of my model, stronger persistent store tastes generate greater correlation between contemporaneous choice and choice two or more purchasing occasions ago conditional on the choice in the previous purchasing occasion than does strong state dependence. This motivates my inclusion of a regression of the consumer's contemporaneous choice on lagged choices among the I-I auxiliary statistics. Dubé et al. (2010) discuss the use of covariate variation for separate identification. Consider a consumer who buys from store f before store f raises its price. The consumer responds by switching to purchase from store g, after which f restores its original price. Under extensive state dependence, the consumer is likely

and all choice is between sellers of this one brand, brand fixed effects would not be identified; they would shift the attractiveness of all alternatives equally. For the same reason, unobserved brand characteristics—a usual source of price endogeneity—do not cause an identification problem in the model.

to purchase from store g, but if the consumer's initial purchase from store f stemmed from favourable tastes for f, then we would expect the consumer to switch back to f. These different implications for switching patterns motivate the "Role of lagged price" I-I auxiliary statistics. One weakness of this approach is that I do not observe repeat purchasing by all consumers—see Table 3—and thus estimates obtained using the approach reflect the preferences of the subset of consumers who do search repeatedly. By assuming a constant state dependence parameter, I extrapolate the extent of state dependence found among repeated consumers to the entire population. The validity of this approach requires that state dependence does not systematically vary across groups of consumers who make different numbers of purchases in the data.

7 Parameter estimates

Table 7 reports parameter estimates. The "Baseline" panel reports results for the baseline model whereas the "Stripped down" panel reports results for a specification without state dependence or persistent heterogeneity. Under the baseline estimates, retailer-specific median search costs among consumers with household incomes under \$75,000 range from \$0.41 to \$1.29. These median search costs are low, relative to the median transaction price of about \$30. In addition, search costs are lowest for 1800 and highest for VD, suggesting that 1800's sales advantage could owe to greater consumer awareness of 1800 relative to its rivals. The estimates suggest, however, that taste heterogeneity and state dependence exercise significant influence on consumer decisions: the σ_γ^2 parameter estimate indicates substantial dispersion in persistent tastes for retailers, the estimate of ϕ implies that having previously purchased from a store raises the consumer valuation of the store by \$4.48 for the median consumer, and the negative estimate of α_1 indicates that higher-income consumers are less price sensitive.

A comparison of the "Baseline" and "Stripped down" results suggests that ruling out state dependence and persistent taste heterogeneity leads to an overstatement of search costs. When these aspects of consumer preferences are ignored, the model requires higher search costs to rationalize highly limited search.[24]

Table 8 reports estimates of the mean consumer taste for retailer f $q_f + \mathbb{E}[\gamma_{if}]$, which I interpret as retailer quality. In line with 1800 selling more than its rivals at higher prices, 1800's estimated quality exceeds those of WM and VD. There are various reasons to expect that 1800 boasted higher quality than VD. In October 2007, 1800's website mentioned that 1800 employed 300 call centre representatives trained in ocular health and answered 90% of calls within 10 seconds. The website also stated that 1800 shipped 90% of orders within 24 hours, offered a "100% satisfaction guarantee" return policy, and accepted returns of unused lenses upon prescriptions changes. By contrast, VD's website in September 2007 did not describe customer service, shipping, or a return policy. A 2017 response by 1800 to a Federal Trade Commission complaint also suggested that offering a high quality of service was central to 1800's business strategy, whereas VD focused on offering lower prices.[25] Furthermore, reviews by online publications suggest that 1800 remains known for its relatively high service quality by 2024.[26] The fact that

[24]The large estimates of median search costs, as well as the large standard errors for these estimates, reflect both higher estimated search costs (compare the $\bar{\kappa}_f$ parameter estimates) and lower estimates of price sensitivity α_0.

[25]See FTC Matter 141 0200, docket no. 9372, "Respondent 1-800 Contacts, Inc.'s Proposed Findings of Fact and Conclusions of Law." The document reads, first, that "1-800 Contacts' founder and former CEO explained that the company's strategy of positioning itself within the market as having the best customer service was based on recognizing that it would be easy for another retailer to match prices but it is very difficult to create a brand and provide great service" and also that "The perception from customer surveys was that companies like Vision Direct [...] offered a price discount, but service quality suffered; for example, they were difficult to reach, there were problems with the contact lenses shipped such as lenses that had already expired, and sketchy packaging, among other issues."

[26]In listing 1800 first in its "Best Places to Buy Contacts Online in 2024, US News and World Report cited its "customer service available 24/7," "free exchanges if your prescription changes," and "generous return/exchange policy." See here: `https://www.usnews.com/360-reviews/personal/best-places-to-buy-contacts-online`. Addi-

1800 has continued to prioritize service quality since 2007–2008 suggests that applicability of this article's empirical findings to contemporary contact lens e-commerce.

The idiosyncratic tastes for retailers γ_{if} could reflect heterogeneity in tastes for the services that retailers differentially offer (e.g., quick shipping, generous return policies) or retailer marketing strategies targeted at specific consumer segments. Taste heterogeneity of this sort likely correlates with consumer characteristics. I find that consumer characteristics substantially explain purchase behaviour: a multinomial logistic regression of store of purchase on consumer characteristics yields a McFadden's R^2 of 0.23. Furthermore, the estimates suggest that consumers who have higher incomes, who have broadband, and who live in smaller households are more likely to purchase from 1800. Such consumer characteristics are determinants of the γ_{if} unobservables. Online Appendix Table O.13 and Figure O.3 detail the regressions outlined above.

Online Appendix O.9 reports estimates for books e-commerce. The results are qualitatively similar to those for contact lenses — the estimated median search cost is \$0.90, close to the estimates for contact lenses.

Table 9 reports various descriptive statistics computed on both the estimation sample and on search outcomes simulated from the estimated model to facilitate an assessment of model fit. The table indicates that the model closely fits moments of the estimation sample.

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tionally, the product review website CNET claimed that 1800 had the best customer service in its review of online contact lens retailers. See here: `https://www.cnet.com/health/personal-care/best-place-to-buy-contacts-online/`.

Table 7: Selected parameter estimates

	Baseline		Stripped down	
Parameter	Estimate	SE	Estimate	SE
q_{1800}	-0.335	0.108	-0.101	0.162
q_{WM}	-2.234	0.166	-1.207	0.250
q_{VD}	0.300	0.086	0.243	0.042
ϕ	0.493	0.126	-	-
α_0	0.110	0.014	0.016	0.024
α_1	-0.084	0.042	-	-
$\bar{\kappa}_{1800}$	-2.711	0.352	-0.310	0.304
$\bar{\kappa}_{\text{WM}}$	-1.887	0.143	0.403	0.228
$\bar{\kappa}_{\text{VD}}$	-1.546	0.221	0.918	0.127
$\Gamma_{1800,\text{VD}}$	-3.257	0.426	0.000	0.000
$\Gamma_{\text{VD},1800}$	-5.574	1.080	0.000	0.000
σ_γ^2	1.298	0.172	-	-
λ	3.986	1.570	-	-
Med. search cost (1800)	0.414	0.166	28.187	47.338
Med. search cost (WM)	0.930	0.144	51.323	77.364
Med. search cost (VD)	1.294	0.343	75.051	115.938

Note: The "Estimate" columns provide point estimates obtained from the indirect inference estimator outlined in Section 6 whereas the "SE" columns report standard errors. I compute standard errors for estimates of the parameters using an analytical expression for the asymptotic variance of indirect-inference estimators; see Online Appendix O.5 for details. I then compute standard errors for the median search costs (in dollars) using the delta method. Each "Med. search cost" figure is the median search in dollar terms for a particular retailer among consumers with household income under \$75,000. Additionally, Γ_{fg} is the mean value of γ_i among consumers with initial state h_{i1} given by $h_{ig1} = 1$.

Table 8: Estimates of store quality

Store f	Mean taste for store f $Q_f = q_f + \mathbb{E}\gamma_{if}$
1800	-1.22
WM	-3.37
VD	-3.67

8 Counterfactual analysis

8.1 Sources of limited consideration

To understand sources of limited search, I simulate search under counterfactual consumer preferences and assess resulting changes in consumer behaviour. This procedure involves simulating search effort outcomes 50 times

Table 9: Model fit

	Share visiting one store	Mean # of visits	Share buying from any	1800	VD	Share paying > min. price	Mean overpay
Observed	0.82	1.20	0.61	0.36	0.22	0.66	3.95
Baseline	0.84	1.18	0.55	0.34	0.20	0.67	4.13

Notes: the table compares observed and simulated search efforts. "Share paying > min. price" reports the share of purchases occurring at a price above the minimum available price for the consumer's brand whereas "Mean overpay" reports the mean difference between the transaction price and the minimum available price.

for each consumer conditional on prices, prescriptions, and initial states. The counterfactual preference changes include

(i) Reducing the median search cost from its estimated value to zero.

(ii) Reducing the state dependence parameter ϕ from its estimated value to zero.

(iii) Reducing vertical differentiation. This involves setting each retailer f's quality Q_f to $r\hat{Q}_f + (1-r)\bar{Q}$, where $\hat{Q}_f$ is f's estimated quality, $\bar{Q}$ is sales-weighted average quality across retailers, and $r \in [0, 1]$. I reduce r from one to zero.

(iv) Reducing horizontal differentiation. I do so by setting each consumer's retailer tastes γ_{if} to $r\gamma_{if} + (1-\gamma_{if})\bar{\gamma}_f$, where $\bar{\gamma}_f$ is the unconditional mean of γ_{if} and $r \in [0, 1]$. I reduce r from one to zero.

Figure 3 displays the results. Reductions in search costs, vertical differentiation, and horizontal differentiation all boost consumer consideration. State dependence plays a smaller role in limiting consideration. Limiting vertical differentiation leads some consumers who previously visited only 1800 to also consider VD, thus raising the average number of visited stores. Conversely, limiting horizontal differentiation leads some consumers who previously visited VD but not 1800 to begin visiting both retailers. This is because visits to VD despite 1800's advantage in terms of quality and search costs require favourable idiosyncratic tastes for VD; limiting these idiosyncratic tastes leads consumers preferring VD in the baseline to begin considering 1800. Reductions of horizontal differentiation eventually reduce consideration because they lead consumers who visited both 1800 and VD to only visit the former.[27] Although search costs contribute to limited consideration, only vertical and horizontal differentiation meaningfully influence the extent to which consumers pay above the minimum available price for contacts. Indeed, reducing vertical differentiation lowers mean overpayment whereas reducing horizontal differentiation raises it. The former finding reflects that—as shown by Figure 3c—reducing 1800's quality advantage over VD leads consumers to substitute to the latter store, which generally offers lower prices. Reducing horizontal differentiation has the opposite effect of boosting the mean overpayment. As noted above, consumers often buy from VD rather than 1800 despite the latter store's quality advantage because of idiosyncratic tastes for the former. Weakening these tastes leads VD consumers to substitute to 1800, thus boosting the mean overpayment.

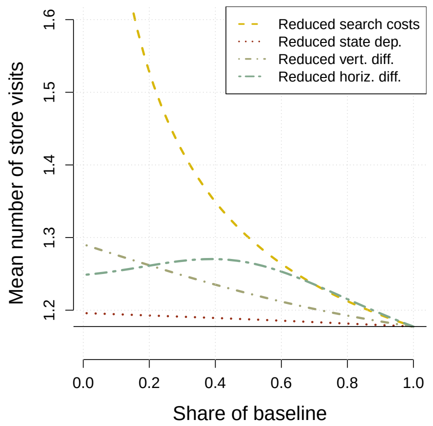
Online Appendix Table O.16 provides results in greater detail for several discrete changes in consumer preferences along with standard errors. Additionally, Online Appendix Table O.8 reports results for the books category, which are similar to those for contact lenses. State dependence, however, plays a larger role in limiting search than persistent unobserved tastes in the books category.

8.2 Sources of market power

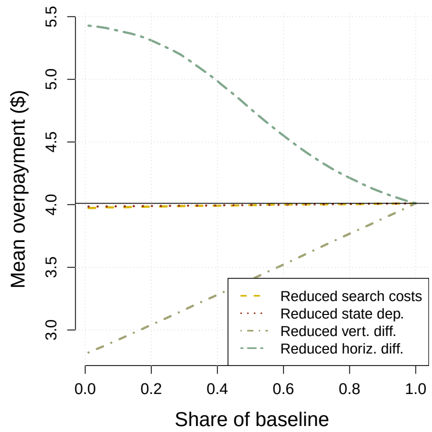
I assess sources of market power by simulating equilibrium markups under counterfactual consumer preferences using the pricing model of Section 5.

[27] Online Appendix Figure O.5—which displays changes in the share of consumers visiting VD, 1800, and both retailers as horizontal differentiation is reduced—documents this phenomenon.

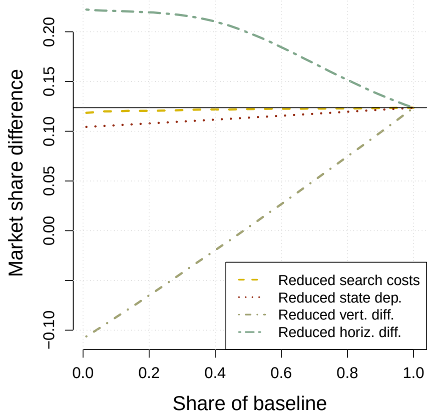
Figure 3: Counterfactual search patterns



(a) Mean number of visited retailers



(b) Mean payment over minimum available price ($)



(c) Difference in market share between 1800 and VD

Notes: the figure plots outcomes of counterfactual search efforts when each of search costs, state dependence, vertical differentiation, and horizontal differentiation are reduced from their baseline extent to zero in the manner described in the main text. The plotted quantities are averages over 5000 simulated search-effort histories (i.e., sequences of distinct search efforts over time) for each consumer in the estimation sample.

Under this model, each store f sets prices p_f to maximize long-run profits

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

given the prices of its competitors. In practice, I use σ_f^L under the model estimates and estimates of marginal costs mc_f obtained by solving firms' first-order conditions for profit maximization under observed prices and estimated long-run demand. Throughout this section, I focus on competition in sales of the toric variety of the popular Acuvue label.

The changes in 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 state dependence: set $\phi = 0$;

(iii) No vertical differentiation: equalize retailer quality $q_f + \mathbb{E}[\gamma_{if}]$ across retailers f at the sales-weighted average retailer quality; and

(iv) No horizontal differentiation: set $\gamma_{if} = \mathbb{E}[\gamma_{if}|f]$ for each consumer i and each store f.

Table 10 reports effects of counterfactual preference changes in percentage terms. Search frictions do not meaningfully affect retailer market power under the estimated model: reducing search costs does little to change markups.[28] Instead, Table 10 suggests that retailer differentiation drives markups and price dispersion. Eliminating 1800's vertical advantage leads to a 20.4% reduction in its markup, increases in rivals' prices, and an overall reduction in markups. This result implies that vertical differentiation sustains price dispersion. Shaked and Sutton (1982) argue that scope for quality differentiation softens price competition by allowing firms to select different quality levels and appeal to market segments with different tastes for quality. This argument seems applicable to contact lens e-commerce based on my results. Horizontal differentiation contributes by far the most to the average markup level, which falls by 54.9% upon its elimination. Figure 4 plots the distribution of markup changes across brands. This figure shows that the

[28] Recall that prices are known to consumers before search in the model. This is relevant as the extent of consumer knowledge of prices generally shapes the effect of search frictions on equilibrium prices. See, e.g., Choi et al. (2018).

results for brands other than Acuvue Toric are similar to those reported in Table 10.

Table 10: Counterfactual markup changes

Panel A: Point estimates (%)

Store	Low search costs	No state dependence	No vert. diff.	No horiz. diff.
1800	-1.1	-1.4	-20.4	-47.3
WM	5.5	1.9	22.6	-11.0
VD	-0.8	-3.4	26.2	-73.1
Average	-0.7	-2.0	-2.2	-54.9

Panel B: Standard errors

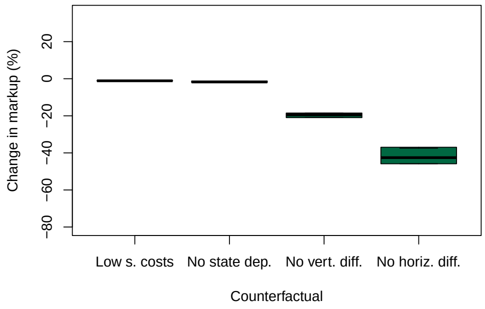
Store	Low search costs	No state dependence	No vert. diff.	No horiz. diff.
1800	0.3	1.1	3.1	3.6
WM	2.0	1.1	7.0	36.9
VD	0.4	1.1	8.8	6.1
Average	0.2	1.0	1.7	2.3

Note: This table presents estimates of percentage changes in markups for Acuvue Toric under counterfactual consumer preference changes. "Average" provides a sales-weighted average of retailer-specific changes. The standard errors were computed using a parametric bootstrap with 100 bootstrap draws.

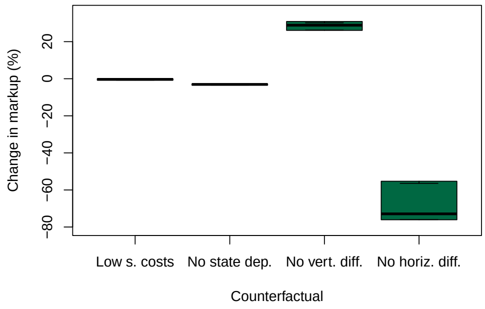
To a small extent, state dependence contributes to retailer market power. The contribution of state dependence to market power has implications for business practices that make switching between stores difficult. A reduction of state dependence could be achieved by, for example, an intermediary service to which the user uploads prescription and delivery information to be shared with other online retailers, thus reducing the hassle of switching. This proposed service resembles e-commerce platforms that provide an interface through which a consumer can interact with many retailers.

Search costs are small and do not meaningfully contribute. As such, easing search using, e.g., comparison tools or transparency regulations, is unlikely to combat market power. Given that searching across contact lens sites is

Figure 4: Markup changes across brands (medians and IQRs)



(a) 1800



(b) VD

Notes: this plot displays the interquartile range (i.e., 25th and 75h percentile) and median of counterfactual markup changes across brands in the estimation sample. It does so separately for 1800 and for VD.

similar to searching the web for other products, the same conclusion may hold for e-commerce more broadly.

8.3 Sources of the market leader's dominance

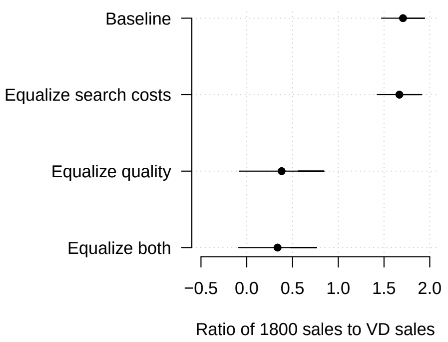
The dominance of 1800 in online contact lens sales in 2007–2018 and the following decade has two primary explanations: greater awareness or perceived superior quality among consumers could explain why 1800 outsells its rivals at higher prices. Whereas greater awareness likely reflects 1800's investment in advertising, perceived superior quality likely reflects 1800's investments in logistics and customer service. I quantitatively assess these explanations by simulating search behaviour under the following changes in consumer preferences:

(i) Equalize search costs: set 1800's search cost parameter $\bar{\kappa}_{1800}$ to the estimate of VD's search cost parameter $\bar{\kappa}_{\text{VD}}$;

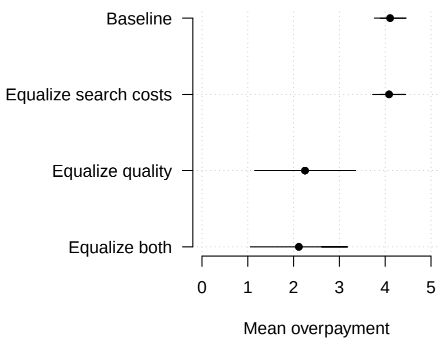
(ii) Equalize quality: set q_{1800} to the estimate of $q_{\text{VD}}+\mathbb{E}[\gamma_{i,\text{VD}}]-\mathbb{E}[\gamma_{i,1800}]$ so as to equalize retailer quality $q_f+\mathbb{E}[\gamma_{if}]$ across retailers $f \in \{1800, \text{VD}\}$; and

Figure 5: Awareness versus quality differentials

(a) 1800's sales advantage



(b) 1800's sales advantage



Notes: this figure provides estimates of (a) the ratio of 1800's sales to VD's sales and (ii) the mean consumer payment for contact lenses in excess of the minimum available price for their prescribed brand under various counterfactual parameters as described in the main text. The black circles provide point estimates whereas the black bars provide 95% confidence intervals. I compute the confidence intervals using a parametric bootstrap procedure with 100 replicates. See

(iii) Equalize both: impose both preferences changes (i) and (ii).

Figure 5 displays the results of the exercise. The figure shows that the quality differential rather than the awareness differential between the largest two contact lens retailers primarily explains 1800's sales advantage over VD: equalizing the retailers' search cost distributions reduces the ratio of 1800's to VD's sales from 1.71 to 1.67, whereas equalizing retailer quality reduces this ratio to 0.38. The figure also shows that 1800's quality advantage underlies consumers' choices to buy contact lenses above their minimum available prices—equalizing quality reduces the mean overpayment by about half—whereas 1800's awareness advantage plays a negligible role in inducing consumers to pay over the minimum available prices for their prescribed brands.

9 Conclusion

This article applied a consumer search model to a panel dataset describing browsing and purchasing in contact lens e-commerce. One contribution of the article is its development of a tractable empirical framework for studying panel 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. Another contribution is in drawing substantial conclusions about limited consideration and market power in e-commerce. The analysis suggests that both search costs and seller differentiation explain limited search, but that only the latter accounts for market power in e-commerce. This result suggests further inquiry into the sources of seller differentiation as a direction for future research.

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Appendices

A Construction of search effort panel

In constructing a search effort around a transaction, I include all visits to 1800 or VM in the K days before the transaction and all visits to WM in the $K' \leq K$ days before. In the baseline specification, $K = 14$ and $K' = 2$. I consider alternative values in Section 3. The reason for using a shorter time window for WM is that consumers may visit Walmart for purposes unrelated to contact lenses; a shorter window may exclude such visits. 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 retailers within R days (1800 and VD) or R' days (WM) of this visit, and I assign these visits to the search effort of the initial visit. In the baseline specification, $R = 7$ and $R' = 2$. I proceed to add visits that are within R (1800 and VM) or R' (WM) days of visits that have already been added to the search effort, and I continue to iteratively add visits until no more visits are added. In the books, iPods, PS3s, and DVDs categories, consumers are not limited by prescriptions to buy a particular product. This renders untenable the assumption that a visit not resulting in a transaction represents a search effort for a known product. I therefore do not construct search efforts that include only non-purchase visits for these categories. To illustrate, if a consumer visits apple.com and does not buy an iPod at a point close in time to this visit, then I would not incorporate the visit to apple.com in any search effort. If I observed a consumer visiting apple.com before purchasing an iPod from bestbuy.com, I would add the visit to apple.com to the search effort associated with the purchase from Best Buy.

B Auxiliary statistics of indirect-inference estimator

The following list describes the I-I auxiliary statistics:

(i) *Stores' visit shares*: the mean of an indicator for whether the consumer visited each store f. These statistics target the $\bar{\kappa}$ parameters.

(ii) *Stores' purchase shares*: for each retailer f, the mean of an indicator for whether the consumer purchased from f. These statistics target the q_f parameters.

(iii) *Consideration set size*: the mean of an indicator for whether the consumer visited all available stores. This statistic targets $\bar{\kappa}$.

(iv) *Inertia share*: the share of search efforts with the same first-visited retailer as the associated consumer's previous search effort. The dataset for this regression excludes consumers' first search efforts in the estimation sample. This statistic targets ϕ and parameters governing the distribution of γ_i.

(v) *Inertia regression*: coefficients from a regression of an indicator for whether a search effort included a visit to store f on store indicators and indicators for whether the consumer bought from f in the previous search effort and in the search effort before that. The dataset for this regression includes three observations for each search effort for which t exceeds three, one for each store. These statistics target ϕ and parameters governing the distribution of γ_i.

(vi) *Role of lagged price*: coefficients from an indicator for whether a search effort ended in a transaction at 1800 on the price of the consumer's brand at 1800 during the search effort t and during the previous search. These statistics target ϕ and parameters governing the distribution of γ_i.

(vii) *Price sensitivity*: coefficients from a regression of an indicator for whether a search effort ended in a transaction at store f on store indicators and the price at f. The regression dataset includes three observations for each effort, one for each store. These statistics target α_i and the q_f parameters.

(viii) *Cross-visiting*: for each pair of distinct stores (f, g), the mean across search efforts in which the consumer's state is given by $h_{igt} = 1$ of an indicator for whether the search effort included a visit to f. These statistics target the parameters Γ_{fg}.

(ix) *Dependence of tastes and prices conditional on initial state*: the slope coefficient from a regression of an indicator for whether a consumer visited store g 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 stores. I use the prices from the time of the consumer's first-observed purchase. I use each store $g \neq f$ in the regressions. This statistic targets λ.

(x) *Price sensitivity heterogeneity*: the slope coefficient from a regression of $(p_{it}^{\text{trans}} - p_{it}^{\text{min}})/p_{it}^{\text{min}}$ on an indicator for consumer i's income exceeding \$75,000. Here, t indicates a transaction, p_{it}^{trans} indicates the transaction price, and p_{it}^{min}

Table 11: Auxiliary model statistics computed on estimation sample

Statistic	Data ($\hat{\beta}_n$) Value	SE	Model ($\tilde{\beta}_n(\hat{\theta})$)
Share visiting 1800	0.688	0.014	0.683
Share visiting WM	0.145	0.010	0.149
Share visiting VD	0.360	0.014	0.348
Share buying 1800	0.337	0.014	0.356
Share buying WM	0.024	0.005	0.019
Share buying VD	0.236	0.012	0.200
Share visiting every store	0.013	0.003	0.013
Inertia share	0.846	0.011	0.844
Inertia reg.: indicator for 1800	0.309	0.011	0.363
Inertia reg.: indicator for VD	0.115	0.010	0.137
Inertia reg.: indicator for WM	0.149	0.011	0.222
Inertia reg.: purchased from store last search effort	0.495	0.017	0.401
Inertia reg.: purchased from store two search efforts ago	0.392	0.018	0.400
Role of lagged price: slope for current price	-0.351	0.252	-0.235
Role of lagged price: slope for lagged price	0.023	0.240	0.093
Price sensitivity: slope	-0.155	0.070	-0.174
Cross-visiting: share of 1800 buyers visiting WM	0.116	0.009	0.124
Cross-visiting: share of 1800 buyers visiting VD	0.033	0.005	0.030
Cross-visiting: share of WM buyers visiting 1800	0.308	0.014	0.389
Cross-visiting: share of WM buyers visiting VD	0.128	0.010	0.191
Cross-visiting: share of VD buyers visiting 1800	0.193	0.012	0.177
Cross-visiting: share of VD buyers visiting WM	0.124	0.010	0.123
Dep. of tastes and prices cond. on initial state: slope	-0.302	0.098	-0.359
Price sensitivity heterogeneity	0.045	0.010	0.054

Notes: See Section 6 for a description of the auxiliary statistics. "SE" column reports asymptotic standard errors. "Model ($\tilde{\beta}_n(\hat{\theta})$)" provides the values of the auxiliary statistics as computed on data simulated from the model under the baseline parameter estimates $\hat{\theta}$.

indicates the minimum available price for the consumer's brand at the time of the transaction. This statistic targets α_1.