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

Michael Sullivan

Department of Economics, Yale University

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Abstract

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 assess these explanations with a consumer search and retailer pricing model that I estimate on data describing web browsing for contact lenses. My approach exploits the data's panel structure in estimating the extent of state dependence and taste heterogeneity. I find that seller differentiation is primarily responsible for limited consideration and market power.

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1 Introduction

The internet facilitates consumer learning about retailers' product offerings, yet consumers exhibit severely limited consideration of sellers and products in online markets. Additionally, online markets for minimally differentiated goods often feature considerable price dispersion, which suggests the presence of market power.[1]

What impedes expansive consumer knowledge and cut-throat price competition in e-commerce markets for homogeneous products (e.g., particular book titles or contact lens boxes)? If internet search were truly costless and sellers' product offerings truly undifferentiated, consumers would compare a product's prices across all available retailers and purchase from the lowest-price seller. That online markets for minimally differentiated products feature limited consideration and price dispersion could reflect that search frictions remain significant online — consumers may buy products above their minimum available prices to avoid further search. Much of the empirical online search literature emphasizes this explanation. When consumers dislike searching, they may buy products above their minimum available prices to avoid further search.[2] Seller differentiation, however, can also explain limited consideration. Even when the characteristics of the product that arrives on a consumer's doorstep do not depend on the consumer's selected retailer, a consumer may differentially value retailers for non-price reasons. Characteristics such as shipping efficiency, reputation, and customer service may vertically differentiate retailers. Consumers who value one-stop shopping—i.e., purchasing varied goods at a single store—may also value the breadth of a retailer's product assortment. Retailers are also differentiated by their user interfaces and branding. Additionally, consumers may prefer to buy from stores that they have previously patronized due to habit formation, store loyalty, or switching costs. If 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).

[2] Hortaçsu and Syverson (2004), Hong and Shum (2006), and Moraga-González and Wildenbeest (2008) invoke search frictions to explain for price dispersion in product markets with little differentiation. Jolivet and Turon (2019) use search frictions *inter alias* to justify consumer choices of dominated alternatives.

consumer knows at the outset of search that they are unlikely to buy from a seller, then the consumer may not visit the seller even under negligible search costs.

Understanding limited search online is important for understanding competition in e-commerce markets and the efficacy of policies intended to remedy market power. If search frictions, e.g., were trifling, then a policy enhancing consumer information would not make e-commerce more competitive.

I empirically investigate sources of limited consideration and market power in US contact lenses e-commerce, an industry that features a small number of retailers that sell lenses purchased from a common set of manufacturers. This setting is attractive for the study of consumer search because consumers require *brand-specific* prescriptions to buy lenses. A consumer prescribed Acuvue Oasys lenses, for instance, cannot substitute the prescription to buy Acuvue 2 or Freshlook lenses. This market feature allows me to credibly assume that search occurs across stores and not across products. Several studies of online search analyze product categories—e.g., books—in which consumers likely search across both products and retailers.[3] In fact, I find that—in books and electronics e-commerce—consumers conduct extensive search within online retailers but little search across retailers. Although contact lens e-commerce is more suitable than books e-commerce for studying cross-site search, I additionally analyze the latter and reach similar conclusions as for contact lenses.

The analysis draws upon panel data of web browsing and transactions. The first analyses describe limited consideration and prices in US e-commerce in 2007–2008; they reveals that consumer consideration is severely limited despite significant cross-seller price variation, which suggests gains from search. In 83% of observed search efforts for contact lenses, the consumer visits only one retailer. Also, the average transaction price for contact lenses is 16% above the

[3]Hong and Shum (2006) and De Los Santos et al. (2012) study search for a specific book title across retailers. Moraga-González and Wildenbeest (2008) study search for a specific computer memory chip product across retailers. Morozov et al. (2021) study search across cosmetics products within a retailer. Jolivet and Turon (2019) study search for a particular CD product within a page of adverts on an e-commerce platform.

minimum price available among the three major retailers for the consumer's prescribed brand. These results are similar for other products: in search for books, iPod music players, PlayStation 3, and DVDs, most consumers visit only one or two online retailers. Additionally, consumers pay on average 35.3% more for books than if they bought at the minimum available price.

To understand limited consideration and retailer market power, I develop a model of sequential consumer search and of retailer price competition. A one-to-one mapping between search effort outcomes and chains of inequalities relating consumer utilities facilitates estimation of the model. I develop and use this mapping, which is implied by the optimal search strategy of Weitzman (1979), to obtain closed-form choice probabilities. Additionally, I develop and apply techniques for estimating a search model on panel data. These techniques address an initial conditions problem and an endogeneity problem, that latter of which arises because, conditional on a consumer's initially observed purchase, the price charged by a store is correlated with the consumer's unobserved tastes. The pricing model features retailers who anticipate the long-run dynamic effects of their pricing decisions.

I find that the low levels of search are primarily explained by store differentiation in spite of low search costs. Eliminating persistent heterogeneity in consumers' store tastes raises the share of consumers visiting multiple stores by over 45 percentage points whereas cutting the median search cost in half only raises this share by about 10 percentage points. The estimated median search cost is 74 cents per website visit, which is much lower than estimates appearing in the literature for comparable settings. Estimates from a model without state dependence and horizontal store differentiation imply a median search cost exceeding $13, suggesting the importance of flexibly modelling taste heterogeneity in estimating search frictions. Additionally, state dependence and consumers' persistent heterogeneous store tastes for stores give rise to equilibrium markups whereas search costs do not significantly contribute to markups. Indeed, removing state dependence reduces equilibrium markups for one popular brand of contact lenses by about 3.5% at the two leading online contact lens retailers, and removing persistent unobserved heterogeneity in consumer tastes for stores reduces equilibrium markups at these retailers by over 35%. Lowering the median search cost by half, meanwhile, barely changes markups. This suggests that search costs are not responsible for market power in contact lens e-commerce. The results for books e-commerce are similar to those for contact lens e-commerce.

Although I study e-commerce, brick-and-mortar retail similarly features competing retailers of minimally differentiated goods that possess market power, and thus my results suggest sources of market power in offline retail. Contact lens e-commerce especially resembles the pharmacy industry wherein consumers purchase homogeneous, prescribed products from competing, oligopolistic retailers. My results suggest that heterogeneity in tastes for pharmacies (owing, e.g., to distance or marketing) and state dependence could explain limited search and market power in the retail prescription drug market.

1.1 Related literature

This article's primary 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, which partly explained price dispersion. Early articles in the empirical consumer search literature—namely Hong and Shum (2006), Hortaçsu and Syverson (2004), and Moraga-González and Wildenbeest (2008)—relied on search frictions to explain price dispersion in homogeneous goods markets.[4] Some recent articles feature models with features other than search frictions that may contribute to price dispersion. Honka (2014) introduces state dependence but not persistent unobserved tastes, whereas Morozov et al. (2021) alternatively model persistent preference heterogeneity but not state dependence. I incorporate both state dependence and persistent

[4]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.

unobserved heterogeneity. Panel data and novel methods facilitate my estimation these components of consumer preferences. Additionally, my article is similar to Morozov et al. (2021) in emphasizing the interaction of preference heterogeneity and search frictions.

My secondary contribution is the development of techniques for estimating a sequential search model on panel data. These techniques draw on the Weitzman (1979) search strategy. Additionally, I follow Moraga-González et al. (2022) in (i) inverting an equation defining reservation utilities and (ii) specifying a search cost distribution to obtain closed-form choice probabilities.

Some articles in the empirical search literature relating to my own are De Los Santos et al. (2012) (e-commerce bookstores), Morozov et al. (2021) (e-commerce for cosmetics), Koulayev (2014) (online hotel booking), Jolivet and Turon (2019) (CDs), Honka (2014) Honka and Chintagunta (2017) (automobile insurance), and Allen et al. (2014) (mortgages).[5] Sorensen (2000) studies sources of price dispersion among pharmacies, a setting similar to my own, and Dubois and Perrone 2015 study limited search of supermarkets. My article also relates to a literature on inertia in consumer choice, especially Dubé et al. (2009) and Dubé et al. (2010). Last, my work 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.

The remainder of the article proceeds as follows. Section 2 discusses the setting and data. Section 3 conducts descriptive analyses. Sections 4 and 5 present the model. Section 6 outlines estimation and Section 7 reports parameter estimates. Section 8 describes counterfactual analyses. Section 9 concludes.

2 Setting and data

This study's primary data source is the Comscore Web Behavior Panel for 2007–2008. This dataset includes online browsing and transactions activities

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

for a panel of US households.[6] As noted by De Los Santos et al. (2012) and Saruya and Sullivan (2022), 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 the identifier of the panelist who visited the domain, the time, the visit's duration, and whether the visit is associated with a transaction.[7] For each transaction, I observe the names of the purchased products, the price and quantity of each product, the total price of the transaction, the time, and the domain on which the transaction occurred.

The contact lens transactions analyzed in this article occur at three retailers that collectively account for about 95% of observed contact lens transactions in the data. These retailers are 1-800 Contacts (1800), Vision Direct (VD), and Walmart (WM). Contact lens e-commerce was sizeable by 2007; 1-800 Contacts made net sales of $125 million in the first half of 2007. Both 1800 and VD almost exclusively sold contact lenses in the sample period.

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 recent observed transaction price until the time of the subsequent observed transaction. This procedure introduces some measurement error into my price variables, but the magnitude of the error is likely to be small because my sample size is reasonably large. As reported by Table 1, the mean gap between transactions for top brands is generally under two weeks. Also, there is little intertemporal variation in brands' prices at a store relative to cross-brand and cross-store price variation.[8] The prices in the time series do not include shipping fees, although 1800 and VD both waived shipping fees for sufficiently large purchases.[9] Additionally, manufacturers often offered consumers rebates for contact lens purchases. Since these rebates were offered by manufacturers

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

[7] 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.

[8] See Table O.11 and Figure O.1, both in the Online Appendix. The figure shows that prices typically stay fixed for a brand/store pair for many weeks at a time.

[9] 1800, for example, offered free shipping on orders over $50.

and not retailers, they should not affect the appeal of buying from one retailer compared to another.

Although I focus on contact lenses, I also analyze online shopping for books, iPod music players, Playstation 3 (PS3) game consoles, and DVDs. I choose these categories because they contain products with numerous observed purchases. Online Appendix O.1 describes the data for these categories.

I construct a panel of search efforts, each of which is a sequence of store visits and an associated purchase decision. The purchasing alternatives here are the visited stores and the outside option of not purchasing online. Figure 1 illustrates a panel of two possible search efforts. 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. In Section 3, I assess robustness to the choice of the maximum number of days before a purchase for a visit to be included in a search effort. To facilitate the treatment of previous purchases as observable variables in studying state dependence, I drop from the estimation sample each consumer's search efforts made before and including the consumer's first purchase. This reduces the number of transactions from 1956 to 1160, and leaves 494 unique consumers in the sample.

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. Under 15% of consumers in the sample switch brands.

Figure 1: Illustration of search efforts

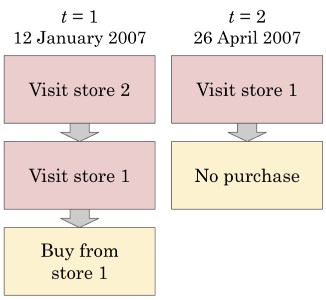


Table 1: Description of transactions in contact lens data

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: the "# trans." column 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.

3 Descriptive analysis

3.1 Overview of data

This section describes the data. To begin, Table 1 reports the number of transactions for the best-selling brands in the sample; there are 42 brands altogether. The interquartile range of transaction prices is \$19.99–38.99, and the median number of boxes purchased is two (one for each eye).

Table 2 reports how often consumers in the sample search for and purchase lenses. Consumers make, on average, 2.5 search efforts and less than two

Table 2: Repeated purchasing in contact lens panel

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

transactions, 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.

Table 3a displays the share of contact lens search efforts involving one, two, and three store visits. The "Baseline" column provides results for search efforts constructed by including visits to 1800 or VD up to 14 days before a purchase using the algorithm described in Appendix A. The "2 days before" column only includes visits made up to two days before a purchase (or, in the case of a search effort without a transaction, two days within another visit). Table 3a reveals that limits of consumer search; 83% of search efforts involve a visit to only one store under the baseline data construction. The table also shows that search efforts are insensitive to the choice of parameters used in constructing search efforts. Tables 3d, 3d, and 3d report the distribution of the number of visited stores across search efforts for other categories. For all categories except PS3s, over 75% of search efforts involve a visit to only one or two stores under the "five days before" definition of a search effort.

Consumers visit few stores despite the possibility of saving on lenses by visiting and purchasing from other stores. Table 4a 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 in which a consumer visits more than one site, the consumer does not choose the

Table 3: Share of search efforts by number of visited stores

(a) Contact lenses

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

(b) Other categories: 2 days before

# of visits	Share of sessions Books	iPod	PS3	DVD
1	0.79	0.48	0.38	0.60
2	0.18	0.34	0.35	0.30
3	0.02	0.16	0.26	0.10
4+	0.00	0.02	0.01	0.00

(c) Other categories: 5 days before

# of visits	Share of sessions Books	iPod	PS3	DVD
1	0.74	0.40	0.32	0.49
2	0.22	0.37	0.27	0.34
3	0.03	0.21	0.33	0.16
4+	0.00	0.02	0.08	0.00

(d) Other categories: 14 days before

# of visits	Share of sessions Books	iPod	PS3	DVD
1	0.66	0.27	0.22	0.35
2	0.28	0.39	0.27	0.42
3	0.06	0.29	0.36	0.22
4+	0.00	0.05	0.16	0.02

the store with the lowest price among visited site. On average, including search efforts in which the consumer does pay the minimum price, the consumer pays 7.1% over the minimum available price among visited sites. Table 4b reports analogous results for other categories. In all categories except PS3s, most consumers pay above the minimum available price.

Some retailers may offer superior customer service or shipping than others, which could rationalize why consumers purchase from these retailers over lower-price rivals. Table 5 reports the number of transactions at each retailer and its average price relative to 1800's price across transactions. The fact that 1800 outsells VD despite charging higher prices suggests that 1800 is more appealing to consumers in non-price dimensions.

Figure 2 reports estimates of regressions of measures of search and purchasing behaviour on various consumer characteristics. The results show that high-income and highly educated consumers purchase contact lens at relatively high prices and that high-income consumers conduct less search. These findings motivate my specification of preferences varying by income in the model.

Table 4: Transactions above minimum available price

(a) Contact lenses

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

(b) Other categories

	Books	iPod	PS3	DVD
Share of transactions above min price	0.70	0.68	0.18	0.51
Average payment over min price ($)	2.10	6.19	6.73	1.83
Average payment over min price (%)	35.29	4.07	1.38	13.30

Notes: this table reports the (i) share of transactions made above the minimum available price (MAP) among analyzed retailers; (ii) the average difference of the transaction price and the MAP, and (iii) the average relative percentage difference of the transaction price over the MAP. For books, the price for the "book club" is set to the price at the book club with the highest sales for the consumer's purchased book (or, in the case that the consumer bought from a different book club, the price at this club). I proceed analogously for the "other" store. For categories including eBay as a retailer, I do not include eBay's price in computing the minimum given that items sold on eBay are often in used condition.

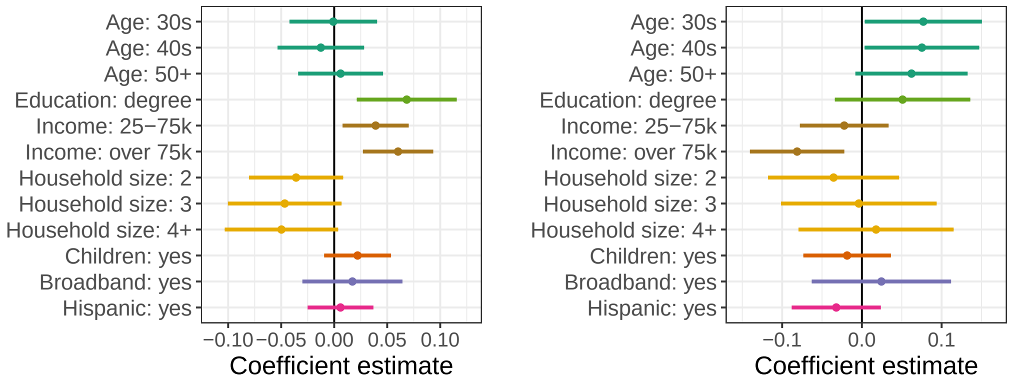
Table 5: Sales and prices by store (contact lenses, 2007–2008)

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.

Figure 2: Correlates of search behaviour

(a) Price excess over minimum (b) Number of stores visited



Note: Figure 2a reports point estimates and 95% confidence intervals from a regression of $(p_t - p_t^{\text{min}})/p_t^{\text{min}}$ on consumer characteristics, where p_t is the price at which the consumer transacts in search effort t and p_i^{min} is the minimum available price for the consumer's brand during t. "Children" indicates the presence of a child in the household. The age and education variables describe the head-of-household. The dependent variable of Figure 2b's regression is the number of stores that a consumer visits in a search effort. Whereas Figure 2a reports results from a regression on search efforts ending in a transaction, Figure 2b reports results from a regression on all search efforts. The R^2s are 0.053 and 0.022 and the sample sizes are 446 and 675. Estimates of intercepts and race indicators are omitted.

3.2 Within versus across store search

The fact that consumers require brand-specific prescriptions to purchase contact lenses makes the assumption that search occurs for a fixed product aross retailers credible in my setting. This assumption may not be appropriate for the commonly studied books category. Table 6 describes search within Amazon and Barnes & Noble's online store in search efforts that result in a book purchase. The median number of pages viewed during a visit to Amazon (Barnes & Noble) is 39 (27), and that the median time spent browsing Amazon is about half an hour (16 minutes). It thus seems that consumers search within sites, possibly over distinct products. Consumers search much less within contact lenses sites: as reported by Appendix Table O.9, the median number of pages is 12 and the median duration is 6 minutes (pooling across retailers). This is consistent with brand-specific prescriptions that eliminate the rationale for within-store, across-brand search. Recall also from Table 3 that most consumers do not visit multiple sites before buying a book online.

Table 6: Within-site search intensity prior to book purchase

(a) Amazon visits

Measure	Mean	Percentile		
		25^{th}	50^{th}	75^{th}
# pages	102.0	16	39	105
Duration	79.9	10	29	79

(b) Barnes & Noble visits

Measure	Mean	Percentile		
		25^{th}	50^{th}	75^{th}
# pages	71.4	10	27	80
Duration	48.5	5	16	62

Note: this table reports summary statistics—the mean, 25^{th} percentile, 50^{th} percentile, and 75^{th} percentile—of the number of pages viewed during a visit to an online bookstore and of the duration of time spent (in minutes) browsing the online bookstore.

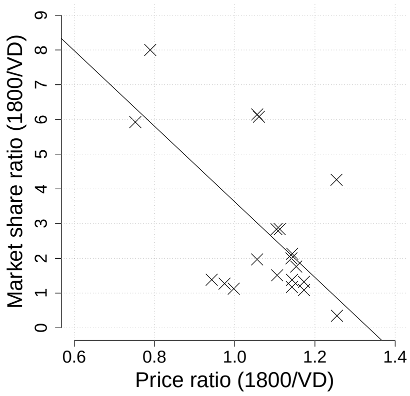
The limited extent of across-store search and significant level of within-store browsing suggests that within-store search may be more relevant than across-retailer search for books, which bolsters the case for preferring the contact lens setting for studying across-retailer search.

3.3 Prices, browsing, and purchasing

I now turn to the role of prices in directing consumer behaviour. Table 5 shows that 1800 boasted the highest sales in 2007–2008 despite charging the highest average prices. This finding could reflect that consumers generally prefer 1800, which leads 1800 to charge 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's relatively expensive brands sell relatively fewer units is informative about consumer price sensitivity. Figure 3, 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. Even though 1800 boasts the highest sales while charging the highest prices on average, the brands for which 1800 charges especially high prices relative to VD's are those for which 1800's sales are especially 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

Figure 3: Prices and intrabrand market shares at 1800 and VD



Note: Each point represents a brand of contact lenses. "Market share ratio (1800/VD)" provides the number of transactions at 1800 for a brand divided by the number of transactions at VD for that brand. "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. The plot also displays a least-squares line of best fit.

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

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

where $y_{it} = \arg\max_f u_{ift}$ is either the store from which the consumer purchases or or the first-visited store in a search effort, i indexes consumers, t indexes search efforts, and p_{ft} 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 7 reports results. Without fixed effects, I estimate that consumers are more likely to purchase from sellers charging higher prices. This relationship

Table 7: 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.

is reversed upon the introduction of fixed effects.[10] Additionally, the first-visited store responds to prices in a similar way as purchases. This suggests that consumers have some knowledge of prices before search.[11]

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. 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. Consumers conduct sequential search according to the optimal strategy of Weitzman (1979). Consumer i's utility

[10] 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 price variation are relevant.

[11] The implied elasticities in Specification 2 of Table 7 fall below one, which is inconsistent with profit maximization with non-negative marginal costs. I attribute this to misspecification of the simple logit demand model; estimates from my panel search model imply reasonable elasticities.

from purchasing from store f during s earch 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. 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* at t. The α_i random variable governs consumer i's price sensitivity; I specify $\alpha_i = \alpha_0 + \alpha_1 I_i$, where I_i is an indicator for consumer i having a household income above \$75,000. Additionaly, the ϕ parameter governs the extent of state dependence. Interpretations of state dependence include habit formation, switching costs, or store loyalty.

I assume that, before search, the consumer knows all but the ε_{ift} match values. Section 4.1 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 sorting alternatives in descending order by *reservation utility* and then visiting stores in this order until obtaining an indirect utility higher than the maximum reservation utility among unsearched alternatives. Consumer i's reservation utility r_{ift} for store f in search effort t, is defined by

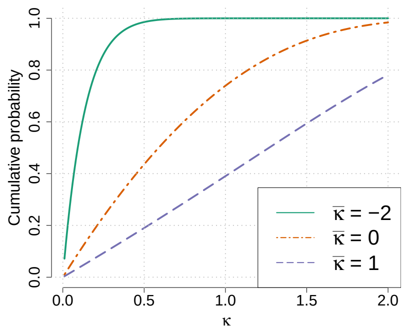
$$\kappa_{ift} = \int_{r_{ift}}^{\infty} (u - r_{ift}) dF_{ift}(u), \tag{4}$$

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

Figure 4: Illustration of the search cost distribution function



functions, a store's reservation utility is decreasing in its search cost. Kim et al. (2010) and Moraga-González et al. (2022) similarly invert equations defining reservation utilities to obtain expressions resembling (4).

There is a convenient parametric distribution of the search costs κ_{ift} that yields tractable choice probabilities for search effort outcomes. Suppose that $\kappa_{ift} \sim F_\kappa(\cdot; \bar{\kappa})$ independently of all else, where

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

Then, we can express equation (5) as

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

where the η_{ift} are mutually independent (across i, f, and t) T1EV random variables. The $\bar{\kappa}$ parameter positively relates with both the mean and variance of the F_κ distribution. Figure 4 plots F_κ for various $\bar{\kappa}$ values.

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

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

Given the distributional assumptions, the search outcome's probability is

$$\begin{aligned} &\frac{e^{\bar{r}_{if}}}{\sum_{g=1}^{F} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}} \times \frac{e^{\bar{r}_{if'}}}{\sum_{g \neq f} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}} \\ &\qquad \times \frac{e^{\bar{u}_{if}}}{\sum_{g \notin \{f, f'\}} e^{\bar{r}_{ig}} + e^{\bar{u}_{i0}} + e^{\bar{u}_{if}} + e^{\bar{u}_{if'}}}, \end{aligned} \tag{7}$$

where $\bar{u}_{ig} = u_{ig} - \varepsilon_{ig}$ and $\bar{r}_{ig} = r_{ig} - \eta_{ig}$. Online Appendix O.2 provides the inequalities corresponding to other outcomes.

The choice probabilities in (7) 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 revealed indirect utilities at each step in search. Last, it would require integration over κ_{ift} and ε_{ift} in order to obtain outcome probabilities. Note that the mapping between chains of inequalities and search effort outcomes reduces the burden of computing choice probabilities even without a parametric assumption on κ_{ift} or the assumption that search costs are iid.[13]

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

[13] Other empirical articles that have exploited rankings of utilities in analyzing sequential search models include Moraga-González et al. (2022) and Morozov et al. (2021). Moraga-González et al. (2022) operationalize the theoretical result (Armstrong 2017 and Choi et al. 2018) that choosing an alternative by following the Weitzman (1979) optimal search strategy is equivalent to choosing the alternative that maximizes the minimum of an alternative's reservation utility and its indirect utility. Morozov et al. (2021) specify separate inequalities for (i) the order of visits, (ii) the consumer's stopping decision, and (iii) the purchase decision, and pool these inequalities to characterize the probability of visit and purchase outcomes. The primary difference between this approach and my own is that I specify inequalities characterizing all stages of a search effort that give rise to closed-form choice probabilities, whereas Morozov et al. (2021) specify multiple inequalities that do not to-

The search cost distributions used in the empirical consumer search literature are not typically chosen for tractablility.[14] Several articles use a log-normal distributions, e.g., Kim et al. (2010) and Morozov et al. (2021).

4.1 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. 2022). The assumption is justified in my context for several reasons. First, regressions from Section 3.3 suggest that consumers respond to prices in choosing stores to visit even when they do not ultimately purchase lenses. This is compatible with the consumer choosing visits based on knowledge of prices. This raises the question of why consumers would know these prices. Recall that prices exhibit little intertemporal variation and that I drop consumers' first search efforts from the sample. Thus, all consumers in the sample have search experience that could provide information about prices. Consumers may also know retailers' prices through advertisements; 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. Another reason to assume search over match values is the presence of non-price retailer characteristics that consumers learn through search, especially shipping time. Contact lenses vary not only by brand but also by other prescription parameters; these include base curve, power, sphere, etc. Prices do not vary by these parameters. Whether a retailer has a specification in stock determines the store's shipping time for an order. Additionally, retailers update their websites to highlight different brands. Variation in brand/site-specific promotion may induce variation in consumer valuation of sites.

The alternative assumption that consumers search over prices faces problems relating to the specification of consumer beliefs. One common approach is

gether imply closed-form choice probabilities.

[14] An exception is Moraga-González et al. (2022), who similarly choose a search cost distribution that ensures a random variable determining choice probabilities is T1EV.

to select a parametric distribution for prices, to estimate this distribution using observed prices, and to assume that consumer beliefs follow this estimated price distribution.[15] My setting features little intertemporal price variation for particular brand/store pairs, which means that each estimated brand/store-specific distribution will concentrate around the mean brand/store price. The assumption that these distributions represent consumer beliefs is therefore operationally similar to assuming that consumers believe that the mean price—which is similar to the price at any point in time—is the current price. Thus, I do not expect the approach of estimating price distributions to substantially differ from my approach.

4.2 Justification of sequential search model

Empirical consumer search studies tend to use either sequential or fixed-sample search models. I specify a sequential search model for two reasons. First, the order of search has empirical significance in my sample: among consumers who visit both 1800 and VD, those who previously purchased from 1800 visited 1800 before VD 58% (standard error: 3.9%) of the time whereas those who previous purchased from VD visited 1800 before VD 46% (standard error: 3.9%) of the time. This finding contradicts the fixed-sample search model, in which the order of search is irrelevant. In addition, sequential search better describes cross-store search for contact lenses. In fixed-sample search, the consumer (i) chooses which stores to visit at the outset of search 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, there is no reason for the consumer to commit to visiting every member of a set of stores when it may be desirable to stop searching after visiting a particularly attractive store. There is similarly no reason for the consumer to commit not to continuing search if no store that the consumer

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

initially searches is attractive.[16]

4.3 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 $\Pr(y_{it}|I_i p_{it}, h_{it}, \gamma_i; \theta)$.[17] 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}.

Integrating over the conditional distribution of γ_i raises two econometric problems. The first is the standard initial condition problem: the distribution of γ_i conditional on p_i and h_{i1} will depend on h_{i1} because h_{i1} reflects consumers' past choices, which depended on γ_i. Thus, we cannot drop h_{i1} from the conditioning set. The second problem, which I call the endogeneity problem, relates to the dependence of γ_i and prices p_i conditional on h_{i1}. To understand this dependence, suppose that store f sold two brands of contact lenses and that its price for the first brand was high relative to other stores whereas its price for the second brand was relatively low. In that case, consumers with

[16] De Los Santos et al. (2012) argue that fixed-sample search better describes search for books across retailers. They argue that consumers' decisions to continue searching after visiting a store do not respond to the price at that store — that is, consumers are not more likely to terminate search after finding a low price. This finding however, can alternatively be explained by price endogeneity, i.e., that price is positively correlated to store quality, and thus stores with low prices tend to be of lower quality, cancelling out the effect of a low price on the consumer's probability of terminating search.

[17] Recall that I_i is an indicator for whether the consumer has a household income over \$75,000.

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:

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

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.[18] First, specifying a parametric distribution of γ_i conditional on the initial state follows Wooldridge (2005).[19] Second, modelling the de-

[18]Morozov et al. (2021) similarly assume a normal distribution for persistent unobserved heterogeneity in their panel model of consumer search online. Whereas I model conditional distributions of persistent tastes, they model the unconditional distribution of persistent tastes; this is enough in their setting because they do not face the initial conditions and endogeneity problems that I face on account of the fact that their model does not feature state dependence.

[19]As discussed by Wooldridge (2005), the primary alternative is to specify the distribution of the initial state conditional on unobserved heterogeneity by, e.g., computing the steady-state distribution of the initial state for a consumer with a particular value of γ_i after specifying a transition process for store prices. This approach is far more computationally burdensome than the Wooldridge (2005)-based approach.

pendence 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. CRE approaches involve explicitly modelling the dependence of unobserved heterogeneity on regressors.[20]

5 Price competition

To analyze retailer 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 pricing game wherein sellers adjust prices in response to changes in payoff-relevant state variables. In my setting, these state variables are the shares of 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 qualitatively 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

$$\rho_f(p, \gamma_i, \alpha_i) = \sum_g \sigma_{fg}(p, \gamma_i, \alpha_i) \rho_g(p, \gamma_i, \alpha_i) \qquad \forall f, \tag{8}$$

where $\sigma_{fg}(p, \gamma_i)$ is the probability with which a consumer with state $h_{igt} = 1$

[20] In the CRE model of Chamberlain (1980), the conditional expectation of the unobserved heterogeneity is a linear function of the explanatory variables for each time period. Mundlak (1978) proposes a related approach that is also widely used. Wooldridge (2010) uses the term "correlated random effects" to refer to both Chamberlain (1980)'s and Mundlak (1978)'s approaches. Like Chamberlain (1980), I specify a parametric form for unobserved heterogeneity conditional on explanatory variables.

buys from store f given prices p. The right-hand side of (8) 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 (8) imposes that the share of type-(γ_i, α_i) consumers in state f does not change after an additional search effort. 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 $\tilde{\beta}_n(\hat{\theta})$:

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

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.[22] Additionally, $\hat{\Omega}_n$ is a weighting matrix; Appendix B discusses the optimal weighting matrix and my procedure for estimating it.

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

[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. Other articles that similarly justify the use of I-I or moment-based estimators include Krasnokutskaya and Seim (2011), Pakes et al. (2007), and Collard-Wexler (2013).

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

sample averages. To summarize the coefficients:

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

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

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

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

(v) *Price sensitivity*: regression of indicators for purchasing at stores on stores' prices.

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

(vii) *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.

(viii) *Price sensitivity heterogeneity*: regression of the consumer's 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 Table 12 details these statistics and reports their values in the data.

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 brands that are more expensive on average. I similarly de-mean prices in the counterfactual simulations, using the average prices in the data rather than counterfactual average prices.

6.2 Identification

I now informally discuss identification of the model. First, I address the price endogeneity problem by assuming that retailer quality does not vary across brands and specifying retailer fixed effects that capture this quality. To relax this, I could allow store qualities to vary in other dimensions—e.g., across time or lens characteristics—and specify fixed effects for interactions of stores and, e.g., time periods or characteristics.

The separate identification of state dependence and persistent unobserved tastes as explanations for inertia in consumer choice is another challenge. Although both state dependence and persistent unobserved tastes 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, a model with stronger persistent store tastes features greater correlation between contemporaneous choice and choice two or more purchasing occasions ago conditional on the choice in the previous purchasing occasion than a model in which state dependence explains inertia. This is because, conditional on the choice made last period, the choice made two periods ago correlates with persistent tastes, which influence contemporaneous choice. This motivates my inclusion of a regression of the consumer's contemporaneous choice on lagged choices among the I-I auxiliary statistics. Another explanation for the separate identification, which Dubé et al. (2010) invoke, involves variation in covariates. Consider a consumer who buys from store f before f store f raises its price. The consumer responds by switching to purchase from store g, after which f lowers its price to the original level. Under extensive state dependence, the consumer is likely 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. Thus, state dependence and persistent tastes for stores imply different predictions for switching patterns. This insight motivates the "Role of lagged price" I-I auxiliary statistics.

Last, consider the identification of the search-cost parameter $\bar{\kappa}$. The fact that search costs, state dependence, and persistent store tastes all limit the number of visited stores poses an identification challenge. Separate identification stems from the fact that state dependence and persistent tastes induce choice dynamics that iid search costs unique to a purchasing occasion do not. Thus, state dependence and persistent tastes are identified by dynamics in consumer choice whereas the magnitude of search costs are identified by the extent of search conditional on these former two aspects of preferences. This identification argument relies on the assumption that search costs are not serially correlated or dependent on previous purchasing choices. I leave the analysis of search costs that are connected across search efforts to future research.

7 Parameter estimates

This section presents the parameter estimates. Table 8 reports estimates of my model's key parameters and the median search cost implied by these estimates. The "Baseline" columns report results for the full model, whereas the "Constrainted" columns report results for a specification without state dependence, persistent unobserved heterogeneity, or heterogeneity in price sensitivity α_i. The median search cost in dollar terms under the baseline estimates is only \$0.88, which is low compared to the median transaction price in my sample of about \$30. My estimates suggest, however, that heterogeneous price sensitivity, state dependence and heterogeneous tastes for sellers as reflected in γ_i exercise significant influence on consumer decisions. First, the negative estimate of α_1 indicates that high-income consumers (who comprise 37% of the sample) are less price sensitive than their low-income peers. As for state dependence, I find that having previously purchased from a store raises a high-income consumer's valuation of the store by \$4.31. The estimated standard deviation of γ_i conditional on initial state and prices is about 1.08, or about \$14.45 in dollar terms for a high-income consumer. Table O.10 in the Online Appendix reports elasticity estimates. Table 9 provides estimates of mean store tastes $q_f + \mathbb{E}[\gamma_{if}]$. In line with 1800 boasting higher sales than its rivals despite higher prices, 1800 has a higher mean store taste than WM and

Table 8: Selected parameter estimates

	Baseline		Constrained	
Parameter	Estimate	SE	Estimate	SE
q_{1800}	1.061	0.110	1.249	0.160
q_{WM}	-2.469	0.243	-0.646	0.220
q_{VD}	0.185	0.055	0.296	0.161
ϕ	0.468	0.146	-	-
α_0	0.147	0.017	0.069	0.028
α_1	-0.072	0.022	-	-
$\bar{\kappa}$	-1.815	0.097	0.603	0.044
$\Gamma_{1800,\text{VD}}$	-3.340	0.251	0.000	0.000
$\Gamma_{\text{VD},1800}$	-5.381	0.424	0.000	0.000
σ_γ^2	1.175	0.038	-	-
λ	3.492	0.801	-	-
Median search cost (utils)	0.11	0.01	0.96	0.03
Median search cost ($)	0.74	0.13	13.85	5.71

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

VD.

A comparison of the "Baseline" columns with the "Constrained" columns suggests that ruling out state dependence and persistent taste heterogeneity leads to an overstatement of search costs. This occurs because state dependence and persistent taste heterogeneity tend to limit consumer consideration by exaggerating utility differences between stores relative to the variability of the match value uncovered by search.

My search cost estimates fall below some others in the empirical online search literature. Hong and Shum (2006), for instance, find median search costs for textbooks between $2.32 and $29.40. De Los Santos et al. (2012) find average search costs of $4.14. Although this comparison is limited by differences between the contact lens and books settings, my results suggest that high search cost estimates in the literature may reflect a failure to account for forms of seller differentiation that limit search.

Online Appendix O.9 reports estimates for books e-commerce. The results

Table 9: Estimates of mean store tastes

Store f	Mean taste for store f $q_f + \mathbb{E}\gamma_{if}$
1800	0.12
WM	-2.96
VD	-3.67

are qualitatively similar to those for contact lenses — the estimated median search cost is \$0.90, close to the estimate of \$0.74 for lenses.

8 Counterfactual analysis

8.1 Sources of limited consideration

My assessment of the sources of limited consideration in e-commerce involves simulating search efforts under counterfactual preference parameters. I consider an aspect of consumer preferences to be a driver of limited consideration if it exerts influence on the extent of search. To produce the simulated datasets discussed throughout this section, I simulate each consumer's history of search efforts 50 times; in each simulation, I draw outcomes conditional on that consumer's prescribed brand, the prices faced by that consumer, and the consumer's initial state. The counterfactual 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: set $q_f + \mathbb{E}[\gamma_{if}] = 0$ for each store f to eliminate mean quality differences between stores;[23]

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

(v) No price sensitivity heterogeneity: set $\alpha_i = \alpha_0$ for all consumers i; and

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

(vi) Logit only: eliminate search costs, state dependence, vertical differentiation, and persistent unobserved store tastes so that only prices and ε_{ijft} shocks differentiate retailers for consumers.

Altering consumer preferences changes the probability that consumers buys from any online store. Thus, the effects of the counterfactual preference changes described above would reflect both a qualitative change in preferences and a change in the magnitude of consumer tastes for e-commerce. To focus on the former, I add a compensating constant $q^{\dagger}$ to each consumer's indirect utility for every online store to ensure the outside good's share is constant across counterfactuals. The value of $q^{\dagger}$ differs across counterfactuals. Appendix Table O.12 provides results without this compensating factor.

Table 10 characterizes consumer search in the sample and in simulated search efforts. Appendix Table O.12 includes additional counterfactuals and standard errors. The "comp." label indicates the $q^{\dagger}$ adjustment described above. A comparison of the first two rows provides an evaluation of model fit; the model's predictions match the data well. The other rows characterize sources of limited search. Persistent unobserved heterogeneity plays the largest role in explaining limited consideration — the share of search efforts involving a visit to more than one store rises from about 16% to 61% upon the elimination of the persistent store tastes that horizontally differentiate sellers. Additionally, the extent to which consumers overpay for lenses decreases in this counterfactual. These results together suggest that consumers' preferences for purchasing from sellers that they idiosyncratically prefer explains why consumers avoids visiting other stores even when these stores offer lower prices. Eliminating state dependence also expands consumer consideration, although it does not meaningfully decrease the amount that consumers overpay for lenses.

Eliminating vertical differentiation also expands consideration. This is because it leads some consumers who previously visited only 1800 to also consider VD. Given 1800's vertical superiority, the elimination of 1800's mean quality advantage over its less expensive competitor VD leads more consumers purchase from VD, which reduces the average overpayment. This indicates that overpayment for lenses is partially justified by superior quality offered by more expensive stores. Reducing search costs, by contrast, has a negligible effect on the extent that consumers overpay.

Online Appendix Table O.7 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. Under this model, each store f sets prices p_f maximize its 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 maximizations under observed prices and estimated long-run demand. Throughout this section, I focus on competition between stores in sales of Acuvue Advance for Astigmatism, a popular brand.

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 persistent unobserved store tastes: set $\gamma_{if} = \mathbb{E}\gamma_{if}$ for each consumer i and each store f; and

(iv) No price sensitivity heterogeneity: set $\alpha_i = \alpha_0$ for each consumer i.

I do not add a constant $q^\dagger$ to consumer utilities under any of these changes.

Table 10: Model fit and counterfactual search patterns

Specification	Share visiting one store only	Mean # of visits	Share buying from... any	1800	VD	Visit order	Share paying $>$ min. price	Mean over-payment ($)
Observed	0.819	1.196	0.610	0.364	0.220	0.496	0.660	3.95
Baseline	0.843	1.170	0.730	0.504	0.210	0.418	0.713	4.36
Low search costs (comp.)	0.745	1.289	0.730	0.502	0.208	0.393	0.714	4.36
No state dep. (comp.)	0.802	1.217	0.730	0.502	0.206	0.417	0.714	4.34
No vertical diff. (comp.)	0.669	1.396	0.730	0.266	0.341	0.608	0.548	2.81
No persistent unobs. (comp.)	0.387	1.672	0.729	0.415	0.312	0.536	0.587	2.94
No price sens. het. (comp.)	0.840	1.173	0.730	0.495	0.218	0.427	0.701	4.19
Logit only (comp.)	0.000	3.000	0.730	0.161	0.352	1.000	0.481	1.83

Notes: The “Share visiting one store only” column provides the share of search efforts involving a visit to only one store; the “Mean # of visits” column provides the average number of visits; and the “Share buying from” columns report the shares of search efforts resolving in a purchase from either any store or from one of the two leading stores, 1800 and VD. The “Visit order” column reports the share of search efforts involving a visit to each of 1800 and VD in which 1800 is visited first. The final two columns characterize the extent to which consumers pay above the minimum available price for contact lenses: “Share paying over min. price” provides the share of search efforts involving the purchase of a contact lens brand at a price above the minimum price available among the three retailers. Last, “Mean overpayment ($)” reports the mean difference between the price at which the consumer purchased contact lenses and the minimum available price for the consumer’s brand across search efforts ending in transactions.

Table 11 reports percentage changes in equilibrium markups relative to the baseline estimated consumer preferences for each set of counterfactual preferences. Note that 1800's relative markup (i.e., price divided by cost) is estimated as 1.87, whereas 1800's sales divided by its costs of goods and services as reported on its Q2 2007 SEC Quarterly Report was 1.69, which is somewhat similar to the estimated markup. Reducing search costs does little to change markups, implying that price dispersion for physically homogeneous goods sold online is not a consequence of search frictions providing sellers with market power. Instead, Table 11 suggests that the sources of market power online are store differentiation, the presence of higher-income consumers who are relatively insensitive to price, and—to a lesser extent—state dependence.

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, billing, and delivery information to be shared with any online retailer the consumer likes, 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.

High-income consumers' low price sensitivity can be interpreted as a higher taste for store quality as in Shaked and Sutton (1982). Shaked and Sutton (1982) argue that scope for quality differentiation softens price competition; this argument seems applicable to contact lens e-commerce, in which both a firm with higher prices and quality (1800) and another with lower prices and quality (VD) earn positive profits by appealing to different market segments.

Search costs in contact lens e-commerce are small and do not meaningfully contribute either to limited search or market power. Given that searching across contact lens sites is qualitatively similar to searching across sites in other product categories, I expect the same conclusion to hold for e-commerce more broadly. Additionally, searching within a site for products seems less difficult than searching across sites since it does not require navigating to sites

Table 11: Percentage changes in markups from static pricing model

Panel A: Point estimates (%)

Store	Low search costs	No state dependence	No persistent unobs.	No price sens. het.
1800	-1.1	-3.4	-36.7	-7.0
WM	5.2	1.8	-24.6	-16.1
VD	-1.3	-3.5	-78.3	-4.5

Panel B: Standard errors

Store	Low search costs	No loyalty	No persistent unobs.	No price sens. het.
1800	0.1	1.1	4.0	2.0
WM	1.3	1.6	5.4	1.2
VD	0.3	1.3	2.1	0.6

Note: This table presents estimates of percentage changes in markups for Acuvue Advance for Astigmatism under counterfactual consumer preferences relative to markups in a pricing equilibrium computed at the estimated model parameters. The standard errors were computed using a parametric bootstrap with 100 bootstrap draws.

via search engines or URL entry. Thus, I expect that the costs of searching within Amazon or eBay, for example, are lower than the search costs that I estimate here. As such, remedies to market power in the industry that aim to make search easier, e.g., comparison tools or transparency regulations, are unlikely to lower prices or improve the consumer experience in online retail.

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. Additionally, my framework can be used to learn about state dependence and persistent unobserved heterogeneity in a search setting from panel data. The article's primary contribution is in drawing substantial conclusions about limited consideration and market power in e-commerce. The analysis suggests that various forms of seller differentiation play a much larger role than search frictions in accounting for these phenomenon. This result suggests inquiry into the sources of seller differentiation—i.e., the γ_i persistent unobserved store tastes in my model—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 products. 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 around such visits in these categories.

B Auxiliary statistics of indirect-inference estimator

The following list describes the I-I auxiliary statistics:

(i) *Stores' visit shares*: the mean across search efforts of an indicator for whether the consumer visited each store f. These statistics target the store qualities q_f and the search cost parameter $\bar{\kappa}$.

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

(iii) *Inertia*: 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 purchased from store f in the previous search effort and in the search effort before that. The dataset used for running this regression includes three observations for each search effort, one corresponding to each of the stores. I include all observations for which t exceeds three. This statistic targets the state dependence parameter ϕ and the parameters governing the distribution of γ_i.

(iv) *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. This statistic targets the state dependence parameter ϕ and the parameters governing the distribution of γ_i.

(v) *Price sensitivity*: coefficients from a regressions of an indicator for whether a search effort ended in a transaction at store f on store indicators and the price of the consumer's brand at store f. The regression dataset includes three observations for each search effort, one corresponding to each of the stores. This statistic targets the price sensitivity parameter α_i and store qualities q_f.

(vi) *Cross-visiting behaviour*: 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. This statistic targets the parameters Γ_{fg}.

(vii) *Dependence of tastes and prices conditional on initial state*: coefficients from a regression of an indicator for whether a consumer visited store g in a search effort 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.

(viii) *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 consumer i's income exceeding \$75,000. Here, t indicates a search effort resulting in a transaction, p_{it}^{trans} indicates the price that consumer i paid for contact lenses in search effort t, and p_{it}^{min} indicates the minimum available price for contact lenses across the three major online retailers during search effort t. This statistic targets the parameter α_1 governing the difference between low-income and high-income consumers' price sensitivities.

Table 12: Auxiliary model statistics computed on estimation sample

Statistic	Value	SE
Share visiting 1800	0.688	0.014
Share visiting WM	0.145	0.010
Share visiting VD	0.360	0.014
Share visiting every store	0.013	0.003
Inertia: indicator for 1800	0.309	0.011
Inertia: indicator for VD	0.115	0.010
Inertia: indicator for WM	0.149	0.011
Inertia: purchased from store last search effort	0.495	0.017
Inertia: purchased from store two search efforts ago	0.392	0.018
Role of lagged price: slope for current price	-0.351	0.252
Role of lagged price: slope for lagged price	0.023	0.240
Price sensitivity: indicator for WM	0.181	0.071
Price sensitivity: indicator for VD	0.377	0.064
Price sensitivity: slope	-0.155	0.070
Cross-visiting behaviour: share of 1800 buyers visiting WM	0.116	0.009
Cross-visiting behaviour: share of 1800 buyers visiting VD	0.033	0.005
Cross-visiting behaviour: share of WM buyers visiting 1800	0.308	0.014
Cross-visiting behaviour: share of WM buyers visiting VD	0.128	0.010
Cross-visiting behaviour: share of VD buyers visiting 1800	0.193	0.012
Cross-visiting behaviour: share of VD buyers visiting WM	0.124	0.010
Dep. of tastes and prices cond. on initial state: slope	-0.302	0.098
Price sensitivity heterogeneity	0.045	0.010

Notes: See Section 6 for a description of the various auxiliary model statistics. The "SE" column reports classical asymptotic standard errors computed under an assumption of homoskedasticity. I do not use the estimated coefficient for the indicator for 1800 in the price sensitivity regression as an auxiliary statistic in my indirect inference estimation. I similarly do not use the intercept estimated in the "Dependence of tastes and prices conditional on initial state" regression.