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Price Dispersion and Informational Frictions: Evidence from Supermarket Purchases

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Abstract

Traditional demand models assume that consumers are perfectly informed about product characteristics, including price. However, this assumption may be too strong. Unannounced sales are a common supermarket practice. As we show, retailers frequently change position in the price rankings, thus making it unlikely that consumers are aware of all deals offered in each period. Further empirical evidence on consumer behavior is also consistent with a model with price information frictions. We develop such a model for horizontally differentiated products and structurally estimate the search cost distribution. The results show that in equilibrium, consumers observe a very limited number of prices before making a purchase decision, which implies that imperfect information is indeed important and that local market power is potentially high. We also show that a full information demand model yields severely biased price elasticities.

Key Words: imperfect information, price dispersion, sales, search costs, product differentiation, consumer behavior, demand estimation, price elasticities.

JEL Classification: D4, D83, L11, L66

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1 Introduction

Traditional demand models assume that consumers are perfectly informed about all product characteristics. However, unannounced, short-term reductions in the prices of certain products (sales) represent a common and frequent supermarket pricing strategy. If consumers cannot perfectly predict the timing of sales at every store, they cannot know what deals are offered by the various stores in each period. Thus, the consumers must incur a cost to determine the prices before making a purchase decision.

Ignoring imperfect price information can lead not only to biased demand parameter estimates but also to wrong implications for competition policy and incorrect inferences concerning retailers' assortment decisions.[1] To verify whether price information frictions are indeed prevalent, we first investigate their importance in consumers' food product choices. We analyze not only price distribution movements but also how transaction prices relate to household characteristics such as the opportunity cost of time, storage costs and number of store visits. We find compelling evidence that price information is not freely and readily available without search. We therefore develop and estimate a demand model with imperfect information on prices in which consumers have heterogeneous tastes and products differ in quality. Consumers sequentially search for their favorite product, and the probability of finding a certain product is both product- and consumer-specific.

Our model is based on Hortaçsu and Syverson (2004), who study the mutual fund industry. Our main contribution has two important dimensions. First, we allow for heterogeneous consumer tastes. Horizontal differentiation is especially important for brick-and-mortar stores because of, for example, geographical location. Ignoring such differentiation could significantly bias demand estimation results. Second, our contribution is also methodological. We suggest a new simple and flexible identification strategy that makes it possible to recover model parameters when both consumer tastes and drawing probabilities are heterogeneous. In Hortaçsu and Syverson, when products are vertically differentiated, identification is possible only if the sampling probabilities are equal across sellers. When these probabilities differ across sellers, identification requires the assumption that products are homogenous. The issue is that although consumers can rank indirect utilities, the econometrician cannot. In the case of homogeneous products, the ranking of indirect utilities simply follows the ranking of observable prices. In

[1] See, for example, Stahl (1989) on the welfare effects of entry, Allen, Clark and Houde (2013) on merger effects, Rhodes (2015) on supermarkets' market power, and Cachon, Terwiesch and Xu (2008) on firms' assortment decisions.

the case of vertical differentiation and identical drawing probabilities across stores, the ranking of utilities follows the ranking of the observable aggregate quantities. Identification is straightforward in these two cases. However, we show that it is also possible to recover the ranking of indirect utilities in the case of both vertically and horizontally differentiated products. This enables identification of the search cost distribution and other model parameters for more general consumer heterogeneity in tastes and drawing probabilities. Our approach is very flexible with respect to probability draws that can be specific to consumer types, as well as to stores and time. We identify these probabilities from observed shopping behavior, as we observe every food purchase and store visit made by households. Hence, we can recover, for each consumer and period, the empirical distribution of store visits and use it in our identification strategy.

There is a growing literature on the estimation of consumer choice with search costs. Hong and Shum (2006), using only price data, identify search costs for books sold online. Also requiring only price data, Moraga-González and Wildenbeest (2006) identify search costs for personal computer memory chips, using data obtained from a web-based search engine. Honka (2014) develops a discrete choice model of demand with non-sequential consumer search applied to auto insurance contracts. Koulayev (2014) studies web searches for hotels. Moraga-González, Sandor and Wildenbeest (2011) study consumer choice of cars with search costs, where consumers' consumption sets are endogenous. Allen, Clark and Houde (2014) develop a model of search in markets with price negotiation and apply it to mortgages in Canada.

Similar to our application, Wildenbeest (2011) studies search for grocery items in brick-and-mortar UK supermarkets. Although he allows for quality differentiation, there is no consumer taste heterogeneity. This is an important restriction in the context of traditional stores because location is an important horizontal attribute of stores that affects consumer preferences.

Another paper that studies search in supermarkets is that of Seiler (2013). However, his setting differs form ours: consumers visit a certain store for exogenous reasons and, once at the store, decide whether to search for the price of a product. Search is therefore a binary decision of whether to walk down the product aisle and is made across products within a store, not across stores. Pires (2015) also studies search within a grocery store but over a specific product category (laundry detergent). Once at the store, consumers decide whether to search and the set of products to search.

Our empirical investigation is performed on a comprehensive consumer-level dataset that includes every food product purchased by a representative survey of French households over 3 years, 1999, 2000, and 2001. We have information on product and store characteristics, as well as household demographics. We focus on 4 product categories: beer, coffee, cola, and whisky.

Consistent with a large body of literature[2], we show that price dispersion is prevalent in the French food market, even after controlling for observed and unobserved product characteristics. We also check for intertemporal price dispersion. If price information is not perfect, then price dispersion should persist over time. Otherwise, consumers would learn the identity of the cheapest store, and all other stores would have zero demand. We observe stores frequently changing rank position in the pricing distribution. Finally, inspired by Aguiar and Hurst (2007), we study the correlation between prices paid and a household's opportunity cost of time. If consumers are imperfectly informed about prices, then families with a high opportunity cost of time – and thus higher search costs – should pay higher prices. Controlling for unobservable household and store characteristics, we find that this is indeed the case. We also find that households with higher opportunity costs of time have a lower probability of paying the lowest price and that they visit fewer stores per period, while prices decrease with the number of per period store visits.

The results from the demand model show that most consumers (approximately 85%) obtain at most three utility quotes before purchasing a product. A large proportion of consumers (between 50% and 60%) observe only the price of the product that they actually purchase. These findings suggest important information frictions. If price information is freely available (in other words, consumers are perfectly informed), we should find that consumers observe all prices before making a purchase. The results also imply that firms have relatively high local market power. We show how to obtain the own- and cross-price elasticities implied by the demand model with imperfect information, and we estimate these price elasticities and compare them to those one would estimate using a perfect information demand model. The perfect information measures are severely biased (often by more than 100%) in directions that vary across products. This is similar to Koulayev (2014)'s results. Our price elasticity results are also consistent with previous studies reporting different directions of the bias depending on the application and market studied. For example, Honka (2014) find perfect information price elasticities that overestimate price elasticities in the imperfect information model. In contrast, De Los Santos, Hortaçsu and Wildenbeest (2012) and Sovinsky (2008), who studies the US personal computers market, finds that the full information model underestimates demand elasticities.

The paper is organized as follows. Section 2, describes the data and the products used in the

[2] See, for instance, Sorensen (2000), Lach (2002), Lewis (2008), Giulietti, Otero and Waterson (2009), and Allen, Clark and Houde (2014). For a review of empirical studies of price dispersion online, see Baye, Morgan, and Scholten (2006).

analysis, while Section 3 presents the reduced-form tests. In Section 4, we describe the model of consumer choice behavior with sequential search and the empirical identification strategy. The results of the estimation of the search cost distribution and price elasticities are presented in Section 5. Finally, the last section concludes.

2 Data and Product Choice

The data set is a representative survey of households distributed across all regions of France. It provides information on three years: 1999, 2000, and 2001. Households register every food product purchased using a scanner. For each product purchased, we have information on its brand and characteristics, including price, pack size, container, label, date of purchase, and the store where it was purchased. We also have comprehensive information on household demographics.

We study 4 product categories: beer, cola, coffee, and whisky. All products are frequently purchased, with the exception of whisky. We choose to include whisky to check whether price dispersion and search activity vary in the case of relatively expensive products. Furthermore, we choose to study branded products, which are the most commonly studied in applications of demand for differentiated products and competition policy. Finally, these products could trigger store visits and single product search.

Household characteristics used in the analysis include the number of store visits per household per week, the age of the household head, a dummy variable indicating the presence of a baby (a child of less than 4 years of age) in the household, the education level of the household head, the household size, and dummy variables indicating whether the household is rich (in the upper half of the income distribution), whether it lives in a rural area, and whether the household head is professionally inactive. The education level variable is organized in six levels, depending on the education status of the household head, starting with no diploma (level 0). This information is missing for some of the households in the sample. The variable indicating whether the household head is inactive is equal to one if the household head is either a student, retired, in long-term unemployment, or has no professional activity. We also use variables proxying for the costs of holding inventories: the frequency of purchase, if the household has a car, if the home has a dedicated room for storage (pantry), and if there is a dog. Those two last variables are proxies for space availability and the size of the home.

Table 1 presents some descriptive statistics on the purchased quantity per purchase occasion and product category, as well as on household characteristics. Quantities are measured in milliliters, except for coffee, which is measured in grams. The least frequently purchased product is whisky. All other products are very frequently purchased. Households visit on average 1.5 stores per week. However, some visit up to 10 stores per week. The frequency of purchase variable measures how many times each household purchased each of the products during the 3-year period. The average value of this variable is 15, but it varies considerably across products and households, and some households very rarely purchase some of these products.

Table 1: Summary statistics

Variables	Mean	Std. Dev.	Min.	Max.	Obs.
Household characteristics					
Age of household head (years)	45.41	14.96	18	94	11,572
Baby (1:yes, 0:no)	0.195	0.396	0	1	11,572
Inactive (1:yes, 0:no)	0.396	0.489	0	1	11,572
Car (1:yes, 0:no)	1.371	0.728	0	7	11,572
Pantry (1:yes, 0:no)	1.313	1.104	0	3	11,572
Dog (1:yes, 0:no)	0.438	0.756	0	8	11,572
Rural (1:yes, 0:no)	0.513	0.500	0	1	11,572
Rich (1:yes, 0:no)	0.308	0.462	0	1	11,572
Household size	2.976	1.436	1	9	11,572
Education level	2.469	1.353	0	5	8,976
Transaction characteristics					
Nb. store visits per week	1.571	0.783	1	10	531,687
Frequency of purchases (number over 3 years)	15.00	21.33	1	154	35,434
Quantity per purchase					
Beer (liters)	3.255	2.695	0.500	54	45,023
Coffee (kg)	0.473	0.301	0.250	6	122,362
Cola (liters)	3.367	3.067	0.330	72	86,127
Whisky (liters)	0.785	0.236	0.700	5	7,642

3 A Map of Price Dispersion in French Supermarkets

We examine price dispersion by focusing on the prices of two tightly defined products within each category. Our product definition allows for only one source of differentiation, i.e., the store where they are purchased. Thus, for example, within the cola category, a product is defined by its brand, whether it comes in a bottle or in a can, the pack size, whether it is diet cola, and the size of the bottle or can. We select products with a high market share that are sold at a large number of stores. In each category, we choose the most frequently purchased product. The second product chosen in a category is a product that, among those most frequently purchased, has an average price that is clearly higher or lower than the first product chosen.[3]

Table 2 provides some descriptive statistics on the price distributions. The first four columns show the average price per liter in the case of liquids or per kilo in the case of coffee, the coefficient of variation, and the ratio of the third to the first quartile, as well as the ratio of the 95% to the 5% quantile. As there is no control for store heterogeneity (or period), even if we are considering tightly defined products, they may nevertheless differ because they embed potentially differentiated characteristics of the store where they are purchased. Thus, part of the price dispersion may be explained by product differentiation and time variation. Although we compare exactly identical goods, they are sold at different stores and in different time periods, which means that the products are not homogenous from the consumer's perspective.

To remove the heterogeneity across stores and periods from prices, we run product-by-product regressions of prices, measured as log deviations from the weekly mean, on month, year and supermarket chain fixed effects, store type, and regional dummies. The residuals of these regressions represent prices of a homogeneous product or of the common attributes of the good (Lach, 2002, Zhao, 2006, and Sorensen, 2000). However, these "residual prices" implicitly assume that final log-prices are linear combinations of the prices of individual attributes (the sum of the price of the homogenous product and the price of the differentiated services offered by the retailer) and can be biased due to mispecification.

The four last columns of Table 2 present some descriptive statistics for the dispersion of the residuals of the fixed effects regressions described above. It includes weekly averages of the first and fourth quartiles and differences between the first and fourth quartiles and the 95% and 5% quantiles (mean values of the residuals are zero by construction).

The statistics show that price dispersion is important in all categories considered. Indeed, regarding the interquartile ratio, we see that 50% of prices in the middle of the distribution differ by up to 34%. This difference is less important for whisky (1%), which is the most expensive product under study. Controlling for observed and unobserved fixed product characteristics de-

[3] We consider the following products (we do not name brands but use A and B to signal that they are different brands): (i) beer brand A, bottle size: 250 ml, pack: 24 bottles, and beer brand B, bottle size: 250 ml, pack: 10 bottles; (ii) coffee brand A, arabica, caffeinated, 1 package per pack, package size 250g, and coffee brand B, degustation, arabica, caffeinated, 1 package per pack, package size 250g; (iii) cola brand A, plastic bottle, non-diet, bottle size: 1500 ml, pack: 1 bottle, and cola brand B, plastic bottle, non-diet, bottle size: 1500 ml, pack: 4 bottle; and (iv) whisky brand A, 1 liter bottle, not aged, blended, and whisky brand B, 1 liter bottle, 5 years aged, blended.

creases price dispersion for all products but whisky A, for which price dispersion increases. Price differences remain, on average, high for many products. In terms of interquartile differences, the difference in the prices in the middle of the price distribution can be as high as 29%.

Table 2: Descriptive Statistics of Pricing Patterns

		Uncontrolled Price Dispersion					Residual Log Price Dispersion	
Category	Product	Avg Price	Standard Deviation	Coef of Variation	Q75/Q25	Q95/Q5	Q75-Q25	Q95-Q5
Beer	A	0.98	0.10	0.10	1.21	1.27	0.12	0.23
	B	1.30	0.10	0.07	1.04	1.26	0.03	0.14
Cola	A	0.705	0.05	0.07	1.08	1.18	0.21	0.48
	B	0.494	0.11	0.23	1.28	1.81	0.21	0.48
Coffee	A	8.73	0.64	0.07	1.10	1.22	0.06	0.16
	B	4.49	0.77	0.17	1.34	1.70	0.29	0.45
Whisky	A	15.5	1.65	0.11	1.01	1.44	0.06	0.21
	B	14.9	0.63	0.04	1.02	1.05	0.02	0.06

Notes: Prices are in levels in the left panel, and in logs in the right panel

3.1 Temporal Price Dispersion

If stores' positions in the price distribution remain constant, then consumers can learn the identity of the cheapest store and there is no imperfect information about prices. That is, before leaving home, consumers know where to find the best deal and do not have to pay the cost of visiting stores to determine which prices are being offered. However, if stores periodically change position in the price ranking, then consumers cannot learn before hand which deals stores are offering in a given period. The existence of temporal price dispersion is therefore direct evidence of the importance of informational frictions, and it does not depend on any restriction on consumer search behavior.[4]

To study the temporal price dispersion, we examine the position of stores in the cross-sectional price distribution and measure how frequently they change position over time. Note that if store services are an important part of the price of the otherwise homogenous product, we could observe low transition probabilities even if the price of the homogeneous product is constantly changing positions in the price ranking. The transition probabilities for the uncontrolled

[4]Standard tests of the importance of search costs consist in regressing measures of price dispersion on proxies for search costs (or search benefits) and on the number of firms in the market. However, Chandra and Tappata (2009) show that the relationship between price dispersion and search costs or the number of firms on the supply side is not necessarily monotone (and not always positive), depending crucially on restrictive assumptions on the consumers' search strategy.

price should therefore be interpreted as a lower bound for the movements of the homogeneous product in the cross-sectional ranking.

Table 3: Stores Transition Probabilities in the Price Ranking

Product	Beer A				Beer B			
Rank t \ Rank at $t+1$	1	2	3	4	1	2	3	4
1	0.472	0.204	0.163	0.120	0.484	0.230	0.138	0.103
2	0.288	0.293	0.234	0.142	0.332	0.361	0.214	0.077
3	0.195	0.214	0.320	0.235	0.15	0.199	0.423	0.198
4	0.189	0.118	0.281	0.341	0.129	0.097	0.200	0.523
Obs	2,642				4,489			
	Coffee A				Coffee B			
Rank t \ Rank at $t+1$	1	2	3	4	1	2	3	4
1	0.583	0.071	0.161	0.146	0.408	0.198	0.200	0.157
2	0.415	0.171	0.220	0.111	0.335	0.264	0.255	0.134
3	0.403	0.098	0.273	0.201	0.235	0.265	0.287	0.191
4	0.351	0.059	0.208	0.337	0.192	0.240	0.304	0.192
Obs	4,558				1,392			
	Cola A				Cola B			
Rank t \ Rank at $t+1$	1	2	3	4	1	2	3	4
1	0.641	0.143	0.119	0.080	0.497	0.197	0.161	0.067
2	0.264	0.467	0.132	0.113	0.353	0.242	0.170	0.104
3	0.235	0.193	0.375	0.184	0.303	0.250	0.230	0.143
4	0.121	0.106	0.164	0.587	0.278	0.185	0.166	0.232
Obs	12,740				1,237			
	Whisky A				Whisky B			
Rank t \ Rank at $t+1$	1	2	3	4	1	2	3	4
1	0.438	0.200	0.182	0.117	0.522	0.159	0.147	0.083
2	0.286	0.289	0.231	0.131	0.408	0.185	0.223	0.076
3	0.233	0.185	0.313	0.202	0.202	0.174	0.261	0.206
4	0.181	0.177	0.247	0.301	0.142	0.162	0.311	0.284
Obs	1,586				862			

Table 3 shows the average (across periods and stores) of the Markovian transition probabilities for each product. For each week, we assign stores to one of the four price intervals limited by the quartiles of the price distribution.[5] The transition probabilities in the table are the empirical probabilities of changing from position j to position k, with $j = 1, 2, 3, 4$ and $k = 1, 2, 3, 4$. When the price for a certain store in a certain period is not observed, the transition probability (for that store and that period) is considered missing.

For all products, the probability of remaining in the first position is higher than the other transition probabilities, averaging between 1/3 and 1/2. The probability of remaining in the same position from one week to the next varies between approximately 25 and 40%. This means there is frequent movement in the price rankings, even over a short period of time. The evidence implies that it is difficult for consumers to keep track of which stores are offering the best deals each week.

3.2 Prices, Store Visits, and the Opportunity Cost of Time

If consumers have to incur a cost to determine prices, households with a higher opportunity cost of time will shop around less and will, on average, pay higher prices for otherwise identical products. A positive correlation between the cost of time and prices paid is therefore evidence that imperfect information about prices affects the demand behavior of consumers.

Notice that this test does not rely on any particular assumptions on consumers' search protocol or stores' pricing strategies. If information on the best deal is not readily and freely available, then consumers with a high opportunity cost of time have a lower probability of finding the best deals (because they search less) and pay on average higher prices. The same reasoning applies for the probability of paying the lowest price available in the market that period.

However, the test does rely on store and time fixed effects correctly controlling for potential quality differences between products purchased at different locations and in different periods. If there are remaining differences between the products, then a correlation between price and the opportunity cost of time could indicate that households with a high opportunity cost of time prefer purchasing at stores that offer more expensive services but not that search costs are relevant.

As in Aguiar and Hurst (2007), to have comparable prices across products and product categories, we use a product price index in which product prices are a quantity-weighted average

[5] That is, if a store is in position 1 at t, this means that its price at t is lower than or equal to the first quartile of the price distribution in that period. The store is in position 2 if its price is between the first and second quartiles and in position 3 if its price is between the second and third quartiles. Finally, the store is in position 4 if its price is greater than the third quartile.

across households using quantities purchased in that period. Then, the category price index is the total expenditure on that category divided by the cost of the same purchased quantities of goods valued at each product price index defined above. This category price index captures how much more or less than the average that the household is paying for a given category. We also regress the probability of paying the lowest price for a product on the opportunity cost of time. In this case, the dependent variable is a binary variable equal to 1 if the price paid by household i in period t for product j is equal to the lowest price (with a 2% margin) observed in the market during that period.

The household characteristics used to capture the opportunity cost of time are the age and its square, education level and professional activity status of the household head, the presence of a baby of less than 4 years old, income level, and household size. We also include controls for region of residence, frequency of purchases, the name of the store where the purchase was made, the size of the store, and the period of purchase. Including the frequency of purchases in the regression controls for the costs of holding inventories. Consumers with a higher cost of holding inventories have to purchase more frequently and are thus less able to avoid high prices. Therefore, we would expect the frequency of purchase to be positively correlated with prices even if there were no search costs. Other controls for the cost of holding inventories are a variable indicating whether the household has a car, whether the household has a dog (having a dog is thought to be positively correlated with size of the home, see Hendel and Nevo, 2006), and whether the household has a pantry.

Finally, we include a variable that measures the number of household store visits each week. This measure comes from the complete dataset, which includes households' purchases of any food category. Hence, it includes all store visits that generated a positive purchase. The number of store visits can be seen as an approximation of the search behavior of households or a proxy for the amount of time the household dedicates to supermarket purchases. Further, note that the larger the number of stores the consumer visits, the more information he gathers on transaction prices and sales in a given period.

Table 4 reports the empirical results. The first four columns show the estimates of the OLS regression, where the dependent variable is the price index of the product (by household and period). The next four columns show the probit model estimates where the dependent variable is a binary variable equal to 1 if the household pays the lowest transaction price in the regional market in that period.

The number of store visits is negatively correlated with prices and positively correlated with the probability of paying the lowest price. Store visit coefficients decrease in absolute value when we include proxies for households' opportunity cost of time. This is expected because these variables largely explain the number of store visits (see Table 5). There is strong empirical evidence supporting the hypothesis that households with a higher opportunity cost of time pay higher prices, even after controlling for store heterogeneity. The relationship between age and prices is U-shaped, whereas the relationship between age and the probability of paying the lowest price has an inverted U-shape. Having a baby increases transaction prices and decreases the probability of paying the lowest price. Being inactive, however, reduces prices paid and increases the probability of paying the lowest price.

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Table 4: Opportunity Cost of Time and Prices

	Transaction price (OLS)				Paying lowest price (Probit)			
Store visits	-0.103***	(0.014)	-0.099***	(0.014)	0.032***	(0.002)	0.031***	(0.002)
Age			-0.023***	(0.006)			0.010***	(0.001)
Age square			0.000***	(0.000)			-0.000***	(0.000)
Baby			0.104***	(0.035)			-0.018***	(0.007)
Inactive			-0.049*	(0.025)			0.033***	(0.005)
Frequency	0.001***	(0.000)	0.002***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Car	-0.382***	(0.064)	-0.375***	(0.064)	0.054***	(0.013)	0.052***	(0.013)
Pantry	-0.002	(0.023)	0.008	(0.023)	0.037***	(0.004)	0.034***	(0.004)
Dog	-0.050**	(0.022)	-0.042*	(0.022)	0.014	(0.004)	0.012***	(0.004)
Rural	-0.030	(0.022)	-0.035	(0.022)	-0.020	(0.004)	-0.018***	(0.004)
Rich	-0.042*	(0.023)	-0.027	(0.023)	0.007	(0.004)	0.006	(0.005)
Household Size	Yes		Yes		Yes		Yes	
Education Level	Yes		Yes		Yes		Yes	
Store Fixed Effects	Yes		Yes		Yes		Yes	
Time Fixed Effects	Yes		Yes		Yes		Yes	
N	445,038				415,438			

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The columns in Table 5 show the coefficient estimates of the regression of the number of stores visited on the opportunity cost of time and other controls (first estimated using OLS and then with a Poisson model) and of a probit model for the probability of visiting more than 1 store per week. Age and store visits have an inverted U-shaped relationship, implying that younger and older consumers visit more stores in a week. Having a baby does not significantly affect store visits, but being inactive is positively correlated with store visits and the probability of visiting more than one store. Living in a rural area and being wealthy are negatively correlated with the number of store visits and the probability of visiting more than one store.

Table 5: Determinants of the number of stores visited

	Store Visits (OLS)		Store Visits (Poisson)		Store Visits>1 (Probit)	
Age	0.018***	(0.000)	0.011***	(0.000)	0.024***	(0.001)
Age square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Baby	-0.008*	(0.004)	-0.004	(0.003)	0.010	(0.007)
Inactive	0.069***	(0.003)	0.043***	(0.002)	0.120***	(0.005)
Car	-0.004	(0.008)	-0.002	(0.005)	0.007	(0.132)
Pantry	-0.005	(0.003)	-0.003	(0.002)	-0.021***	(0.005)
Dog	-0.007**	(0.003)	-0.004**	(0.002)	-0.012	(0.004)
Rural	-0.082***	(0.002)	-0.052***	(0.002)	-0.107***	(0.004)
Rich	-0.022***	(0.003)	-0.014***	(0.002)	-0.019***	(0.005)
Hh size = 2	0.030***	(0.013)	0.021**	(0.009)	0.116***	(0.020)
Hh size = 3	0.072***	(0.013)	0.048***	(0.009)	0.165***	(0.021)
Hh size = 4	0.117***	(0.012)	0.077***	(0.009)	0.255***	(0.021)
Hh size = 5	0.204***	(0.013)	0.130***	(0.009)	0.343***	(0.021)
Hh size = 6	0 201***	(0.015)	0.129***	(0.010)	0.328***	(0.023)
Hh size = 7	0.394***	(0.021)	0.235***	(0.012)	0.636***	(0.032)
Hh size = 8	0.239***	(0.034)	0.149***	(0.020)	0.344***	(0.049)
Hh size = 9	1.069***	(0.078)	0.545***	(0.031)	0.903***	(0.077)
Education level 1	-0.049***	(0.006)	-0.030***	(0.004)	-0.076***	(0.010)
Education level 2	-0.057***	(0.006)	-0.035***	(0.003)	-0.086***	(0.009)
Education level 3	-0.066***	(0.006)	-0.041***	(0.004)	-0.086***	(0.010)
Education level 4	-0.119***	(0.007)	-0.076***	(0.004)	-0.174***	(0.012)
Education level 5	-0.077***	(0.007)	-0.048***	(0.004)	-0.086***	(0.011)
Time Fixed Effects	Yes		Yes		Yes	
Product Fixed Effects	Yes		Yes		Yes	
N	338,961		338,961		338,961	

Notes: t statistics in parentheses; * p<0.10,** p<0.05,*** p<0.01

4 Consumer Behavior with Search Costs

We have shown evidence consistent with imperfect information about prices, which means that consumers have to incur a cost to determine which prices are being offered on the market in a certain period of time. We now consider a choice model with costly search and develop an empirical strategy to estimate the search cost distribution and the choice model parameters when consumers are imperfectly informed.

Our demand model with search costs builds on Hortaçsu and Syverson (2004). However, in their model, consumers are identical except for search costs, whereas we allow for observable heterogeneity in preferences. This means that in our model products are both vertically and horizontally differentiated (i.e., consumers do not all agree on the value of each product attribute). The horizontal dimension will be related to some observable consumer characteristics.

Another key difference between our approach and theirs relates to the identification strategy. They identify model parameters in two cases: when products are considered homogeneous but the probability of visiting a given store is store specific and when products are vertically differentiated but drawing probabilities are homogeneous across stores. Under our identification strategy, we are able to identify model parameters when products are both vertically and horizontally differentiated and drawing probabilities are store, consumer, and period specific.

4.1 Model of Consumer Behavior

Consumers purchase at most one unit of the product. Before purchasing, consumers sequentially search for the product with the highest indirect utility. Search is costly, and its cost is heterogeneously distributed in the population of consumers. The cost of the first quote is normalized to zero. This ensures that everyone willing to purchase a product will do so. The indirect utility of a consumer of type i from purchasing product j in period t is denoted u_{ijt}. Note that within each consumer type i, search costs may vary, though valuations may not. We assume consumers search with replacement.

Let $F_{it}(\cdot)$ be the belief distribution of indirect utilities u_{ijt} of a type-i consumer. Then, the optimal search rule for a consumer of type i with search cost c_i who has already found the highest (among past searches) indirect utility u^*_{it} is to search once more if the sunk cost of searching is lower than the expected utility gain conditional on finding a better alternative:

$$c_i \leqslant \int_{u^*_{it}}^{\bar{u}_{it}} (u - u^*_{it})\, dF_{it}(u) \tag{1}$$

where $\bar{u}_{it}$ is the upper bound of the support of $F_{it}(\cdot)$. The above condition means that the marginal cost of searching once more is smaller than or equal to the expected gain from searching once more given u_{it}^{*}.

We assume that consumers know $F_{it}(\cdot)$, which means that they know the support of the distribution of indirect utilities, and hence they can label the N_i available products in ascending order with respect to indirect utility: $u_{i1t} < u_{i2t} < ... < u_{iN_it}$. For simplicity, we assume that there are no two products (stores) that provide the same indirect utility. Notice that we index the number of available products N_i by the consumer type i. This is to clarify that consumers do not necessarily have access to the same products because they shop at different markets. Note also that we index the ranking of indirect utilities ($j = 1, .., N_i$) by t, the period of the purchase, because the ranking may change from one period to the next.

As all indirect utilities of stores are strictly different, we obtain:

$$F_i\left(u\right) \equiv P\left(u_{ijt} \leq u\right) = \sum\nolimits_{k=1}^{N_i} \phi_{ik} \mathbf{1}_{\{u_{ikt} \leq u\}} \tag{2}$$

where ϕ_{ik} is the probability that the store ranked k is sampled by consumer i (this probability belief is known by consumers and common to all consumers of type i) and $\mathbf{1}_{\{u_{ikt} \leq u\}} = 1$ if and only if $u_{ikt} \leq u$.

Using (1) and (2), yields the following cutoff points for the search cost distribution:

$$c_{ij}^{t} \equiv \sum\nolimits_{k=j+1}^{N_i} \phi_{ik}\left(u_{ikt} - u_{ijt}\right) \tag{3}$$

where c_{ij}^{t} is the search cost level that makes any consumer of type i indifferent between purchasing at store j and searching once more (i.e., it is the lowest possible search cost of any type-i consumer who purchases product j). Because j is already quoted, products with indirect utility lower than u_{ijt} do not enter the calculation of the expected gain from searching once more (right-hand side of the above equation).

Note that although search costs are assumed to be time invariant, cutoff points depend on the period of purchase. Note also that $c_{iN_i}^{t} = 0$ and that the expected gain from an additional search decreases with the index of the product, and hence, $c_{i1}^{t} > .. > c_{iN-1}^{t} > c_{iN}^{t} = 0$.

Then, a consumer will purchase the worst product if he searches only once and finds the lowest utility product in his first and only draw. The probability of sampling store $j = 1$ on the first draw is equal to ϕ_{i1}. Therefore, the demand for the lowest indirect utility store in period t from type-i consumers is equal to

$$q_{i1}^{t} = \phi_{i1}\left[1 - G\left(c_{i1}^{t}\right)\right] \tag{4}$$

where G is the cumulative distribution function of search costs. Note that no type-i consumer whose search cost is below c_{i1}^{t} purchases product 1 because he is always better off (in expected utility) by searching once more.

Following the same type of reasoning, as in Hortaçsu and Syverson (2004), we obtain the demand for the second lowest indirect utility store (numbered 2) as

$$q_{i2}^t = \phi_{i2} \left[1 + \frac{\phi_{i1} G\left(c_{i1}^t\right)}{1-\phi_{i1}} - \frac{G\left(c_{i2}^t\right)}{1-\phi_{i1}} \right] \tag{5}$$

and for stores ranked $j = 3, .., N_i$ in the indirect utility ranks:

$$q_{ij}^t = \phi_{ij} \left[\sum_{k=1}^{j} \frac{G\left(c_{ik-1}^t\right) - G\left(c_{ik}^t\right)}{1 - \sum_{l=0}^{k-1} \phi_{il}} \right] \tag{6}$$

which can be re-written as

$$q_{ij}^t = \phi_{ij} \left[1 + \sum_{k=1}^{j-1} \frac{\phi_{ik} G\left(c_{ik}^t\right)}{\left(1 - \sum_{l=0}^{k} \phi_{il}\right)\left(1 - \sum_{l=0}^{k-1} \phi_{il}\right)} - \frac{G\left(c_{ij}^t\right)}{1 - \sum_{l=0}^{j-1} \phi_{il}} \right] \tag{7}$$

where by convention $G\left(c_{i0}^t\right) = 1$ and $\phi_{i0} = 0$

4.2 Discussion of Assumptions

When shopping at supermarkets, consumers frequently purchase not an individual item but a basket of goods. Purchasing a basket of goods is an equilibrium response for the existence of search costs, which in our setting also include transportation costs. If search costs were zero, consumers would buy each good at the store offering it at the lowest price.

However, is true that even if perfectly informed about prices, consumers could decide to buy all products in only one store to minimize travel. Arguably, modeling the search for a food basket is a more realistic description of consumers' grocery-shopping behavior than the search for a single product. However, considering the search for a basket of goods can be complex, especially with respect to one-stop versus multiple-stop shopping. If a consumer is searching for a basket of goods, he may buy a part of the basket in the first visit, another part in the second visit and so on until he purchases all items on his shopping list. The theoretical problem allowing for multiple search and multiple-stop shopping is frequently intractable, and empirical identification when search behavior is unobservable may be difficult to obtain.[6] We are not aware of any paper in the literature that identifies the parameters of the search model in the context of multiple-stop shopping. Wildenbeest (2011) considers the search for a basket of food products. However, he does not allow consumers to purchase different items from the basket in different stores. In this case, consumers are concerned only with the total price or the total utility of the bundle, and the multiproduct problem degenerates into a single product model. Using data only on those purchases made under the same roof introduces selection bias and

[6] See, for example, Carlson and McAfee (1984) and Zhou (2014).

probably an overestimation of search costs because the estimation process excludes the segment of consumers with low transportation costs (or a low value of time) who are willing to shop around.

Notice that search costs in our setting are the costs of determining transaction prices in a certain period. This includes the transportation cost of reaching the store and assessing prices (or browsing the internet or calling a friend), finding the product aisle and the product within the aisle, registering the information, performing mental calculations, etc. We do not separately identify these potentially different components of search costs. What is important here is measuring the total marginal cost of search, or the total marginal cost of price information.

Following the empirical literature on search costs, we assume that there is perfect recall, that is, consumers can return to previously searched stores at no additional cost. This is an important assumption when the number of stores is finite because it guarantees that the optimal search-stopping rule is stationary. Without perfect recall, the marginal cost of search depends on the search history and the number of non-sampled stores (Jansen and Parakhonyak, 2014), making identification extremely difficult. When the number of stores is infinite, stationarity does not require perfect recall. In our application, there is a limited number of stores from which consumers can search. However, we could assume that consumers perceive the number of potential price draws as large because, in principle, they could continue searching the same stores over time. Furthermore, an important part of the search cost may be finding the location of the product in the aisle, mentally registering the price and performing the relevant calculations. Hence, if one has to return to a previously searched product, one need not incur these costs again.[7]

In our model, consumers search sequentially for the best deal. This means that, at every price draw, they decide whether to continue searching by comparing the cost of an additional search with the expected benefit of an additional search. An alternative to sequential search is to assume non-sequential or fixed-sample search. In this case, before leaving home, consumers decide on how many stores to visit before making a purchase decision. Hence, the number of price draws is independent of the realizations of each draw.

De Los Santos, Hortaçsu and Wildenbeest (2012) test between a sequential and a non-sequential search model using data on web browsing and purchase behavior. They find evidence that non-sequential search, or fixed-sample search, provides a better description of how consumers search for books online. We believe this is a less credible search protocol for the case of brick-and-mortar supermarkets. It would imply, for instance, that even when consumers find a

[7] The consumer does not need to remember all prices or indirect utilities, just the best deal.

very good deal for an item in an early draw, they maintain the initial plan of visiting a fixed number of stores. It seems more realistic to assume that consumers leave home to purchase an item, and when they find it at a price lower than a certain reservation price, they buy the item during that visit and stop searching, which is the behavior implied by the sequential search assumption.

4.3 Identification

First, let us assume that we (as econometricians) know the consumer type i drawing probability ϕ_{ij} of a store ranked j. If we observe indirect utility rankings, then it is straightforward to obtain $G(c_{ij}^t)$, for $j = 1, .., N_i$, by solving the system of equations (4) to (6) above, using observed purchases in store j by consumer type i and the probabilities ϕ_{ij}.

The problem is that the support of the indirect utilities is unknown to the econometrician. In the case in which there is only price differentiation, these consumer-specific rankings are simply the observed price ranks. Otherwise, we cannot use prices to rank each alternative's indirect utilities, which depend on consumer preferences for horizontally differentiated goods.

Hortaçsu and Syverson (2004) first identify parameters by assuming that products are homogeneous. In this case, prices rank indirect utilities. Then, they assume vertical differentiation but restrict drawing probabilities to be equal across products and periods. However, thanks to the observation of purchase quantity and the identification of drawing probabilities from all store visits, we can identify the model parameters even when products are differentiated and drawing probabilities vary across stores, consumers, and period.

Note that (7) implies:

$$\frac{q_{ij}^t}{\phi_{ij}} - \frac{q_{ij-1}^t}{\phi_{ij-1}} = \frac{G(c_{ij-1}^t) - G(c_{ij}^t)}{1 - \sum_{l=0}^{j-1} \phi_{il}} > 0$$

which means that

$$0 < \frac{q_{i1}^t}{\phi_{i1}} < \frac{q_{i2}^t}{\phi_{i2}} < ... < \frac{q_{iN_i}^t}{\phi_{iN_i}}$$

Hence, if for any store s, we know quantities q_{is}^t and the probabilities of drawing that store ϕ_{is}, we know the elements of the vector of ratios $\left\{ \frac{q_{ir}^t}{\phi_{ir}} \right\}_{r=1,..,N_i}$ and can then recover the ranking of indirect utilities of the different stores for each type i. Thus the rank $j(s)$ of store s will be:

$$j(s) = \sum\nolimits_{r=1}^{N_i} 1_{\left\{ \frac{q_{ir}^t}{\phi_{ir}} < \frac{q_{is}^t}{\phi_{is}} \right\}} \tag{8}$$

and for simplicity of notation, we will write q_{ij}^t for $q_{ij(s)}^t$ and ϕ_{ij} for $\phi_{ij(s)}$ for any store s.

Knowing $\frac{q_{ij}^t}{\phi_{ij}}$ and ϕ_{ij}, equations (4) to (7) provide the following triangular system in the unknowns $G(c_{ij}^t)$ given all choice probabilities $\phi_{ij} \in (0,1)$:

$$\begin{cases} \frac{q_{i1}^t}{\phi_{i1}} = 1 - G\left(c_{i1}^t\right) \\ \frac{q_{i2}^t}{\phi_{i2}} = 1 + \frac{\phi_{i1}}{1-\phi_{i1}} G\left(c_{i1}^t\right) - \frac{1}{1-\phi_{i1}} G\left(c_{i2}^t\right) \\ \frac{q_{i3}^t}{\phi_{i3}} = 1 + \frac{\phi_{i1}}{1-\phi_{i1}} G\left(c_{i1}^t\right) + \frac{\phi_{i2}}{(1-\phi_{i1})(1-\phi_{i1}-\phi_{i2})} G\left(c_{i2}^t\right) - \frac{1}{(1-\phi_{i1}-\phi_{i2})} G\left(c_{i3}^t\right) \\ .. \\ \frac{q_{ij}^t}{\phi_{ij}} = 1 + \sum_{k=1}^{j-1} \frac{\phi_{ik} G\left(c_{ik}^t\right)}{\left(1-\sum_{l=0}^{k}\phi_{il}\right)\left(1-\sum_{l=0}^{k-1}\phi_{il}\right)} - \frac{G\left(c_{ij}^t\right)}{1-\sum_{l=0}^{j-1}\phi_{il}} \end{cases}$$

that we can solve to find:

$$\begin{cases} G\left(c_{i1}^t\right) = 1 - \frac{q_{i1}^t}{\phi_{i1}} \\ G\left(c_{i2}^t\right) = 1 - q_{i1}^t - (1-\phi_{i1}) \frac{q_{i2}^t}{\phi_{i2}} \\ ... \\ G\left(c_{ij}^t\right) = 1 - \sum_{k=1}^{j} \left(\frac{q_{ik}^t}{\phi_{ik}} - \frac{q_{ik-1}^t}{\phi_{ik-1}}\right)\left(1 - \sum_{l=0}^{k-1}\phi_{il}\right) \end{cases} \tag{9}$$

The above system enables identification of the value of the search cost cumulative distribution function evaluated at the cutoff points, that is $G(c_{ij}^t)$ for $j = 1, .., N_i$.

If we know the cumulative distribution function G and if it has non-zero density on its support such that G is invertible, we can invert G and identify c_{ij}^t by:

$$c_{ij}^t = G^{-1}\left(G(c_{ij}^t)\right)$$

and identify the indirect utilities up to a constant by solving the system of equations given by (3). Let us then assume that $G(.)$ belongs to a known family of c.d.f. parameterized by θ and denoted $G(., \theta)$. The lowest utility in each period is normalized to zero. Hence, there are $N_i - 1$ equations and $N_i - 1$ unknown values u_{ik}^t for each type i consumer:

$$u_{ikt} = \frac{c_{i1}^t}{\sum_{j=2}^{N}\phi_{ij}} + \sum_{k'=2}^{k-1} \frac{\phi_{ik'}^t c_{ik'}}{\left(\sum_{j=k'+1}^{N}\phi_{ij}\right)\left(\sum_{j=k'}^{N}\phi_{ij}\right)} - \frac{c_{ik}^t}{\sum_{j=k}^{N}\phi_{ij}} \tag{10}$$

for $k = 2, .., N_i$ and $u_{i1}^t = 0$.

Indirect utilities u_{ij}^t depend on joint characteristics of the consumer and store denoted x_{ijt}, common parameters γ_t, price p_{jt} and a consumer-store-specific random deviation to mean utility v_{ijt} such that:

$$u_{ijt} = x_{ijt}\beta + \gamma_t - \alpha_i p_{jt} + v_{ijt} \tag{11}$$

In practice, x_{ijt} are observable characteristics of the store (that may vary with the consumer type), γ_t are time-period fixed effects, p_{jt} is the price paid for product j in period t, and α_i and β are parameters. Consumers' valuation of product characteristics has both horizontal and vertical dimensions.

The probability ϕ_{is} that a consumer of type i finds store s can be identified empirically from the observation of all store visits made by the different households. Using data on all searches that generated a positive purchase of at least one product category (not only the categories we focus on) allows for such identification.[8] Once ϕ_{is} is identified, as the rank $j(s)$ of store s in the indirect utility space is identified using (8), we obtain the drawing probability of rank j store for consumer type i as $\phi_{ij} = \sum_{s=1}^{N_i} 1_{\{j(s)=j\}} \phi_{is}$.

Then, (9) yields:

$$c_{ij}^{t}(\theta) = G^{-1}\left(1 - \sum_{k=1}^{j}\left(\frac{q_{ik}^{t}}{\phi_{ik}} - \frac{q_{ik-1}^{t}}{\phi_{ik-1}}\right)\left(1 - \sum_{l=0}^{k-1}\phi_{il}\right), \theta\right)$$

Using (10), we have

$$u_{i2t}(\theta) = \frac{c_{i1}^{t}(\theta) - c_{i2}^{t}(\theta)}{\sum_{j=2}^{N}\phi_{ij}}$$

and for $k \geq 3$,

$$u_{ikt}(\theta) = \frac{c_{i1}^{t}(\theta)}{\sum_{j=2}^{N}\phi_{ij}} + \sum_{k'=2}^{k-1}\frac{\phi_{ik'}c_{ik'}^{t}(\theta)}{\left(\sum_{j=k'+1}^{N}\phi_{ij}\right)\left(\sum_{j=k'}^{N}\phi_{ij}\right)} - \frac{c_{ik}^{t}(\theta)}{\sum_{j=k}^{N}\phi_{ij}}$$

Note that by construction $u_{ikt}(\theta) > u_{ik-1t}(\theta)$ because

$$u_{ikt}(\theta) - u_{ik-1t}(\theta) = \frac{c_{ik-1}^{t}(\theta) - c_{ik}^{t}(\theta)}{\sum_{j=k}^{N}\phi_{ij}} > 0$$

As prices may be endogenously chosen after stores observe v_{ijt}, this may generate a correlation between v_{ijt} and the prices p_{jt}. We thus cannot use an orthogonality condition between prices and unobserved shocks v_{ijt}; instead, we assume that we observe some instrumental variables z_{ijt} that are uncorrelated with v_{ijt}, such that (11) gives the following moment condition:

$$E\left[\left(u_{ijt}(\theta) - x_{ijt}\beta - \gamma_t + \alpha_i p_{jt}\right) z_{ijt}\right] = 0 \tag{12}$$

Using this moment condition allows us to identify the parameters θ, β, γ_t, α_i provided the usual rank condition for GMM.

5 Estimation and Empirical Results

5.1 Search Cost and Preferences Estimates

We define consumer types using the region of residence, whether they live in an urban or rural area, and whether their income is above or below the median income ("rich" or "poor",

[8] Another route would be to parameterize the probability of sampling a certain store and estimate its parameters as in Hortaçsu and Syverson (2004).

respectively). Hence, there are four types of consumers per region: poor and urban, poor and rural, rich and urban, and rich and rural.

We assume that search costs are log-normally distributed over the population of consumers, thus taking $G(.,\theta)$ as log-normal. The search cost model is estimated for beer, cola, coffee, and whisky. Different products within the category differ with respect to the store where they are bought but also with respect to other observable characteristics of the products. The observed product characteristics that enter the utility function are product brand and container material. Store and region fixed effects capture observable and unobservable characteristics of the store. We also include time period fixed effects (year and month) that capture common shocks. Price coefficients are allowed to vary with consumer type (α_i).

As instruments, we use the weekly average price paid by other household types living in the same region, as well as lagged prices. These instruments are assumed to be uncorrelated with consumer-specific taste shocks v_{ijt}but are likely correlated with store j's price p_{jt}, such that the rank condition of the GMM estimation method is satisfied.

Drawing probabilities are identified and estimated from the data of all purchases made by the consumer. We observe all households' store visits that generated a purchase. We thus identify the probability a type-i household visits a store in a week t as the ratio of the number of visits to store j during t by all households of type i, over their total number of store visits during that week.

Table 7 displays the average (across regions and periods) of the cumulative distribution function values $G(c_{ij}^t)$ evaluated at the search cost cutoffs c_{ij}^t for each type of consumer and store ranked $j = 1, .., 5$, and each of the four products studied. We denote by G_j these averages for $j = 1, .., 5$.

On average, the proportion of people that do not search $(1 - G1)$ is between 50% and 60%, depending on the product and consumer type. The proportion of people who search more than once does not vary substantially across products. In general, people living in urban areas are more likely than their rural counterparts to search at least once, but there is no consistent difference in the proportion of people searching across income levels. The proportion of people searching decreases rapidly with the number of searches: approximately 20% of consumers search once $(G_1 - G_2)$, only half of them search twice $(G_2 - G_3)$, and less than 1% search 3 times.

Table 7: C.d.f. value estimates at search cutoffs points

Product	Consumer Type		G1	G2	G3	G4	G5
Beer							
	urban	poor	0.501	0.308	0.177	0.083	0.025
		rich	0.467	0.273	0.146	0.062	0.021
	rural	poor	0.442	0.263	0.146	0.065	0.021
		rich	0.466	0.280	0.144	0.059	0.015
Coffee							
	urban	poor	0.446	0.262	0.149	0.070	0.023
		rich	0.462	0.278	0.157	0.071	0.022
	rural	poor	0.415	0.241	0.132	0.063	0.020
		rich	0.450	0.273	0.155	0.076	0.025
Cola							
	urban	poor	0.485	0.297	0.168	0.082	0.027
		rich	0.457	0.272	0.143	0.060	0.016
	rural	poor	0.454	0.284	0.164	0.080	0.025
		rich	0.475	0.295	0.165	0.074	0.023
Whisky							
	urban	poor	0.447	0.252	0.132	0.052	0.015
		rich	0.405	0.189	0.102	0.060	0.060
	rural	poor	0.471	0.250	0.108	0.046	0.013
		rich	0.421	0.206	0.096	0.042	0.009

Notes: Each cell displays the mean across regions and periods of the per product per consumer type share of consumers that are willing to search at least j times for Gj.

Table 8 shows the results of the estimation of the utility parameters. All price coefficients are negative and significant, except for rural and poor whisky consumers, for whom it is not significantly different from zero. In general, urban households have higher (in absolute terms) price coefficients than rural households. Cola's indirect utilities are more price sensitive than those of any other product. Indirect utilities not only have different price slopes depending on the type but also different intercepts (significant coefficients for rich and rural), making clear the importance of allowing for heterogeneous tastes.

Table 8: GMM estimation of utility parameters

	Product			
	Beer	Coffee	Cola	Whisky
Price Coefficients (α_i)				
(urban, poor)	-0.004***	-0.028***	-0.261***	-0.011***
	0.001	0.002	0.017	0.001
(urban, rich)	-0.111***	-0.030***	-0.143***	-0.003***
	0.008	0.002	0.013	0.001
(rural, poor)	-0.054***	-0.022***	-0.203***	0.000
	0.006	0.002	0.017	0.000
(rural, rich)	-0.066***	-0.036***	-0.169***	-0.002***
	0.006	0.003	0.015	0.001
Rich	0.274***	0.282***	0.008***	-0.030***
	0.013	0.014	0.002	0.009
Rural	-0.022***	-0.004***	0.062***	-0.116***
	0.003	0.001	0.007	0.012
Store fixed effects	Yes	Yes	Yes	Yes
Other product characteristics	Yes	Yes	Yes	Yes
Region and period fixed effects	Yes	Yes	Yes	Yes
N	18,392	21,657	20,181	14,184

Notes: t statistics in parentheses; IV estimation;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; other product characteristics are brand and container material.

5.2 Price Elasticities

Having estimated the search cost distribution and consumer preferences, we can estimate the own- and cross-price elasticities of demand in this consumer search model. In our consumer search model, consumers rank store-specific indirect utilities that depend on price. Thus, prices affect the demanded quantity at the chosen store among those searched. However, price also affect search behavior by changing the share of consumers willing to search once, twice, three times, etc., which changes the composition of consumers purchasing at each store and who may end up preferring a given store. We derive the full expressions for own- and cross-price elasticities in the Appendix, but the partial derivatives with respect to price at store l of the store s demand are:

$$\frac{\partial q_{is}^{t}(\mathbf{p})}{\partial p_{lt}} = \sum_{j=1}^{N_i} \left[\frac{\partial P(j(s)=j)}{\partial p_{lt}} q_{ij}^{t}(\mathbf{p}) + P(j(s)=j) \frac{\partial q_{ij}^{t}(\mathbf{p})}{\partial p_{lt}} \right] \tag{13}$$

where $P(j(s)=j)$ is the probability that store s is ranked j among indirect utilities. Moreover, the derivations in the Appendix show that when one store changes its own price, it affects the rank of that store in the indirect utility space of each consumer type, as well as the indifference cutoff points in the search cost distribution.

This shows that information frictions on the side of the consumer (the search cost distribution), as well as the drawing probabilities of each store available to the consumer, plays an important role in the price elasticity of demand at each store in addition to the usual effect of consumers' marginal utility of income α_i.

For the sake of comparison, we use the specification of (11) and estimate consumer preferences under the assumption that there are no informational frictions. In this case, we simply need to estimate a logit model (Berry, 1994) using the same instrumental variables as in the search model to obtain consumers' preference estimates and thus own- and cross-price elasticities.

In Tables 9 through 12, we report estimated price elasticities yielded by our search model, as well as the price elasticities obtained in the model with no information frictions. The tables provide the average price elasticities across consumer types and periods per store and product category.

All diagonal elements (own-price elasticities) are negative, as expected, with the exception of whisky own-price elasticities in the perfect information logit model. The logit model assumes that consumers observe all prices before making a purchase. Hence, when consumers do not buy the product at the best price, they appear to be price-insensitive, whereas in reality, they had been uninformed about it. Coffee, and then cola, are the product categories with highest own- and cross-price elasticities, whereas whisky is the product category with less elastic demand. Notice that the full information logit model yields biased price elasticities. The direction of the bias, however, depends on the product. In the case of beer and coffee, the logit price elasticities underestimate the price elasticities in the search model. Conversely, cola price elasticities are consistently higher under the search model than under the logit model. These results are in line with Koulayev (2014), who also finds that the bias of the price elasticities of the full information model can go either way.

Table 9: Price Elasticities in Search and Full Information Models (Beer)

	Model	store 1	store 2	store 3	store 4	store 5	store 6
store 1	search	-0.044	0.021	0.014	0.032	0.017	0.014
		(0.112)	(0.042)	(0.115)	(0.805)	(0.443)	(0.390)
	logit	-0.008	0.012	0.018	0.017	0.024	0.012
		(0.082)	(0.064)	(0.061)	(0.059)	(0.068)	(0.039)
store 2	search	0.026	-0.314	0.067	0.071	0.092	0.089
		(0.039)	(0.501)	(0.118)	(0.148)	(0.459)	(0.140)
	logit	0.001	-0.103	0.019	0.018	0.029	0.015
		(0.017)	(0.282)	(0.057)	(0.058)	(0.073)	(0.044)
store 3	search	0.026	0.069	-0.339	0.083	0.088	0.100
		(0.039)	(0.113)	(0.599)	(0.246)	(0.209)	(0.183)
	logit	0.002	0.014	-0.104	0.019	0.030	0.015
		(0.020)	(0.049)	(0.234)	(0.059)	(0.074)	(0.043)
store 4	search	0.050	0.140	0.133	-0.749	0.154	0.165
		(0.068)	(0.239)	(0.219)	(1.195)	(0.211)	(0.213)
	logit	0.001	0.014	0.021	-0.130	0.029	0.021
		(0.023)	(0.049)	(0.054)	(0.262)	(0.066)	(0.050)
store 5	search	0.018	0.046	0.044	4.539	-0.284	0.070
		(0.031)	(0.106)	(0.100)	(278.821)	(0.618)	(0.175)
	logit	0.000	0.011	0.017	0.017	-0.096	0.013
		(0.023)	(0.063)	(0.060)	(0.060)	(0.231)	(0.041)
store 6	search	0.012	0.031	0.031	0.083	0.042	-0.248
		(0.022)	(0.063)	(0.061)	(3.156)	(0.176)	(2.183)
	logit	0.001	0.013	0.019	0.018	0.026	-0.091
		(0.021)	(0.063)	(0.059)	(0.059)	(0.070)	(0.217)

Notes: Mean elasticities across consumer types and periods with standard deviations in parentheses

Table 10: Price Elasticities in Search and Full Information Models (Coffee)

	Model	store 1	store 2	store 3	store 4	store 5	store 6
store 1	search	-0.102	0.049	0.073	-10.906	-8.323	-100.341
		(0.189)	(0.057)	(1.150)	(761.047)	(546.391)	(5009.560)
	logit	-0.120	0.085	0.115	0.098	0.123	0.059
		(0.108)	(0.082)	(0.097)	(0.112)	(0.110)	(0.089)
store 2	search	0.074	-1.103	0.264	0.254	0.277	0.325
		(0.112)	(1.567)	(0.361)	(0.403)	(0.404)	(0.408)
	logit	0.017	-0.551	0.113	0.100	0.130	0.067
		(0.023)	(0.230)	(0.095)	(0.113)	(0.109)	(0.091)
store 3	search	0.066	0.212	-1.015	0.222	0.234	0.286
		(0.084)	(0.284)	(1.297)	(0.424)	(1.436)	(0.723)
	logit	0.019	0.084	-0.526	0.099	0.128	0.064
		(0.024)	(0.080)	(0.210)	(0.113)	(0.110)	(0.091)
store 4	search	0.160	0.560	0.594	-2.853	0.600	0.686
		(0.166)	(0.617)	(0.617)	(3.101)	(0.599)	(0.616)
	logit	0.017	0.077	0.107	-0.619	0.131	0.087
		(0.021)	(0.073)	(0.090)	(0.248)	(0.107)	(0.095)
store 5	search	0.053	0.180	0.192	0.191	-0.960	0.242
		(0.064)	(0.238)	(0.242)	(0.419)	(1.817)	(0.574)
	logit	0.018	0.083	0.114	0.101	-0.537	0.063
		(0.024)	(0.079)	(0.097)	(0.112)	(0.213)	(0.090)
store 6	search	0.040	0.134	0.142	0.144	30.670	-0.970
		(0.052)	(0.167)	(0.190)	(0.633)	(1978.501)	(1.913)
	logit	0.019	0.084	0.115	0.099	0.124	-0.493
		(0.025)	(0.081)	(0.097)	(0.113)	(0.109)	(0.200)

Notes: Mean elasticities across consumer types and periods with standard deviations in parentheses

Table 11: Price Elasticities in Search and Full Information Models (Cola)

	Model	store 1	store 2	store 3	store 4	store 5	store 6
store 1	search	-0.093	0.047	0.046	0.036	0.036	-0.025
		(0.182)	(0.057)	(0.241)	(2.685)	(2.428)	(4.538)
	logit	-0.415	0.237	0.291	0.231	0.299	0.118
		(0.411)	(0.213)	(0.250)	(0.281)	(0.285)	(0.204)
store 2	search	0.047	-0.667	0.153	-3.727	-2.123	-1.829
		(0.056)	(0.986)	(0.220)	(248.021)	(132.817)	(86.331)
	logit	0.070	-1.404	0.278	0.225	0.317	0.138
		(0.094)	(0.414)	(0.240)	(0.275)	(0.284)	(0.214)
store 3	search	0.052	0.156	-0.780	0.173	-14.498	0.230
		(0.065)	(0.226)	(1.095)	(0.298)	(858.276)	(0.858)
	logit	0.066	0.220	-1.432	0.237	0.330	0.141
		(0.083)	(0.193)	(0.416)	(0.280)	(0.283)	(0.215)
store 4	search	0.134	0.423	0.452	-2.208	0.427	0.484
		(0.130)	(0.491)	(0.497)	(2.535)	(0.422)	(0.402)
	logit	0.063	0.208	0.273	-1.641	0.349	0.198
		(0.090)	(0.186)	(0.227)	(0.481)	(0.267)	(0.232)
store 5	search	0.036	0.108	0.113	0.123	-0.645	0.167
		(0.046)	(0.153)	(0.163)	(0.277)	(0.933)	(0.264)
	logit	0.068	0.219	0.280	0.393	-1.431	0.131
		(0.091)	(0.196)	(0.238)	(0.266)	(0.348)	(0.211)
store 6	search	0.027	0.086	0.091	0.097	0.093	-0.827
		(0.039)	(0.132)	(0.148)	(0.230)	(0.771)	(0.962)
	logit	0.071	0.229	0.285	0.241	0.308	-1.356
		(0.094)	(0.203)	(0.246)	(0.282)	(0.285)	(0.337)

Notes: Mean elasticities across consumer types and periods with standard deviations in parentheses

Table 12: Price Elasticities in Search and Full Information Models (Whisky)

	Model	store 1	store 2	store 3	store 4	store 5	store 6
store 1	search	-0.021	0.007	0.006	-4.323	-5.617	-0.094
		(0.068)	(0.021)	(0.107)	(172.205)	(152.593)	(2.069)
	logit	0.147	-0.046	-0.044	-0.019	-0.013	-0.004
		(0.198)	(0.100)	(0.090)	(0.057)	(0.046)	(0.027)
store 2	search	0.010	-0.085	0.023	0.018	0.024	0.053
		(0.016)	(0.147)	(0.049)	(0.065)	(0.146)	(0.117)
	logit	-0.047	0.306	-0.052	-0.025	-0.020	-0.007
		(0.089)	(0.268)	(0.089)	(0.063)	(0.056)	0.036)
store 3	search	0.011	0.016	-0.091	0.025	0.036	0.057
		(0.021)	(0.039)	(0.231)	(0.207)	(0.238)	(0.107)
	logit	-0.048	-0.049	0.269	-0.022	-0.019	-0.006
		(0.099)	(0.103)	(0.251)	(0.059)	(0.053)	(0.032)
store 4	search	0.026	0.038	0.051	-0.289	0.059	0.142
		(0.055)	(0.092)	(0.119)	(0.6719	(0.125)	(0.199)
	logit	-0.036	-0.041	-0.048	0.296	-0.026	-0.012
		(0.073)	(0.081)	(0.0859	(0.268)	(0.060)	(0.044)
store 5	search	0.008	0.014	0.019	0.020	-0.200	0.083
		(0.027)	(0.041)	(0.052)	(0.070)	(0.404)	(0.114)
	logit	-0.035	-0.042	-0.047	-0.022	0.276	-0.007
		(0.071)	(0.096)	(0.094)	(0.061)	(0.276)	(0.034)
store 6	search	0.007	0.012	0.016	0.016	0.031	-0.321
		(0.017)	(0.032)	(0.047)	(0.160)	(0.156)	(0.495)
	logit	-0.051	-0.040	-0.043	-0.019	-0.015	0.247
		(0.103)	(0.088)	(0.087)	(0.057)	(0.048)	(0.239)

Notes: Mean elasticities across consumer types and periods with standard deviations in parentheses

6 Conclusion

Price dispersion is an important characteristic of the French food market. Price dispersion is also persistent over time, with stores frequently changing positions in the price ranking, implying that it is difficult for consumers to be perfectly informed about prices in every period. We find empirical evidence consistent with a demand model with imperfectly informed consumers who need to engage in costly search to find the available deals. We show that consumers with a high opportunity cost of time search less and pay higher prices on average. Moreover, the number of stores that a household visits in a certain week, which can be seen as a proxy for search activity, is negatively correlated with prices.

We develop an empirical strategy to estimate the magnitude and distribution of sequential search costs. Products are vertically differentiated, and consumer tastes are heterogeneous. We identify the search cost distribution without having to make any restriction on the drawing probabilities of stores. The drawing probabilities are recovered from the data and are heterogeneous across time, store chain, and household type.

The results of the structural estimation show that search costs for the products considered (beer, coffee, cola, and whisky) are high and that the majority of consumers do not search much. There is also indication that urban consumers tend to search more than rural consumers, which is likely related to higher store density in urban areas, which decreases the cost of visiting multiple stores. Price elasticity measures show that the perfect information model yields biased elasticities. The magnitude of the bias is large, and its direction depends on the product. This is in line with Koulayev (2014)'s results. Further note that previous literature reports both overestimation (Sovinsky, 2008) and underestimation (De los Santos, Hortaçsu and Wildenbeest, 2012, Honka, 2014) of the imperfect information measures.

7 Appendix

7.1 Own and Cross-price elasticities in the Search Model

For any of the store $s \in \{1,..,N\}$ and any consumer type i, the store s demand $q^t_{i,s}$ by type i is

$$q^t_{i,s}\left(\mathbf{p_t}\right) = \sum\nolimits_{j=1}^{N} P\left(j(s)=j\right) q^t_{ij}\left(\mathbf{p_t}\right)$$

where $j(s)$ is the utility rank of store s among all stores available for consumer i and q^t_{ij} is the demand to store ranked j by consumer i at t that depends on the vectors of all prices $\mathbf{p_t}$.

Then, assuming that v_{ijt} is i.i.d. type I extreme value in (11), we have can write $P\left(j(s)=j\right)$ as a function of all characteristics and prices. Actually, denoting Θ^s_j the set of subsets of size $j-1$ of the set $\{1,...,N\}\setminus\{s\}$, we have

$$\begin{aligned} P\left(j(s)=1\right) &= P\left(u_{ist} \leq u_{irt} \; ;\forall \; r\in\{1,...,N\}\right) \\ &= \frac{1}{1+\sum_{r=1}^{N}\exp\left(\left(x_{ist}-x_{irt}\right)\beta-\alpha\left(p_{st}-p_{rt}\right)\right)} \end{aligned}$$

and for $j=2,..,N$

$$P\left(j(s)=j\right) = \sum\nolimits_{\Omega\in\Theta^s_j} P\left(u_{irt} < u_{ist} \leq u_{ir't} \; ;\forall \; r\in\Omega, \forall r' \notin \Omega\right)$$

because the probability that store s is of rank j is equal to the probability that $j-1$ stores have lower utility and $N-j+1$ have higher utility, and this happen for all possible combinations in two groups of the other $N-1$ stores (the group of stores with lower utility being denoted Ω and the group of stores not belonging to Ω that will have higher utility than s).

For a given store s, the set Θ_j^s is thus

$$\Theta_j^s = \bigcup_{\Omega} \underbrace{\Omega \subset \{1,2,..,N\}}_{s.t.\ card(\Omega)=j-1 \text{ and } s\notin\Omega}$$

Then, for any set $\Omega \in \Theta_j^s$, the probability that u_{ist} is the larger in $\Omega \cup \{s\}$ and the smaller in $\{1,...,N\}\setminus\Omega$ is

$$\begin{aligned} & P\left(u_{irt} < u_{ist} \leq u_{ir't}; \forall r \in \Omega, r' \notin \Omega\right) \\ = & P\left(u_{irt} < u_{ist}\ ; \forall\ r \in \Omega\right) P\left(u_{ist} \leq u_{ir't}\ ; \forall\ r' \notin \Omega\right) \\ = & \pi_{s,\Omega}^{\max}\left(\mathbf{p}\right) \pi_{s,\Omega}^{\min}\left(\mathbf{p}\right) \end{aligned}$$

where

$$\pi_{s,\Omega}^{\max}\left(\mathbf{p}\right) \equiv P\left(u_{irt} < u_{ist}\ ; \forall\ r \in \Omega\right) = \frac{1}{1+\sum_{r\in\Omega} \exp\left(\left(x_{irt}-x_{ist}\right)\beta - \alpha\left(p_{rt}-p_{st}\right)\right)}$$

and

$$\begin{aligned} \pi_{s,\Omega}^{\min}\left(\mathbf{p}\right) & \equiv P\left(u_{ist} \leq u_{ir't}\ ; \forall\ r' \notin \Omega\right) = \prod_{r'\notin\Omega} P\left(u_{ist} \leq u_{ir't}\right) \\ & = \prod_{r'\notin\Omega} \frac{1}{1+\exp\left(\left(x_{ir't}-x_{ist}\right)\beta - \alpha\left(p_{r't}-p_{st}\right)\right)} \end{aligned}$$

We can now write

$$\begin{aligned} \frac{\partial P\left(j(s)=j\right)}{\partial p_{lt}} & = \sum_{\Omega\in\Theta_j^s} \frac{\partial}{\partial p_{lt}} P\left(u_{irt} < u_{ist} < u_{ir't}\ ; \forall\ r \in \Omega_j^s, \forall r' \notin \Omega_j^s\right) \\ & = \sum_{\Omega\in\Theta_j^s} \pi_{s,\Omega}^{\max}\left(\mathbf{p}\right) \frac{\partial \pi_{s,\Omega}^{\min}\left(\mathbf{p}\right)}{\partial p_{lt}} + \pi_{s,\Omega}^{\min}\left(\mathbf{p}\right) \frac{\partial \pi_{s,\Omega}^{\max}\left(\mathbf{p}\right)}{\partial p_{lt}} \end{aligned}$$

where $\frac{\partial \pi_{s,\Omega}^{\min}(\mathbf{p})}{\partial p_{lt}}$ and $\frac{\partial \pi_{s,\Omega}^{\max}(\mathbf{p})}{\partial p_{lt}}$ are as below.

If $l = s$:

$$\begin{aligned} & \frac{\partial \pi_{s,\Omega}^{\min}\left(\mathbf{p}\right)}{\partial p_{lt}} \\ = & \alpha \sum_{r'\notin\Omega} \left[\frac{\exp\left(\left(x_{ir't}-x_{ist}\right)\beta - \alpha\left(p_{r't}-p_{st}\right)\right)}{\left[1+\exp\left(\left(x_{ir't}-x_{ist}\right)\beta - \alpha\left(p_{r't}-p_{st}\right)\right)\right]^2} \prod_{r\notin\Omega\setminus\{r'\}} \frac{1}{1+\exp\left(\left(x_{irt}-x_{ist}\right)\beta - \alpha\left(p_{rt}-p_{st}\right)\right)} \right] \\ = & \alpha \sum_{r'\notin\Omega} \left[\frac{\exp\left(\left(x_{ir't}-x_{ist}\right)\beta - \alpha\left(p_{r't}-p_{st}\right)\right)}{\left[1+\exp\left(\left(x_{ir't}-x_{ist}\right)\beta - \alpha\left(p_{r't}-p_{st}\right)\right)\right]} \prod_{r\notin\Omega} \frac{1}{1+\exp\left(\left(x_{irt}-x_{ist}\right)\beta - \alpha\left(p_{rt}-p_{st}\right)\right)} \right] \end{aligned}$$

and thus

$$\frac{\partial \pi_{s,\Omega}^{\min}(\mathbf{p})}{\partial p_{lt}} = \alpha \pi_{s,\Omega}^{\min}(\mathbf{p}) \sum_{r' \notin \Omega} \frac{\exp\left(\left(x_{ir't} - x_{ist}\right)\beta - \alpha\left(p_{r't} - p_{st}\right)\right)}{\left[1 + \exp\left(\left(x_{ir't} - x_{ist}\right)\beta - \alpha\left(p_{r't} - p_{st}\right)\right)\right]} \text{ if } l = s$$

If $l \neq s$ and $l \notin \Omega$:

$$\begin{aligned}
\frac{\partial \pi_{s,\Omega}^{\min}(\mathbf{p})}{\partial p_{lt}} &= \prod_{r \notin \Omega, r \neq l} \frac{1}{1 + \exp\left(\left(x_{irt} - x_{ist}\right)\beta - \alpha\left(p_{rt} - p_{st}\right)\right)} \frac{\alpha \exp\left(\left(x_{ilt} - x_{ist}\right)\beta - \alpha\left(p_{lt} - p_{st}\right)\right)}{\left[1 + \exp\left(\left(x_{ilt} - x_{ist}\right)\beta - \alpha\left(p_{lt} - p_{st}\right)\right)\right]^2} \\
&= \alpha \pi_{s,\Omega}^{\min}(\mathbf{p}) \frac{\exp\left(\left(x_{ilt} - x_{ist}\right)\beta - \alpha\left(p_{lt} - p_{st}\right)\right)}{\left[1 + \exp\left(\left(x_{ilt} - x_{ist}\right)\beta - \alpha\left(p_{lt} - p_{st}\right)\right)\right]}
\end{aligned}$$

If $l \neq s$ and $l \in \Omega$:

$$\frac{\partial \pi_{s,\Omega}^{\min}(\mathbf{p})}{\partial p_{lt}} = 0$$

We also have

$$\begin{aligned}
\frac{\partial \pi_{s,\Omega}^{\max}(\mathbf{p})}{\partial p_{lt}} &= \frac{\partial}{\partial p_{lt}} \left(\frac{1}{1 + \sum_{r \in \Omega} \exp\left(\left(x_{irt} - x_{ist}\right)\beta - \alpha\left(p_{rt} - p_{st}\right)\right)} \right) \\
&= -1_{\{s=l, l \notin \Omega\}} \frac{\alpha \sum_{r \in \Omega} \exp\left(\left(x_{irt} - x_{ilt}\right)\beta - \alpha\left(p_{rt} - p_{lt}\right)\right)}{\left(1 + \sum_{r \in \Omega} \exp\left(\left(x_{irt} - x_{ilt}\right)\beta - \alpha\left(p_{rt} - p_{lt}\right)\right)\right)^2} \\
&\quad +1_{\{l \in \Omega, l \neq s\}} \frac{\alpha \exp\left(\left(x_{ilt} - x_{ist}\right)\beta - \alpha\left(p_{lt} - p_{st}\right)\right)}{\left[1 + \sum_{r \in \Omega} \exp\left(\left(x_{irt} - x_{ist}\right)\beta - \alpha\left(p_{rt} - p_{st}\right)\right)\right]^2} \\
&= -1_{\{s=l, l \notin \Omega\}} \alpha \pi_{l,\Omega}^{\max}(\mathbf{p}) \left(1 - \pi_{l,\Omega}^{\max}(\mathbf{p})\right) \\
&\quad +1_{\{l \in \Omega, l \neq s\}} \alpha \exp\left(\left(x_{ilt} - x_{ist}\right)\beta - \alpha\left(p_{lt} - p_{st}\right)\right) \pi_{s,\Omega}^{\max}(\mathbf{p})^2
\end{aligned}$$

This allows to obtain $\frac{\partial q_{i,s}^t(\mathbf{p_t})}{\partial p_{lt}}$ using

$$\frac{\partial q_{is}^t(\mathbf{p})}{\partial p_{lt}} = \sum_{j=1}^{N_i} \left[\frac{\partial P(j(s) = j)}{\partial p_{lt}} q_{ij}^t(\mathbf{p}) + P(j(s) = j) \frac{\partial q_{ij}^t(\mathbf{p})}{\partial p_{lt}} \right] \tag{14}$$

where

$$\frac{\partial q_{ij}^t(\mathbf{p})}{\partial p_{lt}} = \phi_{ij} \sum_{k=1}^{j-1} \frac{\phi_{ik} g\left(c_{ik}^t\right) \frac{\partial c_{ik}^t}{\partial p_{lt}}}{\left(1 - \sum_{k'=0}^{k} \phi_{ik'}\right)\left(1 - \sum_{k'=0}^{k-1} \phi_{ik'}\right)} - \phi_{ij} g\left(c_{ij}^t\right) \frac{\partial c_{ij}^t}{\partial p_{lt}} \sum_{k=1}^{j-1} \frac{1}{1 - \sum_{k'=0}^{j-1} \phi_{ik'}}$$

that is

$$\begin{aligned}
\frac{\partial q_{ij}^t(\mathbf{p})}{\partial p_{lt}} &= -\alpha \phi_{ij} \sum_{k=1}^{j-1} \frac{\phi_{ik} g\left(c_{ik}^t\right) \sum_{k'=k+1}^{N_i} \phi_{ik'} \left(1_{\{j(l)=k'\}} - 1_{\{j(l)=k\}}\right)}{\left(1 - \sum_{k'=0}^{k} \phi_{ik'}\right)\left(1 - \sum_{k'=0}^{k-1} \phi_{ik'}\right)} \\
&\quad +\alpha \phi_{ij} g\left(c_{ij}^t\right) \left(\sum_{k=1}^{j-1} \frac{1}{1 - \sum_{k'=0}^{j-1} \phi_{ik'}} \right) \left(\sum_{k'=j+1}^{N_i} \phi_{ik'} \left(1_{\{j(l)=k'\}} - 1_{\{j(l)=j\}}\right) \right)
\end{aligned}$$

because using (3), we have

$$\frac{\partial c_{ik}^t}{\partial p_{lt}} = \sum_{k'=k+1}^{N_i} \phi_{ik'} \frac{\partial}{\partial p_{lt}} \left(u_{ik't} - u_{ikt}\right) = -\alpha \sum_{k'=k+1}^{N_i} \phi_{ik'} \left(1_{\{j(l)=k'\}} - 1_{\{j(l)=k\}}\right)$$

and

$$q_{ij}^t = \phi_{ij} \left[1 + \sum_{k=1}^{j-1} \frac{\phi_{ik} G\left(c_{ik}^t\right)}{\left(1 - \sum_{k'=0}^{k} \phi_{ik'}\right)\left(1 - \sum_{k'=0}^{k-1} \phi_{ik'}\right)} - \frac{G\left(c_{ij}^t\right)}{1 - \sum_{k'=0}^{j-1} \phi_{ik'}} \right]$$

where by convention $G\left(c_{i0}^t\right) = 1$ and $\phi_{i0} = 0$.

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