Multiproduct retailing and consumer shopping patterns: The role of shopping costs

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Abstract

We structurally identify consumer shopping costs —real or perceived costs of dealing with a store— using scanner data on grocery purchases of French households. We present a model of demand for multiple stores and products consisting of an optimal stopping problem in terms of individual shopping costs. This rule determines whether to visit one or multiple stores at a shopping period. We then estimate the parameters of the model and recover the distribution of shopping costs. We quantify the total shopping cost in 18.7 € per store sourced on average. This cost has two components, namely, the mean fixed shopping cost, 1.53 € and mean total transport cost of 17.1 € per trip. We show that consumers able to source three or more grocery store have zero shopping costs, which rationalizes the low proportion of three-stop shoppers observed in our data. Theory predicts that when shopping costs are included in economic analysis, some seemingly pro-competitive practices can be welfare reducing and motivate policy intervention. Such striking findings remain empirically untested. This paper is a first step towards filling this gap.

JEL Codes: D03, D12, L13, L22, L81.

Keywords: Grocery retailing, supermarket chains, shopping costs, one- and multistop shopping, Method of Simulated Moments.

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1 Introduction

Consumers have heterogeneous shopping patterns (see Figure 1 below). This heterogeneity might be explained by several factors such as preferences, demographics, geographic location, information frictions, differentiated retailers, and time availability for shopping activities. Previous literature has introduced a concept that accounts for some (or most) determinants: *shopping costs* (Klemperer, 1992, Klemperer and Padilla, 1997, Armstrong and Vickers, 2010, and Chen and Rey, 2012, 2013). In line with this literature, we will call *shopping costs* all real or perceived costs a consumer incurs when sourcing a grocery store. Economic theory shows that in a context of multiproduct retailing and consumer shopping costs, several practices that would otherwise be considered good from a social welfare perspective can motivate anti competitive behavior among firms. However, there is not much empirical support for such findings, in part because the introduction of shopping costs in a structural model of demand is a challenging task. This motivates the following questions. First, is it possible to quantify shopping costs from observed consumer shopping behavior? Second, will accounting for shopping costs in a multiproduct demand model lead to a better understanding of consumer heterogeneity in shopping patterns? Finally, to what extent the inclusion of shopping costs would be crucial for policy analysis? In this paper, we develop and estimate a structural model of multiproduct demand for groceries in which shopping costs play a key role in consumer decision making. This framework enables us identify the distribution of consumer shopping costs.

We will say that two consumers have heterogeneous shopping patterns when they visit a different number of stores within the same shopping period. Therefore, a consumer sourcing a single store within, say, a week will be a *one-stop shopper* and a consumer visiting several separate suppliers within the same week will be a *multistop shopper*. Consumer shopping costs, which may depend on stores' characteristics (e.g. transport costs depend on store location; the opportunity cost of time from shopping depends on store size) and may as well be informative about consumers' tastes for shopping, account for such differences.[1]

The inclusion of shopping costs in the analysis of multiproduct demand and supply may change policy conclusions dramatically. Consider, for instance, the case of multiproduct retailers competing head-to-head by selling homogeneous products. In the presence of shopping costs, customers will stick with a single retailer because the benefit from visiting an additional supplier need not compensate the shopping cost. As a consequence, competition is reduced and prices are higher. In contrast, if product lines are differentiated, retailers may be tempted to undercut prices to make one-stop shoppers become multistop by patronizing several separate suppliers (Klemperer, 1992). Another theory result states that the presence of shopping costs can lead to the introduction of too many varieties of products with respect to the social optimum. When a retailer introduces a new product, the mass of one-stop shoppers increases because more consumers prefer to concentrate purchases with the retailer supplying a wider product range and save on shopping costs. As a consequence, rivals' profits decrease (Klemperer and Padilla, 1997).

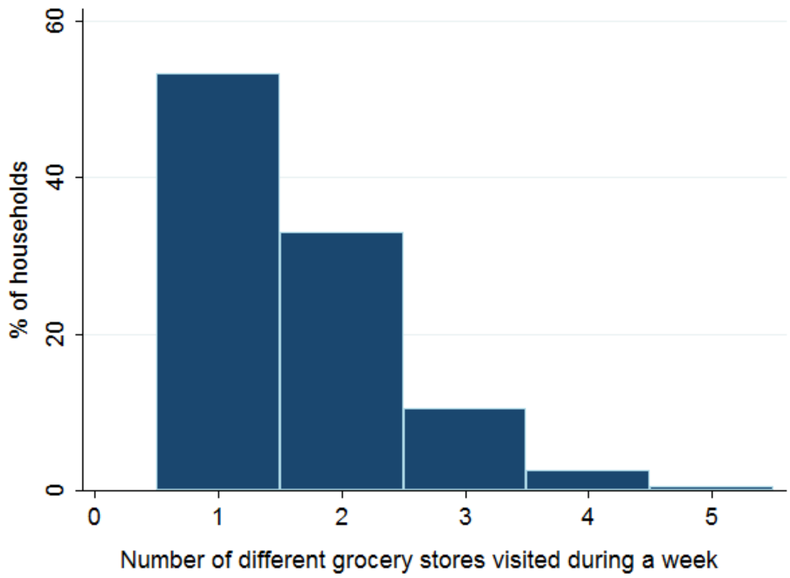
The presence of heterogeneous customers might as well be a way to price discriminate between one-stop and multistop shoppers. Large retailers may adopt loss-leading strategies when competing with smaller rivals. By doing this, they do not want to push rivals out of the market but keep them in instead, and exploit multistop customers. Hence, pricing

[1] Klemperer (1992) distinguishes among consumer costs in the following way: "...consumer's total costs include purchase cost and utility losses from substituting products with less-preferred characteristics for the preferred product(s) not actually purchased [transport costs of the standard models à la Hotelling] (...) Consumers also face shopping costs that are increasing in the number of suppliers used." p.742.

below cost is an exploitative device rather than a predatory practice (Chen and Rey, 2012). Finally, in a setting of competition between large retailers, in which each has a comparative advantage on some products, cross subsidization strategies may be competitive. Below-cost pricing is again not predatory and it can be good for consumers. This implies that banning this practice may hurt consumers and reduce social welfare (Chen and Rey, 2013).

From an empirical point of view, we can readily find support for the idea that shopping patterns are heterogeneous and that this heterogeneity is explained by differences in shopping costs. Figure 1 displays the distribution of the population by the average number of different retailers visited within a week. Moreover, we performed reduced form regressions of the number of different supermarkets visited in a week (which constitutes an indicator of multistop shopping behavior) on demographic variables that are proxies for shopping costs (such as income, age, household size, number of children under 16, etc.) and control for household storage capacity, among others. We found strong empirical evidence showing that multistop shopping depends on how busy the household members could be, i.e. how costly it might be to spend a lot of time in shopping activities.

Figure 1: Distribution of household by average number of stores visited in a week, 2005



Notes: The observed distribution has a longer tail than displayed by the graph as we observe households visiting up to 8 separate retailers per week. However, 99.8% of the observations are concentrated up to 5 stops.

This paper provides a framework to assess the role of shopping costs in explaining heterogeneous shopping patterns. To do so we develop a structural model in the spirit of the main theoretical contributions on the topic. Consumer optimal shopping behavior is given by a threshold strategy where the choice between one- or multistop shopping depends on the size of the individual's shopping costs. We are able to take the model to data through parametric specifications of consumer utility and shopping cost along with some distributional assumptions on the unobserved shocks. We use scanner data on household grocery purchases in France in 2005, which is representative of French households and contains information on a wide product range and household demographics. As for grocery stores, an additional data set allows us to observe store characteristics and location.

By solving the implied optimal stopping problem of a consumer who needs to decide how many stores to source, we are able to recover the distribution of shopping costs. We quantify the total shopping cost in 18.7 € per store sourced on average. This cost has two components, namely, the mean fixed shopping cost, 1.53 €and the total transport cost of 17.1 €per trip to a given store. Moreover, we are able to compute the transport and total costs of shopping by store format. Transport and total costs of shopping are decreasing in the size of the stores, on average, as smaller formats are closer to downtowns. The largest total shopping cost, 24.7 €, are incurred by consumers who source big-box stores, because they are farther away from downtown. Sourcing a supermarket or a hard-discounter implies total costs of shopping of 14.3 € and 13.4 € per trip, respectively. Finally, the costs of sourcing a convenience store, 4.8 € per trip, are the lowest provided that they are located in downtown. We find that individuals who source three or more stores in a week have zero shopping costs. This might be an indicator that those households actually visiting more than two separate stores a week should have a strong preference for shopping. In fact, the predicted proportions of shoppers by number of stops are 90.1% of one-stop shoppers, 9.7% of two-stop shoppers and only 0.26% do three-stop shopping.

Related literature

The literature including or measuring explicitly consumer-related costs from an empirical point of view, can be summarized in three categories: *i*) search cost literature,[2] *ii*) switching costs literature,[3] and *iii*) shopping costs literature. In recent years there has been a considerable number of contributions developing models and empirical strategies that allow to identify search costs —these include Hong and Shum (2006), Moraga-Gonzalez et al. (2011), Hortaçsu and Syverson (2004), Dubois and Perrone (2010) and Wildenbeest (2011)— and switching costs —these include Dubé et al. (2010), Handel (2010) and Honka (2012).

Less attention has been put on shopping costs. To the best of our knowledge, few empirical papers include explicitly shopping costs when it comes to explain time use or supermarket choice. Brief (1967) models consumer shopping patterns in a Hotelling framework, and estimates transportation as part of consumers' shopping costs.[4] His identification strategy consists of using 'the shopping costs elasticity of demand', as he claims these costs are not directly identifiable. Aguiar and Hurst (2007) evaluate how households substitute time for money by optimally combining shopping activities with home production. They argue that multistop shoppers exist because they want to reduce the price paid for a good, which requires more time. As opposed to them, one-stop shoppers may find it optimal to become frequent customers of the same store and benefit from sales and discounts. All this implies a cost in terms of the time needed to carry out the shopping

[2]Both shopping and search costs are often referred to as the opportunity cost of time when people go search (for search costs)/shopping (for shopping costs). The difference stems from the purpose of the time expended, whether the consumer ends up buying a product she was looking for or not, and the available information on prices or product characteristics in different locations (sellers). Search costs appear whenever consumers face search frictions caused by information asymmetries. As for shopping costs, they account for the opportunity costs of time related to the shopping activity which may include a previous search if needed.

[3]As stated by Kemplerer and Padilla (1997), shopping costs differ from switching costs in that the latter derives from the economies of scale from repeated purchases of a product while the former is associated with economies of scope from buying related products.

[4]Brief (1967) claims that the final price paid by a consumer has two components, namely, the "pure" price of the good and the marginal cost of shopping for it. These shopping costs include both explicit, such as transportation costs, and implicit, such as the opportunity costs of shopping, which are related to the "purchaser's valuation of time and inconvenience associated with the shopping trip.".

activity, which is accounted for in their modeling. In a similar setting, Aguiar et al. (2012) analyze the time use during recessions, including the time spent in shopping.

In the analysis of store choice in the presence of shopping costs, our paper closely relates to Shciraldi, Seiler and Smith (2011). They evaluate the effects of big-box retailing on competition, allowing for the fact that customers may do one- or two-stop shopping. This observed heterogeneity allows them to identify individual shopping costs. However, our approach differs from theirs in at least an important way. In line with previous theory literature, we adopt the view that heterogeneous shopping patterns stem from differences in shopping costs as a modeling feature. In other words, in our model the number of stops is endogenously determined by a stopping rule involving the extra utility and extra costs of sourcing an additional store. This fact enables us to empirically identify the distribution of shopping costs. In this sense, our approach is more closely related to the empirical literature on search costs previously mentioned. In particular, our setup relates to Hortaçsu and Syverson (2004), and Dubois and Perrone (2010).

The rest of the paper is organized as follows. Section 2 presents the data and a preliminary analysis of consumers' shopping behavior based on descriptive statistics and reduced form regressions. Section 3 outlines the structural model of multiproduct demand and consumer shopping behavior in the presence of shopping costs. Section 4 describes our empirical strategy, discusses identification and presents the estimation procedure. Section 5 describes the results. We examine the robustness of our results in Section 6. Finally, Section 7 concludes and discusses directions for further research.

2 Grocery retailing, shopping patterns and opportunity cost of time

This Section aims at giving an overview of the data we use, and a first look at customers' shopping behavior.

2.1 The data

This paper uses two complementary data sets. Data on household purchases is obtained from the TNS Worldpanel data base by the TNS-Sofres Institute. It is homescan data on grocery purchases made by a representative sample of 7,490 households in France during 2005. These data are collected by household members themselves with the help of scanning devices. Most households integrating the panel were randomly sampled since 1998 (the TNS Worldpanel is a continuous panel database starting from 1998). Every year, a bunch of new randomly selected households is added to the panel either as a replacement of another household rarely reporting data or because sample size is increased.

The data set contains information on 352 different grocery products from around 90 grocery stores including hyper- and supermarkets, convenience stores, hard-discounters and specialized stores. The data is reported at the purchase level, so we observe product characteristics such as total quantity, total expenditure, the tore where it was purchased from, brand, etc. In addition, the data include a range of household demographics such as household size, number of children, location, income, number of cars, internet access, storage capacity etc.

On the other hand, data on stores' characteristics is obtained from the Atlas LSA 2005. It includes information by store category (Hyper-, supermarket, convenience and hard-discount stores) on store location, surface, no. checkouts, no. parking spots, etc. In particular, store location is key to our analysis as it will enable us to identify transport costs. This will become apparent in Section 4.1.

2.2 Customer profile

Table 1 gives summary statistics for demographic characteristics of french households observed in the data. The average household in France consists of three members, the household's head age[5] being 51 years old, with approximately 2,350 euros of income per month and at least one car. Only half of the households in the sample reported having internet access at home which may give a clue on why internet purchases are not so important in our data set. As for storage capacity and home production, 79% of the households have storage rooms at home and 69% an independent freezer, which may explain low frequency of shopping for some households or one-stop shopping behavior. In particular, it is remarkable that about 39% reported to produce vegetables at home, which along with the fact that less than 30% of the households are located at rural areas, may be an indicator of less need for shopping or low frequency of shopping as well.

Table 1: Summary statistics for household characteristics

Variable	Mean	Median	Sd	Min	Max
Demographics					
HH size	2.96	3	1.38	1	9
Income (€/month)	2,352	2,100	1,106	150	7,000
Children under 15 (prop. of HH)	0.35	0	0.48	0	1
HH head's age	50.6	49	14.32	22	76
Lives in city	0.73	1	0.44	0	1
Car	1.55	2	0.80	0	8
Home internet access	0.49	0	0.50	0	1
Storage capacity					
Independent freezer	0.69	1	0.46	0	1
Freezer capacity $> 150L$	0.58	1	0.49	0	1
Storage room at home	0.79	1	0.41	0	1
Vegetables production at home	0.39	0	0.49	0	1

Table 2 displays details on consumer shopping patterns. On average, households tend to favor multistop shopping. The average french household visits two separate grocery stores in a week and tend to do a single trip per week to the same store. The average number of days between shopping occasions is 5 days. Notice there is some heterogeneity here, which is indicated by a standard deviation of 4.7 days: some households go every day to a grocery store whereas for some others it takes up to ten days to go back to a store.

Larger store formats are preferred by consumers: on average, the two most frequently visited store formats are Supermarkets and Hypermarkets with 48.4% and 40.5% share on total visits per week. Convenience stores, the small downtown stores supplying a reduced product range generally at higher prices, get the lowest share of visits, with 1.9%. Although convenience stores have the advantage of being within walking distance to households location, as opposed to hypermarket that are located outside city centers, the preference for larger stores may be explained by several factors such as bulk shopping, lower prices sales and promotions (that may be more intense in larger stores) and a larger

[5] By household head we mean the person mainly in charge of the household's grocery shopping.

product range.

Table 2: Summary statistics for household shopping patterns

Variable	Mean	Median	Sd	Min	Max
No. Trips to same grocery store/week	1.37	1	0.72	1	7
No. separate grocery stores visited/week	1.65	1	0.83	1	8
Days between visits	5.09	4	4.73	1	232
Visits by format (% of total/week)					
Hypermarket	40.48	32.2	34.4	0	100
Supermarket	48.38	47.6	32.6	0	100
Convenience	1.92	0.0	8.7	0	100
Hard discount	9.22	3.7	11.6	0	50

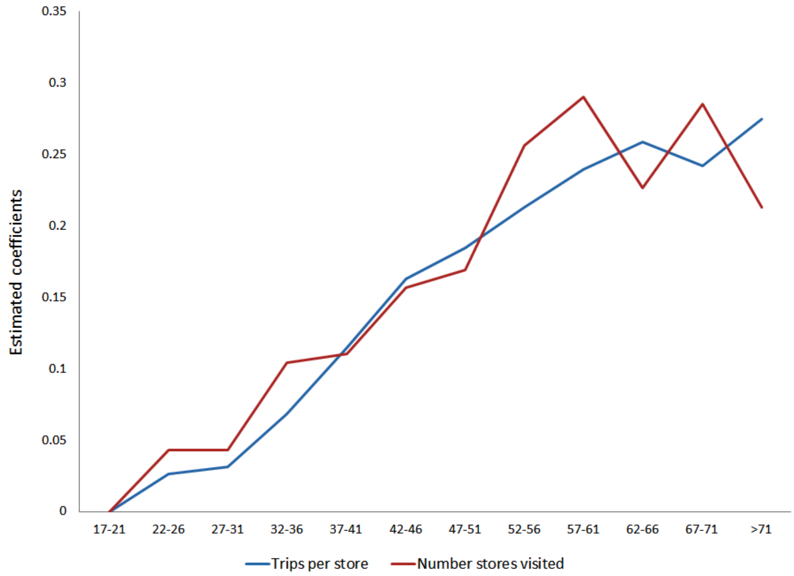
Interestingly, households tend to concentrate purchases of particular product categories in the same store format. Table 3 gives transition probabilities of visiting a particular store format this week for dairy products conditional on the store format sourced the previous week. The probability of keeping the same store format in most cases is larger than the probability of switching store formats. In particular, the lowest probabilities of switching are for those households sourcing hyper- and supermarkets in the past, which is in line with the preference for larger store formats reported in Table 2. Moreover, those households patronizing specialized and other smaller stores ('others') are more likely to switch to a hyper- or a supermarket next period.

Table 3: Transition matrix for purchases of dairy products by store format

		Purchase at t				
		Hyper	**Super**	**Convenience**	**Hard discount**	**Other**
	Hyper	0.68	0.16	0.16	0.27	0.28
At	**Super**	0.17	0.67	0.25	0.31	0.37
t+1	**Convenience**	0.01	0.01	0.46	0.01	0.02
	Hard discount	0.12	0.12	0.09	0.38	0.10
	Other	0.03	0.04	0.04	0.02	0.23

Age can be seen as a good indicator of the opportunity cost of time. Aguiar and Hurst (2007) find that older people often pay lower prices because their frequency of both shop trips and retailers visited increases, presumably due to a lower cost of time. In our data we found a similar relationship between shopping frequency indicators and age. Figure 2 shows that both the number of trips per store and the number of different stores visited a month increase with age. Older people go shopping more frequently performing more visits to the same retailer as well as more visits to separate retailers than their younger counterparts. This can be thought of as older people with higher taste for shopping and quality doing more multistop shopping in order to get the best products. It might as well be interpreted as a way to search for the best deals, from an information friction viewpoint. However, the low shopping costs reasoning seems to be more appealing to us because frequent shopping allows people to be better informed about prices and promotional activities without the need to do a search each time they want to go shopping.

Figure 2: Frequency of shopping by age ranges, 2005



Notes: Both lines show the results of independent regressions of each variable (*Trips per store* and *Number of stores visited*) on age categories and other demographic controls (income, hh size, car dummy, storage capacity, etc.). Results are based on 5 million observations. All estimates are significant at 1% confidence level.

2.3 Reduced-form results

Recall that shopping costs are the costs of dealing with a store. This implies that multistop shopping, i.e., visiting several separate suppliers in a given shopping period, should be negatively correlated with the consumers' physical as well as time costs. Such a correlation will constitute key empirical evidence of the role of shopping costs on consumer shopping behavior.

In line with theory, we measure multistop shopping as the number of different suppliers visited within a week by the consumer. We regress this variable on the distance from household location to stores and a set of household demographic characteristics which proxy opportunity cost of time, to study the correlation between shopping costs and multistop shopping behavior. Dummy variables to control for region fixed-effects are added in all regressions. Supermarket and time dummies are included gradually in order to assess their effect on the estimates. Further, we add some controls on household storage capacity that can determine the frequency of shopping during the week, namely, type of living place (apartment, farm), storage room, independent freezer, and the size of the largest freezer at home. Table 4 gives the results. Most coefficients are of the expected sign and statistically significant at 1% confidence level.

Results provide us with strong empirical evidence on how households' ability to patronize multiple stores depends on how costly it will be in terms of time and distance. Interestingly, we find that bigger households living in urban areas tend to favor multistop shopping. On the other hand, higher income people as well as households with babies do less stops on average due, presumably, to a larger opportunity cost of time. Similarly, internet access reduces the number of stops as people can shop online and use home delivery services, which might involve savings on transport costs and time. Growing vegetables at home also reduces the number of stops people want to make probably due to lesser needs for staples. People living in an apartment tend to source more stores as compared to those who live in a house. In contrast, those who live in a larger place, such as a farm, do less stops as compared to families living in a house. This can be explained by the fact that in general, people living in apartments are more likely to be located at or closer to downtown and are more proxy to stores than houses (that are mostly located outside downtown) and farms. It also could indicate that apartments have lower storage capacity than houses and farms.

Distance to stores are negatively correlated with the number of stores visited in a week as expected (see column (1) of Table 4). The longer the trip a consumer needs to make to join a store the larger the transport costs. Notice that distances were excluded from specifications displayed in columns (2) and (3) due to the inclusion of store fixed effects that are capturing location as a store characteristic. Finally, in specification given in column (1) we find a negative correlation with car ownership, which can be explained by the fact that people with a car can do bulk shopping at a big-box store, generally located outside downtown areas. However, this relationship becomes positive and non significant in specifications two and three as we introduce store and time dummies.

3 Consumer shopping behavior with shopping costs

Our general strategy is to identify all parameters of the model and retrieve shopping costs cutoffs by setting out a model of demand for multiple grocery products. This way, we can avoid any difficulties related to unobserved data on costs and structure of the supply side.

Our structural model allows for consumer heterogeneity in two dimensions, namely, in the valuation for a particular product and in shopping costs. To keep exposition simple, without loss of generality, we present a model of three grocery stores which will capture the basic intuition of one- and multistop shopping behavior and the role of shopping costs.

3.1 General set-up

Demand for grocery products is characterized by different consumers indexed by $i = \{1, \ldots, I\}$ with idiosyncratic valuations for grocery products $k = 1, \ldots, K$.[6] Although valuations and demands may vary with time, we drop the time subscript t for the sake of exposition unless it is strictly necessary. A customer i purchasing product k from store $r \in \{0, \ldots, R\}$ derives a net utility $\overline{v}_{ikr}$.[7]

Consumers want to purchase bundles of these products. Let $\mathcal{B} = \{1, \ldots, R^K\}$ be the set of all possible bundles consisting of combinations of products-stores available in the market, i.e. our bundles account not only for which product was purchased, but what supplier it was purchased from as well. A consumer can either concentrate all her purchases with a single store (*one-stop shopping*) or buy subsets of products from several separate suppliers (*multistop shopping*). At the end of the day, each individual's shopping behavior will be determined by her idiosyncratic cost of shopping.

In the formulation of the model, we focus on the fixed component of the total shopping costs that may account for consumers' taste for shopping. From now on, we will refer to this fixed cost as "shopping costs" and denote it s_i. Physical transport costs, which are an

[6] All consumers having access to the same product range might seem a strong assumption. However, this help us reducing dimensionality issues in the estimation part. An extension of the paper would relax this assumption and allow for heterogeneous choice sets.

[7] For now, we do not specify a functional form for the utility now as it is not necessary for setting out the model. We will assume a parametric specification at the empirical implementation stage in Section 4.

Table 4: Results for number of different stores visited per week

Variable	(1)	(2)	(3)
HH head's age	0.0025***	0.0032***	0.0032***
	(0.0000)	(0.0000)	(0.0000)
Log Income	-0.0541***	-0.0106***	-0.0104***
	(0.0009)	(0.0009)	(0.0009)
HH size	0.0781***	0.0691***	0.0692***
	(0.0004)	(0.0004)	(0.0004)
Car	-0.0177***	0.0030	0.0031
	(0.0019)	(0.0019)	(0.0019)
Lives in city	0.0416***	0.0517***	0.0516***
	(0.0009)	(0.0009)	(0.0009)
Lives in an appartment	0.0699***	0.0620***	0.0622***
	(0.0011)	(0.0011)	(0.0011)
Lives in a farm	-0.1791***	-0.1605***	-0.1601***
	(0.0028)	(0.0027)	(0.0027)
Baby	-0.1155***	-0.0901***	-0.0898***
	(0.0012)	(0.0011)	(0.0011)
Home internet access	-0.0147***	-0.0086***	-0.0086***
	(0.0008)	(0.0008)	(0.0008)
Grow vegetables home	-0.0122***	-0.0095***	-0.0101***
	(0.0009)	(0.0009)	(0.0009)
Distance to store (km)	-0.0002***		
	(0.0000)		
Constant	1.8866***	1.9142***	1.9153***
	(0.0073)	(0.0075)	(0.0080)
HH storage capacity controls	Yes	Yes	Yes
Dummies per region	Yes	Yes	Yes
Store FE		Yes	Yes
Week FE			Yes
R^2	0.0249	0.074	0.0764

Notes: Regressions are based on 4.72 million observations. Asymptotically robust s.e. are reported in parentheses.
*** Significant at 0.1%.

important component of the total cost of shopping, will be accounted for in the empirical implementation of the model by including distances to stores in the utility specification (see Section 4).[8]. Accordingly, shopping costs are assumed to be independent of store characteristics (size, facilities, location, etc.) and time invariant. Furthermore, we assume s_i is a random draw from a continuous distribution function $G(\cdot)$ and positive density $g(\cdot)$ everywhere.

Finally, we suppose consumers are well informed about prices and product characteristics. Therefore, we assume away information frictions and so consumers' need for searching activities to gather information about prices, qualities and the like.[9]

A consumer i, whose shopping costs of using store r are denoted s_i, is supposed to have an optimal shopping behavior. This implies she should optimally make a decision that involves choosing between being a one-stop or a multistop shopper and where to go and buy each of the K products of his desired bundle b.

Suppose there are three grocery stores in the market indexed by $r \in \{A, B, C\}$. A consumer will favor multistop shopping if her shopping costs are small enough, otherwise she will optimally concentrate all her purchases with a single store. Roughly speaking, the choice set of consumer i will be restricted by the number of separate stores she can source given her shopping costs, so that her choice will consist of picking the mix of products-stores that maximize the overall value of the desired bundle. In this sense, a three-stop shopper who can visit all three stores will pick the best product from the three alternatives in the market within each category. A two-stop shopper will pick the mix of two stores maximizing the utility of the desired bundle from all the combinations of products-stores possible. Her final bundle will consist of two sub-bundles each containing the best product out of two alternatives in each product category. Finally, a one-stop shopper will pick the store offering the largest overall value of the whole bundle of products.

Formally, let γD_{ir}, for all$r \in \{A, B, C\}$ represent consumer's i transport costs, with D_{ir} being the distance traveled by a consumer i from his household location to store $r's$ location and γ a parameter that captures consumer's valuation of the physical and perceived costs of the trip to the store. Define the utility net of transport costs, of a shopper that can only source one of the three stores in the market as

$$v_i^1 = \max \left\{ \sum_{k=1}^{K} \overline{v}_{ikA} - \gamma D_{iA}, \sum_{k=1}^{K} \overline{v}_{ikB} - \gamma D_{iB}, \sum_{k=1}^{K} \overline{v}_{ikC} - \gamma D_{iC} \right\}. \tag{1}$$

Similarly, a two-stop shopper has net utility given by

$$\begin{aligned} v_i^2 = \max \Bigg\{ & \sum_{k=1}^{K} \max\{\overline{v}_{ikA}, \overline{v}_{ikB}\} - \gamma(D_{iA} + D_{iB}) \ , \\ & \sum_{k=1}^{K} \max\{\overline{v}_{ikA}, \overline{v}_{ikC}\} - \gamma(D_{iA} + D_{iB}), \\ & \sum_{k=1}^{K} \max\{\overline{v}_{ikB}, \overline{v}_{ikC}\} - \gamma(D_{iA} + D_{iB}) \Bigg\}. \end{aligned} \tag{2}$$

[8]Due to some data limitations, we can only compute distances from the zip code of a given household to the zip code of a given store. Consequently, transport costs will be the same for all individuals living in the same zip code area. See Section 4.1 for further details

[9]This might seem a strong assumption, even though we believe frequent grocery shopping make better informed households and reduce the need to engage in costly search. A more general set up would allow for positive search costs. However, this is out of the scope of this paper and we leave it for a future extension.

Finally, a consumer able to source the three stores has net utility given by

$$v_i^3 = \sum_{k=1}^{K} \max\{\overline{v}_{ikA}, \overline{v}_{ikB}, \overline{v}_{ikC}\} - \sum_{r\in\{A,B,C\}} \gamma D_{ir}. \tag{3}$$

Notice that expressions in (1), (2), and (3) are particular cases of a more general utility function in which, conditional on shopping costs, a n-stop shopper is picking the subset of stores that maximize the overall utility of the desired bundle. For a one-stop shopper, these subsets are singletons, for a two-stop shopper they contain two elements and for a three-stop shopper each subset of stores contains exactly the number of stores in the market, which is why she does not need to maximize over mixes of suppliers.[10]

Suppose $v_i^1 - s_i > 0$ so that all consumers will go shopping at least once. To determine the number of stops to be made, consumer i will compare the extra utility of doing n-stop shopping with the extra costs, taking into account that the total cost of shopping increases with the number of different stores visited. A consumer will optimally decide to do three-stop shopping only if the net utility of visiting three separate stores is larger than what she could obtain by doing either one- or two-stop shopping instead. Formally,

$$v_i^3 - 3s_i \geqslant \max\{v_i^2 - 2s_i, v_i^1 - s_i\}$$

Let $\delta_i^3 \equiv v_i^3 - v_i^2$ be the incremental utility of visiting three stores rather than two, and $\Delta_i^3 \equiv v_i^3 - v_i^1$ be the extra utility of deciding to source either one or three stores. The optimal shopping rule for a three-stop shopper is

$$s_i \leqslant \min\left\{\delta_i^3, \frac{\Delta_i^3}{2}\right\} \tag{4}$$

Similarly, a consumer will optimally decide to do two-stop shopping if and only if

$$v_i^2 - 2s_i \geqslant \max\{v_i^1 - s_i, v_i^3 - 3s_i\}$$

Similarly, let $\delta_i^2 \equiv v_i^2 - v_i^1$ be the incremental utility of sourcing two stores rather than one. Hence, a consumer i will do two-stop shopping as long as

$$\delta_i^3 < s_i \leqslant \delta_i^2 \tag{5}$$

Finally, a consumer will optimally decide to do one-stop shopping if and only if

$$v_i^1 - s_i \geqslant \max\{v_i^2 - 2s_i, v_i^3 - 3s_i\}$$

from which we can derive the optimal shopping rule of a one-stop shopper as

$$s_i > \max\left\{\delta_i^2, \frac{\Delta_i^3}{2}\right\} \tag{6}$$

In general, the optimal shopping rule for consumer i says that she will choose the mix of suppliers to maximize his utility, conditional on the extra shopping cost being at most the extra utility obtained from sourcing additional stores.

[10] The general expression of the utility and choice of a n-stop shopper are described in Appendix A.

Equations (4), (5) and (6) suggest we can derive critical cutoff points of the distribution of shopping costs. It is necessary though to determine how are δ_i^2, δ_i^3 and $\Delta_i^3/2$ ordered. From six possible orderings only one survives,[11] namely,

$$\delta_i^3 < \frac{\Delta_i^3}{2} < \delta_i^2, \tag{7}$$

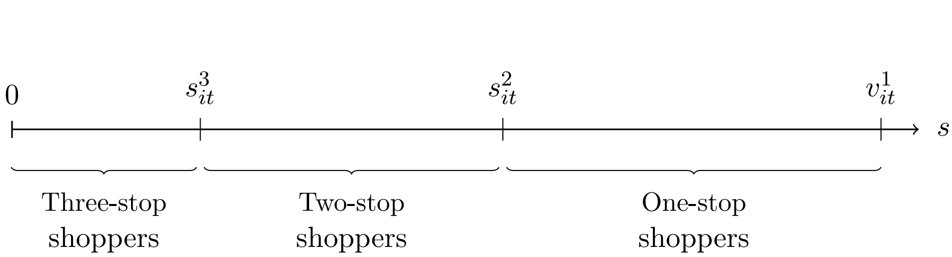
Given (7), the highest possible shopping costs of any consumer able to do multistop shopping at either two or three stores in equilibrium are given respectively by the following critical cutoff points:

$$\begin{aligned} s_{it}^2 &= \delta_{it}^2, && \text{for two-stop shopping, and} \\ s_{it}^3 &= \delta_{it}^3, && \text{for three-stop shopping.} \end{aligned} \tag{8}$$

Notice that cutoff points in (8) depend on the period of purchase —the subscript t was added— because it depends on utilities that may vary across periods. This contrast with individual shopping costs which are assumed to be time invariant. Cutoffs in (8) say that for given shopping costs, consumers only care about marginal extra utility of visiting an additional store to make their final decision on how many stores they should optimally source. Moreover, one-, two- and three-stop shopping patterns arise and will be defined over all the support of $G(\cdot)$ –see Figure 3.[12]

Assume $v_{it}^1 - s_i > 0$ for all $i = 1, \dots, I$ so that all consumers will do at least one shopping trip per week. This is, the outside option is chosen with probability zero implying $G(v_{it}^1) = 1$. The intuition behind this is as follows: a likely outside alternative to grocery shopping is home production, which consists of households transforming time and market goods into consumption products according to a given home production function (see Aguiar and Hurst, 2007). Yet, even if the household chooses to produce at home most of its preferred products, there is still a bunch of them that will be too costly to produce compared to the retail price (e.g. toothpaste, toothbrush, cleaning products, bulbs, medicines, etc.). Then, we can think of household members going from time to time to a store to get the set of products they are not able to produce at home (or even the inputs to produce at home the final products they wish to consume).[13]

Figure 3: One-, two- and three-stop shopping



[11] We explain why this is so in Appendix B.

[12] Notice that the kind of behavior according to which a shopper evaluates extreme choices such as visiting all retailers against only one does not appear to be relevant here.

[13] The outside option might as well be thought of as not shopping on a weekly basis (for instance, going once a month or every other month). However, in our data the proportion of households not purchasing on a weekly basis corresponds to 8%.

3.2 Aggregate demand

Let $\mathcal{B}_{2i}, \mathcal{B}_{3i} \in \mathcal{B}_i$ be subsets of bundles involving two- and three-stop shopping, respectively. Total demand for product $k = 1, \ldots, K_i$ supplied by retailer r from all types of shoppers is given by

$$\begin{aligned} q_{krt}\left(\mathbf{p_t}\right) = \left[1 - G\left(s^2_{it}\left(\mathbf{p_t}\right)\right)\right] P^1_{it}(X_{\mathcal{B}_i};\theta) \\ + \left[G\left(s^2_{it}\left(\mathbf{p_t}\right)\right) - G\left(s^3_{it}\left(\mathbf{p_t}\right)\right)\right] \prod_{\{b\in\mathcal{B}_{2i}\,|\,kr\in b\}} P^2_{it}(X_{\mathcal{B}_i};\theta) \\ + G\left(s^3_{it}\left(\mathbf{p_t}\right)\right) \prod_{\{b\in\mathcal{B}_{3i}\,|\,kr\in b\}} P^3_{it}(X_{\mathcal{B}_i};\theta), \end{aligned} \tag{9}$$

where P^3_{it} is the probability that a one-stop shopper decides to stop at r, P^2_{it} is the probability that a two-stop shopper chooses to source retailer r as one of the two retailers she will optimally stop at, and P^3_{it} is the probability that a three-stop shopper decides to pick a bundle b including product kr. All these probabilities are known by consumers.

The own- and cross-price elasticities of demand are given by the standard formula $\eta_{krht} = \frac{\partial q_{krt}}{\partial p_{kht}} \frac{p_{kht}}{q_{krt}}$. It is important to note that a price change may affect not only the market shares per type of shopper but also the shopping costs cutoff values provided that they depend on utilities. As a consequence, the distribution of shoppers between one-, two- and multistop shopping changes. In fact, an increase in product k's price at retailer r reduces the indirect utility of consumer i making a stop at r. She may therefore consider to make less stops and purchase a substitute for this product from rival retailer, say h, as the extra gain in utility from sourcing an additional store may not compensate the extra shopping cost.

4 Empirical implementation

As described in Section 3, consumer choice set consists of bundles of products that can be purchased from one or several stores. Accordingly, if we consider R stores and K products, we would have to deal with a choice set of R^K alternative bundles for each individual, which grows exponentially as R or K increases, resulting in a dimensionality problem which will make estimation challenging and burdensome, whereas it might not change the results in an important way. We circumvent this problem by restricting attention to a reduced set of products and grocery stores. We select pre-packaged bread, ready-to-eat breakfast cereal (hereafter *RTEBC*) and yogurt as the products to be included in our analysis, provided that they meet the following conditions. First, they are staples and so they are frequently purchased and heavily consumed by french households (see Table 5). Second, they belong to different categories of products, which ensures we can observe enough variation in shopping patterns as people may tend to concentrate purchases of the same category in a particular store but might want to diversify across categories. Finally, these products are likely to be of unit demand, i.e., consumers tend to consume one serving of the product at a time and to not mix varieties (see Table 5 for details on how we define servings).

Concerning grocery stores, we restrict attention to the two leading supermarket chains in France selected according to their national market share in 2005. The remaining grocery stores observed in our data are treated as part of a composite store which sells the three products we referred to above and constitute an outside option to the two leading chains. In other words, consumers have three alternative stores in their choice set: two insiders and

Table 5: Chacteristics of the selected producs

Product	**Serving** (in grams)	**Consumers (% of pop.)**[a] Kids	Adults	**Position among 352 products**[b]
Yogurt	125	90.7	83	2
Pre-packaged bread	28	95.2	98.5	20
Breakfast cereals	34	60.4	16.8	30

Notes: [a] Étude Inca (Afssa) 2006-2007 by *Agence Française de Securité Sanitaire des Aliments.* Yogurt and pre-packaged bread appear in the Inca study as part of broader categoires including similar products, namely, "bread and dried bread" and "Ultra-fresh dairy", respectively. Percentages of consumption correspond to consumption of all products in the categories.
[b] These are the positions of the considered products in a ranking of the 352 observed products in our data set, TNS Worldpanel 2005 by frequency of purchase.

an outside option. This will be enough to describe one- and multistop shopping behavior and to estimate shopping costs cutoffs.

Notice that a bundle can consist partially or fully of products purchased from the outside retailer. Consider, for example, the case of three stores {A, B, O} supplying three products $k = 1, 2, 3$. Let two bundles be $b = \{1_A, 2_B, 3_O\}$ and $b' = \{1_O, 2_O, 3_O\}$. The former will be the choice of a three-stop shopper purchasing product 1 from store A, product 2 from B and product 3 from the outside store O, whereas the latter corresponds to the choice of a one-stop shopper purchasing all products from the outside store. We call the latter bundle the outside good or the zero bundle, $b = 0$.

We empirically specify the utility of consumer i from purchasing good k from store r at time t as

$$\overline{v}_{ikrt} = \begin{cases} -\alpha p_{krt} + X_{kr}\beta + \xi_t + \epsilon_{ikrt}, & \text{if} \quad r = \{A, B\} \\ \epsilon_{ikOt}, & \text{if} \quad r = O \end{cases} \tag{10}$$

where, p_{krt} is the price of good k at store r, X_{kr} are product-store observed characteristics, ξ_t are time fixed effects, ϵ_{ikrt} is an idiosyncratic shock to utility, which rationalizes all remaining week-to-week individual variation in choices, and α and β are parameters common to all individuals. For simplicity, we normalize the mean utility of the product varieties supplied by outside store to zero.

Notice that equations (1) through (3) along with equation (10) fully specify the utilities of one and multi-stop shoppers as a function of price of the product, product characteristics, and distance to the stores, among others. Put it that way, our utility accounts for both vertical and horizontal dimensions of consumers' valuations for products. The former is captured by included product-store characteristics. The horizontal differentiation aspect is captured by distances which vary across postal codes.[14]

Further, we assume that individual shopping costs are a parametric function of a common shopping cost across all consumers ς, which can be thought of as the minimum cost every consumer bears due to the need of going shopping, and an individual deviation from this mean η_i, which rationalizes the individual heterogeneity in shopping costs, this yields

[14] If several goods are purchased at the same retailer, the distance to it will only be counted once; the distance will be divided evenly across goods purchased from the same retailer.

$$s_i = \varsigma + \eta_i \tag{11}$$

we assume $\eta_i \sim \mathcal{N}(0, 1)$.

Remark that even though the choice set for all consumers is the same (i.e. all products from all retailers are available for purchase), consumers with large enough shopping costs visiting an inferior number of retailers than there is in the market, are not able to choose the first best option from each product category. Therefore, shopping costs limit the set of alternatives available for one- and two-stop shoppers. Under our setup, this can be thought of as the result of a constrained maximization processes rather than suboptimal choices or mistakes.

4.1 Identification

Equation (8) show that we can identify critical cutoff points of the distribution of shopping costs if we are able to both observe the optimal shopping patterns of one-stop and multistop shoppers and identify the parameters of the per product utilities involved in the computation of the nth cutoff point. In other words, for each individual we need to identify the utility of her actual choice, say two-stop shopping, and the utility she would have derived had she chosen one-stop shopping instead. To do this, we exploit the panel structure of our data. For most households we observe enough cross-section variation in choices of products and stores, which allows us to identify the utility parameters. In particular, the price coefficient, it is separately identified from the mean utility from choice data alone due to the observed variation in prices per product. The predicted probabilities will vary due to this variation in prices, which generates enough moments to identify the price coefficient.

On the other hand, (fixed) shopping costs and shopping costs cutoffs are identified from the observed week-to-week variation in shopping patterns, i.e. a household making one-stop shopping this week might be doing multistop shopping next week, meaning that a given household can be more or less time constrained in different weeks. A key point in the identification of fixed shopping costs is the inclusion of other sources of shopping costs that may vary across retailers and periods. An important component in this class of costs is transport costs. Following Dubois and Jódar-Rosell (2010), we empirically identify transport costs by including distances from households' locations designated by postal codes. All households located at a same postal code will have the same distance to retailers nearby.[15] The inclusion of distances to stores will be useful for two purposes: they will capture the horizontal dimension of consumers' preferences for product characteristics and, on the other hand, will allow as to identify the disutility of transport. By adding this information to the model along with the unit demand assumption, the remaining variation in shopping costs across consumers can be interpreted as a pure idiosyncratic shopping cost that is constant across stores, consistent with our set up.

Finally, the identification of aggregate demand requires the computation of the mass of one-, two- and three-stop shoppers, which in equation (9) are defined as the differences of the distribution of shopping costs $G(\cdot)$ evaluated at two different cutoff values. Given our setup, we are able to compute those values from the empirical distribution of customers between one-, two- and three-stop shopping that we observe in our data.

There may be some endogeneity problems, in particular that of the correlation between prices and the utility shock. In addition, the method of estimation we apply and describe

[15] Due to data limitations, we do not observe the exact locations of neither households nor retailers but postal codes only. As a consequence, we are not able to compute exact distances.

below relies on moment conditions, which requires a set of exogenous instruments. To account for this, we follow Nevo (2001) and use average regional prices of the product to be instrumented for as IV's. These IV's are standard in the IO literature and are proved to work well. We provide further details on the validity of instruments in subsection 4.3.

4.2 Estimation

In this section we present details on how we estimate the utility parameters, and the mean and cutoff values of the distribution of shopping costs. We estimate the parameters of the model presented in the previous section using the data described in Section 2. Consistent with this reduced product set and the assumptions of the model described in Section 3, the final sample we use consist of localities where we observe one-, two- and three-stop shopping behavior and households purchasing at least one unit of each product considered here (see Appendix C for further details on how we define units and how we deal with these three goods in a discrete choice context).

The key point of our estimation strategy is to exploit population moment conditions and estimate the parameters of the model by the method of moments for reasons that will become clear below. Therefore, we need to express our discrete choice problem as moments and match population moments with empirical moments in the data. Recall the choice problem we are analyzing. A consumer who wish to buy a set of products K, faces a set $\mathcal{B}$ of mutually exclusive and exhaustive alternatives consisting of combinations of products and retailers available in the market. She will purchase the K products from $n \in \{1, 2, 3\}$ stores, call it bundle $b \in \mathcal{B} = \{1, \dots, 27\}$, such that she can obtain the highest utility net of shopping costs. This maximizing behavior defines the set of unobservables leading to the choice of bundle b as

$$A_{ibt}(X_{\mathcal{B}}; \theta) = \{(\epsilon_{it}, \eta_i) | v^n_{ibt} - ns_i > v^m_{ib't} - ms_i \; \forall m \in \{1, 2, 3\}, b' \in \mathcal{B}\}$$

where $X_{\mathcal{B}}$ is a matrix of characteristics of all alternatives including prices. The response probability of alternative b as a function of characteristics of products and retailers, given the parameters, is given by

$$P_{\mathcal{B}}(b|X_{\mathcal{B}}; \theta) = \int_{A_{ibt}} dF(\epsilon) dF(\eta) \tag{12}$$

A natural way to estimate the parameters of the model seem to be the maximization of the log-likelihood function

$$L(X_{\mathcal{B}}, d, \theta) = \sum_{i,b,t} \mathbb{1}_{ibt} \log P_{\mathcal{B}}(b|X_{\mathcal{B}}; \theta) \tag{13}$$

However, given the functional form of the utilities specified in equations (1) through (3), maximum likelihood estimation turns out to be extremely difficult to implement as the likelihood of the problem is very nonlinear in the utility shocks. We overcome this problem by using the Method of Simulated Moments (MSM) introduced by McFadden (1989) and Pakes and Pollard (1989).

Let $d_{ibt} = \mathbb{1}\{v^n_{ibt} - ns_i > v^m_{ib't} - ms_i\}$ be the indicator that bundle $b \in \mathcal{B}$ implying n number of stops was chosen by consumer i. This information is observed in the data for each consumer i every week. The expected value of d_{ibt} conditional on a set of measured characteristics $X_{\mathcal{B}}$ writes as

$$\mathbb{E}[d_{ibt}|X_{\mathcal{B}}, \theta] = P_{\mathcal{B}}(d_{ibt} = 1|X_{\mathcal{B}}; \theta) \tag{14}$$

To simulate $P(\cdot)$, we proceed as follows:

1. We build the whole choice set consumers face independently of their shopping costs. This is, we constructed bundles as all possible combinations of three retailers and three goods. As a whole, we obtained a choice set of 27 bundles that account for all possible shopping patterns, for instance, purchasing all three products from retailer one implies one-stop shopping.

2. We assume the shock to utility ϵ_{ikrt} is distributed i.i.d. type one extreme value take S random draws $\epsilon^s_{ikrt} \forall s = 1, \ldots, S$ per individual, product, retailer and week. Similarly, we assume the shopping costs shock η_i is distributed i.i.d. standard normal and take S random draws $\eta^s_i \forall s = 1, \ldots, S$ per individual. Consistent with our assumption of constant shopping costs, we replicate this draws for all retailers and periods whenever we observe purchases by consumer i.

3. Using a vector of initial parameter values, $\theta_0 = (\alpha_0, \beta_0, \gamma_0, \varsigma_0)$ randomly drawn from a normal distribution, along with drawn shocks $(\epsilon^s_{ikrt}, \eta^s_i)$ we are able to compute utilities for all product-retailer choices and consumers, as well as shopping costs to simulate the consumer choice problem described in our modeling framework for each $s = 1, \ldots, S$.

4. From these simulations, we observe what bundle (retailers-products combination) maximizes the utility net of shopping costs of each individual in a given week and form an indicator variable for the implied choices, which we denote $d^s_{ibt} \forall\, b \in \mathcal{B}, s = 1, \ldots, S$.

5. Finally, we approximate the choice probability as

$$\check{P}_{\mathcal{B}}(d_{ibt} = 1 | X_{\mathcal{B}}, \theta) = \frac{1}{S} \sum_{s=1}^{S} d^s_{ibt} \tag{15}$$

Plugging the simulated statistics into (14), rearranging and introducing instruments that may be functions of $X_{\mathcal{B}}$ (we defer to the next subsection the discussion of the instruments we use), we have the following moment conditions

$$\mathbb{E} \begin{bmatrix} w_{1i}\left(d_{i1t} - \check{P}_{\mathcal{B}}(d_{i1t} = 1 | X_{\mathcal{B}}, \theta)\right) \\ \vdots \\ w_{Ni}\left(d_{i27t} - \check{P}_{\mathcal{B}}(d_{i27t} = 1 | X_{\mathcal{B}}, \theta)\right) \end{bmatrix} = 0$$

We estimate the parameters of the model by making the sum of the squares of the residuals inside the expectation above across individuals as close as possible to zero. Formally,

$$\min_{\theta} \left[\sum_{i=1}^{I} Q(w_i, X_{\mathcal{B}}, d_{it}, \theta) \right]' \left[\sum_{i=1}^{I} Q(w_i, X_{\mathcal{B}}, d_{it}, \theta) \right],$$

where $Q(\cdot) = \left[w_{1i}\left(d_{i1t} - \check{P}_s(d_{i1t} = 1 | X_{\mathcal{B}}, \theta)\right), \ldots, w_{Ni}\left(d_{i27t} - \check{P}_s(d_{i27t} = 1 | X_{\mathcal{B}}, \theta)\right)\right]'$.

The Method of Simulated Moments (MSM) estimator is then given by

$$\hat{\theta}_{MSM} = \arg\min_{\theta} [d - P(\theta)]' W' W [d - P(\theta)],$$

where $W = [w_1, ..., w_I]$ is a $N \times I$ matrix of instruments.

Given the way simulated probabilities are computed in (15), they are not continuous in θ. It implies that the objective function previously described, which is a sum of simulated probabilities, is not continuous either. As a consequence, analytical methods cannot be used in the optimization process nor standard optimal instruments (which are derivatives of the simulated probabilities evaluated at a consistent estimator of the true parameters) nor the computation of standard errors (which require the use, among other things, the first derivative of the GMM objective function). These discontinuities do not jeopardize the consistency of simulation estimators. Pakes and Pollard (1989) derive asymptotic properties for a broad class of simulation estimators (including McFadden's MSM) that cover cases where the objective function is discontinuous in the parameters. In practice, to circumvent the discontinuity problem we use a numerical search ('Pattern search') method in the optimization process. As for the computation of standard errors, we apply parametric bootstrap methods.

4.3 Instruments

In order to obtain consistent estimates of the parameters of the model, we require to deal with the potential correlation of prices with the error term of the model, ϵ_{ikrt}. In our framework, this error term, known by the consumer but unobserved by the econometrician, is interpreted as a shock to utility that affects demand. If we assume that firms, that may observe these shocks through the observed demand curves, will react to changes in ϵ_{ikrt} by adjusting prices, it will bias the estimate of price sensitivity, α.

To treat this endogeneity problem we assume for simplicity that marginal costs are linear and depend on product and store characteristics and cost shifters, and that markets are competitive so that firms set prices at marginal cost.[16] However, as we do not observe any cost shifters in our data set, we use average regional prices of the same product in all the 21 French administrative regions (excluding the department to be instrumented for from the average price of the region it is located in) as proxies for marginal costs information. Following Nevo (2001), after controlling for product-retailer-specific means, individual shocks might still be correlated within a city but are uncorrelated with product valuations of people from other regions. This implies that in case a demand shock happens in one region, only the local price will be affected. This guarantees the exogeneity condition of prices. Now, what makes average regional prices good instruments is the fact that prices from two different locations (cities, departments, etc.) in a country are linked by common marginal costs as long as they are produced (supplied) by the same manufacturer (retailer) or under a standardized process.[17]

5 Results

Table 6 displays MSM estimates of the utility parameters, according to two specifications. The first column corresponds to the simplest model including the main covariates and controlling for product and time fixed-effects. The second column shows the results of a specification including IV's. Most coefficients are significant, and results are as expected: demands are downward sloping and the estimate for the distance shows that the value of a product decreases as the retailer is farther away from customer's dwelling. The estimate for mean shopping costs is also positive (as expected) and significant in both regressions.

[16] In a discrete choice framework, Reynaert and Verboven (2014) examine both perfect and imperfect competition cases and obtain similar results.

[17] Although the independence assumption seems reasonable, there may be cases were it cannot hold as, for example, a national demand shock as pointed out by Nevo (2001).

After introducing IV's in the model, we obtain a larger price estimate which may indicate a downward bias in the estimate without instruments. On the other hand, the coefficients for distance seemed to be biased upwards, as we obtained a lower estimate. Finally, the men shopping cost estimate does not differ when we add IV's.

Table 6: Estimates for the utility parameters and shopping costs[a]

Variable	(1)	(2)
Price (€/basket[b])	-1.43^{**}	-1.91^{**}
	(0.72)	(0.83)
Distance (km)	-9.03^{***}	-8.14^{***}
	(3.18)	(1.80)
Mean Utility Bread (28gr)	1.98^{**}	-0.12
	(0.91)	(1.29)
Mean Utility Cereal (35 gr)	-0.22	-0.01
	(0.59)	(0.53)
Mean Utility Yoghurt (125 gr)	0.20	2.21^{*}
	(0.83)	(1.25)
Mean Shopping Costs	2.92^{***}	2.93^{***}
	(0.15)	(0.31)
Time fixed-effects	Yes	Yes
Instruments[c]		Yes

Notes: [a] Based on 6,192 observations consisting of purchases of the three considered products made by 2,929 in 2005. Bootstrap standard errors are in parenthesis.
[b] A basket contains a serving of each of the considered products: a slice of bread (28g), a bowl of cereal (35g) and one yogurt (125g).
[c] Instruments include prices of the same good from other geographic locations, as well as bundle dummy variables.
*,**,*** are significant at 10, 5 and 1% confidence levels.

Table 7 displays the estimates for the mean shopping cost and the distance in euros. It also shows the values in euros of the average cutoffs of the distribution of shopping costs in euros, calculated following equation (8) and using the predicted utilities. In order to translate these values into euros, we divided each of them by the absolute value of the estimated price coefficient. The estimate for the distance, obtained in principle as the disutility of transport, is reinterpreted here as cost. To do this, we took the absolute value of the original estimate and divide it by the absolute value of the price coefficient.

In line with this, the average fixed cost of shopping is 1.5 € per trip. In addition, visiting a grocery store implies a cost of 4.26 € per km, for the average consumer. The distance between the median consumer's dweling to a store is 4 km, which multiplied by the transport cost per km gives a total transport cost of 17.1 €. Summing up with the mean shopping cost per trip, gives an average total cost of shopping of 18.7 € per retailer sourced (see Table 8).

As for shopping costs cutoffs, our results indicate that consumers should have almost-zero shopping costs to be able to source more than two retailers in a week. This rationalizes the small proportion of three-stop shoppers observed in our data. Notice that the threshold of three-stop shopping, s^3, in column (2) of Table 7 is negative. As stated previously, shopping costs may account for consumer's taste for shopping. In line with this, a shopper having a negative shopping cost means that she has a stronger taste for shopping, so that using multiple suppliers makes her total cost of the shopping experience lower than than it would be had she decide to concentrate purchases with a single supplier.

One-stop shoppers are all those having shopping costs beyond 2.12 € per trip. A former one-stop shopper will find it optimal to source an additional retailer if her shopping costs were slightly lower than 2.12 €, yet sourcing a third retailer may require a large decrease in shopping costs, such as having more time available or enjoying a lot multi-stop shopping in a given week. The estimates allow us to retrieve the predicted proportion of shoppers by number of stops: 90.1% are one-stop shoppers, 9.7% are two-stop shoppers and only 0.26% do three-stop shopping.

Table 7: Mean shopping costs, mean distance and average shopping costs cutoff (across periods and consumers) in euros[a]

	(1)	(2)
Total shopping costs		
Mean shopping cost	2.04	1.53
Mean transport cost	6.31	4.26
Average shopping costs cutoffs		
One-two stops ($\hat{s}^2$)	2.85	2.12
Two-three stops ($\hat{s}^3$)	0.02	-0.02
Predicted distribution of shoppers (% of total)		
One-stop shoppers		90.07
Two-stop shoppers		9.68
Three-stop shoppers		0.26

Notes: [a] To transform estimates into euros, we divide each coefficient by the absolute value of the price coefficient.
[b] To interpret the coefficient for distance as a transport cost, we take the absolute value of the original estimate presented in Table 6. It is negative in principle because it enters an utility function, expressing therefore a disutility of transportation.

Table 8 gives total transport costs and total cost of shopping (transport plus fixed shopping costs) by store format. The median distance to a big box (or hypermarket) store is 5.4 km, which multiplied by the transport costs per km gives a total transport cost of 23.2 €, and by adding the mean shopping cost of 1.53 €per trip to a store, gives a total cost of shopping of 24.7 € the average consumer bears each time he visits a large store. Transport and total costs are decreasing in the size of the stores, on average, as smaller formats are closer to downtowns. Sourcing a supermarket or a hard-discounter implies transport costs of 12.8 € and 11.9 € per trip, and total costs of shopping of 14.3 € and 13.4 € per trip, respectively. Finally, the costs of sourcing a convenience store are the lowest provided that they are located in downtowns: the median distance to a convenience is 0.8 km, the transport costs are 3.2 € and the total costs of shopping are 4.8 € per trip.

In Table 9, we present own- and cross-price elasticities. Due to the discontinuity of the predicted choice probabilities described in the estimation section, we cannot compute the derivatives of the demand functions with respect to price analytically. To overcome this problem, we simulated a price increase of 20% for one product at a time, recomputed the utilities for each product for each individuals and retrieved predicted choice probabilities again, to finally get new demands. We take the difference in the new demand and the baseline demand and divide the difference by the price change. Following the standard formula, we then obtained price elasticities of demand as the product of the numerical derivative and the original price, divided by the baseline quantity.

Table 8: Transport costs and total shopping costs (fixed plus transport), by store format (averages across periods and consumers) in euros[a]

Store format	Median Distance (km)[a]	Transport costs (€)[b]	Total costs of shopping (€) [c]
Hypermarket	5.4	23.2	24.7
Supermarket	3.0	12.8	14.3
Hard discounter	2.8	11.9	13.4
Convenience	0.8	3.2	4.8
Overall average	4.0	17.1	18.7

Notes: [a] We use the median of the distance and not the mean, to avoid the effects of outliers.
[b] Computed as the mean transport cost, 4.26 €/km given in column (2) of Table 7, times the median distance.
[c] Computed as the sum of Transport costs plus the mean shopping cost of 1.53€per trip, in column (2) of Table 7.

As expected, we obtain negative own-price elasticities and positive cross-price elasticities for the same product category across retailers. This indicates that, on average, consumers may switch retailers when the price of the desired product increases in their patronized retailers. Interestingly, within retailer cross-price elasticities are negative. This means that a price increase in a particular product causes a drop in demand for all other products the consumer intends to purchase. This complementarity effect might be driven by the larger mass of one-stop shoppers. For given prices of the products, a one-stop shopper should pick the retailer in which she derives the maximum value of the desired bundle. If the price of a product category raises in the chosen retailer, the shopper would need to source a competing retailer due to the impossibility of sourcing two or more.

Table 9: Mean elasticities (across periods and consumers)

Changing price	Retailer 1			Retailer 2			Outisde retailer		
	Bread	Cereal	Yogurt	Bread	Cereal	Yogurt	Bread	Cereal	Yogurt
Retailer 1									
Bread	-0.0044	-0.0042	-0.0039	0.0040	0.0040	0.0037	0.0061	0.0053	0.0075
Cereal	-0.0070	-0.0080	-0.0065	0.0054	0.0059	0.0053	0.0074	0.0084	0.0095
Yogurt	-0.0087	-0.0088	-0.0098	0.0069	0.0069	0.0076	0.0072	0.0069	0.0125
Retailer 2									
Bread	0.0041	0.0040	0.0038	-0.0046	-0.0043	-0.0040	0.0064	0.0056	0.0079
Cereal	0.0059	0.0062	0.0057	-0.0069	-0.0080	-0.0064	0.0078	0.0090	0.0104
Yogurt	0.0074	0.0074	0.0080	-0.0089	-0.0090	-0.0100	0.0079	0.0076	0.0136

Notes: Elasticities were computed according to the standard formula: $\eta_{ikrht} = \frac{\partial q_{ikrt}}{\partial p_{kht}} \frac{p_{kht}}{q_{ikrt}}$. Derivatives were computed numerically due to the discontinuity of predicted choice probabilities. Row titles indicate the product which price is changing. Column headers indicate the sensitivity of the demand for a particular product to a 20% price change.

6 Robustness checks

A first concern when using simulated methods is whether the results are sensitive to changes in starting values. To be sure that our estimates were robust to changes in the vector of initial parameters, θ_0, we performed the whole estimation process described in

Subsection 4.2 using ten different sets of pseudorandom draws from a normal, as starting values. We obtained similar estimates at each iteration which may as well be interpreted as an indicator of convergence. The final results, which are shown in Table 6 are those corresponding to the minimum value of the objective function out of ten available.

We also conducted a sample selection check. The final sample used for the estimates presented previously was selected by restricting attention to those households purchasing the three products considered here in a given week, consistent with our assumption of inelastic demand for a unit of each product. We therefore dropped households not fulfilling this condition. To find out if our results were robust, we used an alternative sample with tighter restrictions on the selection of the households, namely, if we observed a zip code with at least one household not purchasing the three products in a given week, we dropped the entire local market. We were left with 1,027 observations corresponding to purchases made by 541 households. We used the same estimation method and instruments as for our final results. However, due to the few observations in this sample, we could not include product fixed-effects. Results were similar in the direction and statistical significance of the estimates, except for the distance that became non significant with the use of IV's (see Table 10). In this sense, the results do not seem to be driven by sample selection. However,concerning the magnitude of estimates we have a remarkable difference. This might be driven by the fact that there is much less variation in the new sample and the omission of product dummies (that capture consumers' valuation for product characteristics). In particular, the average shopping costs cutoffs, expressed in euros, are very small as compared to those in Table 6. This is due, in part, to a larger estimate of the price coefficient. Nevertheless, their relative position remains similar and lead to the same conclusions as those derived before.

Table 10: Results based on an alternative sample[a]

Variable	(1)	(2)
Price (€/basket[b])	-3.75***	-3.78***
	(0.61)	(0.25)
Distance (km)	-13.48**	-5.71
	(5.34)	(3.88)
Mean Shopping Costs	0.80***	0.41***
	(0.23)	(0.08)
Time dummies	Yes	Yes
Instruments		Yes
Av. shopping costs cutoffs (in €)		
One-Two stops ($\hat{s}^2$)		0.26
One-Three stops ($\hat{\Delta}^{31}/2$)		0.13
Two-Three stops ($\hat{s}^3$)		0.01

Notes: [a]Based on 1,027 observations of purchases made by 541 households. Bootstrap standard errors are in parenthesis.
[b] A basket contains a serving of each of the considered products: a slice of bread (28g), a bowl of cereal (35g) and one yogurt (125g).
*,**,*** are significant at 10, 5 and 1% confidence levels.

7 Concluding remarks

Theory has shown that in the presence of of shopping costs, the real or perceived costs of dealing with a supplier, policy conclusions might change dramatically. In particular, some pro-competitive practices, such as head-to-head competition with homogeneous product lines (Klemperer, 1992) or the introduction of a new product variety (Klemperer and Padilla, 1997), can hurt consumers and motivate policy intervention. On the other hand, some seemingly anti-competitive practices, such as below-cost pricing, can be welfare enhancing and should not be banned (Chen and Rey, 2013).

From an empirical point of view, this motivates many important questions that remain unanswered. First, is it possible to quantify shopping costs from consumers' observed shopping behavior? Second, will accounting for shopping costs in a multiproduct demand model lead to a better understanding of consumer heterogeneity in shopping patterns? Finally, to what extent the inclusion of shopping costs would be crucial for policy analysis? This paper presents and then estimates a model of multiproduct demand for groceries in which customers, that differ in shopping costs, can choose between sourcing one or multiple retailers in the same shopping period. This framework allow us to retrieve the distribution of shopping costs.

We quantify the total shopping cost in 18.7 € per store sourced on average. This cost has two components, namely, the mean fixed shopping cost, 1.53 € and the total transport cost of 17.1 € per trip to a given store. Moreover, we are able to compute the transport and total costs of shopping by store format. Transport and total costs of shopping are decreasing in the size of the stores, on average, as smaller formats are closer to downtowns. The largest total shopping costs, 24.7 €, are incurred by consumers who source big-box stores, because they are farther away from downtown. Sourcing a supermarket or a hard-discounter implies total costs of shopping of 14.3 € and 13.4 € per trip, respectively. Finally, the costs of sourcing a convenience store, 4.8 € per trip, are the lowest provided that they are located in downtown. We find that individuals who source more than two suppliers in a week have zero (even negative) shopping costs. This rationalizes the low proportion of individuals making three and more stops in the same week observed in the data. This might be an indicator that those households actually visiting more than two separate stores a week should have a strong preference for shopping. In fact, The predicted proportions of shoppers by number of stops are 90.1% of one-stop shoppers, 9.7% of two-stop shoppers and only 0.26% do three-stop shopping.

There are several avenues of further research that can be empirically addressed using our framework. A first avenue is related to below-cost pricing. According to the OECD (2005), laws preventing resale below-cost (RBC) and claiming to protect high-price, low-volume stores from large competitors who can afford lower prices might be introducing unnecessary constraints. Evidence from countries without RBC laws shows that smaller competitors need not be pushed out of the market if they are not protected. Chen and Rey (2012,2013) show that in the presence of shopping costs, loss-leading strategies and cross subsidies are not predatory, and the latter might even be welfare enhancing. Empirical evidence showing what would happen if RBC laws are eliminated would help in this debate.

A second avenue concerns the implications of product delisting. In recent years, a considerably concentrated retail sector has brought the attention on the possible consequences of retailer buyer power on upstream firms. A retailer can, for example, stop carrying a product to punish a particular supplier for not agreeing on her requests. It might as well use delisting as a threat, so that she can get better terms of trade. How will demand react to the delisting of a product? Will consumers substitute brands in the same store or will decide to source an alternative store? What is the role of shopping costs in this decision? These are questions to be addressed.

Finally, theoretical and empirical analyses should be done on retailers' motivations to raise consumers shopping costs and the consequences of such strategies for competition and consumer welfare. One-stop shopping make more powerful retailers. Klemprer (1992) predicts that if consumers are not interested to source multiple retailers, prices will tend to be high. It might be the case that consumers face such high shopping costs that they are not able to do multistop shopping even if they would like to. Retailers might use their market power to raise customers shopping costs by making the shopping experience more tiring or complicated, so that their share of one-stop shoppers increases.

Appendix

A The utility function of a n-stop shopper

We can give a general expression for the optimal decision rule of a n-stop shopper, $n \in N = \{1, \cdots, R_i\}$, $R_i \leqslant R$, being R the total number of grocery stores in the market, as follows. Assume a n-stop shopper compares bundles of the desired products from all the possible combinations of n stores. Denote each of these combinations by $j \in \{1, \cdots, J_i^n\}$, where according to combinatorics theory, the total number of combinations of R elements taken n at a time is given by $J_i^n = R_i!/n!(R_i - n)!$ Consumer i will choose the mix j of n stores such that

$$\sum_{k=1}^{K_i} \max\{v_{ikrt}\}_{r \in j} \geqslant \sum_{k=1}^{K_i} \max\{v_{ikr't}\}_{r' \in l} \; \forall \; l = 1, \cdots, J_i$$

For instance, in a context with $R = 3$ stores, a one-stop shopper $n = 1$ will pick the best combination of one store out of $J_i^1 = 3$ possible {A},{B},{C}, and pick the best mix such that it yields the largest overall value of the desired bundle. Similarly, a two-stop shopper, $n = 2$, will compare all $J_i^2 = 3$ possible combinations of two stores ({A,B},{B,C},{A,C}) and pick the best according to the rule above. For a three-stop shopper, $n = 3$, the number of combinations of three stores taken three at a time is $J_i^3 = 1$, i.e. {A,B,C} which explains why he is not maximizing over several subsets of stores in equation (**??**).

B Cases for extra utilities ordering

As stated in Section 3, we can derive critical cutoff points on the shopping costs distribution from equations (4), (5) and (6) as functions of δ_{it}^2, δ_{it}^3 and $\Delta_{it}^3/2$. As these numbers represent utilities for different, say, products, their ordering can vary from a consumer to another. Therefore, we need to establish what the cutoffs would be in a case by case analysis.

From three objects, we can have six possible orderings:

$$
\begin{array}{llll}
(C1) & \delta^2_{it} > \dfrac{\Delta^3_{it}}{2} > \delta^3_{it}, & (C2) & \delta^3_{it} > \dfrac{\Delta^3_{it}}{2} > \delta^2_{it}, \\
(C3) & \dfrac{\Delta^3_{it}}{2} > \delta^3_{it} > \delta^2_{it}, & (C4) & \dfrac{\Delta^3_{it}}{2} > \delta^2_{it} > \delta^3_{it}, \\
(C5) & \delta^3_{it} > \delta^2_{it} > \dfrac{\Delta^3_{it}}{2}, & (C6) & \delta^2_{it} > \delta^3_{it} > \dfrac{\Delta^3_{it}}{2},
\end{array}
$$

From the six cases above, only $(C1)$ survives, the remaining are contradictory. To see why, notice that the incremental utility of sourcing two additional stores, $\Delta^3_{it} := v^3_{it} - v^1_{it}$, can be written as the sum of the two marginal utilities of going from one to two stores and from two to three. This is: $\Delta^3_{it} = \delta^2_{it} + \delta^3_{it}$. Therefore, if we assume, for instance, that $\frac{\Delta^3_{it}}{2} > \delta^3_{it}$ as in in $(C3)$, then

$$
\frac{v^3_{it} - v^2_{it}}{2} + \frac{v^2_{it} - v^1_{it}}{2} > v^2_{it} - v^1_{it} \equiv \delta^3_{it}
$$

which after some manipulations leads to $\delta^2_{it} > \delta^3_{it}$, i.e. a contradiction. In a similar fashion, the proofs for the other cases follow.

C Data manipulation for structural estimation

Three brands are taken into the analysis, ready-to-eat breakfast cereals (RTEBC), yogurt and bread, which are among the most purchased products in France. It is often the case that people do not only buy one brand, or even one unit of the same brand at a time, instead, they can buy several varieties of the same product to have different choices at home (different flavors, fruit contents, etc.). However, following Nevo (2001), we claim that an individual normally consumes one yogurt (125 grams per portion), one serving of cereal (35 grams per portion), and one serving of bread (28 grams per portion) at a time, so that the choice is discrete in this sense. Of course there could be cases in which some people consume more than one brand, or serving, at a time. Although we believe this is not the general case, the assumption can be seen as an approximation to the real demand problem.

The final sample used for the estimates presented in Section 6 was selected by restricting attention to those households purchasing the three products considered here in a given week and excluding all those households not fulfilling this condition. This sample consists of 6,192 observations of purchases of the three considered products made by 2,929 in 2005.

In our scanner data we do not observe prices but total expenditure and total quantity purchased for each product and store sourced by each household. Consequently, a price variable was created in the following way: first, we compute the sum of expenditures over localities (defined by zip codes), month, and stores and number of servings of each product purchased by each consumer. Second, we divided the total expenditure on a given product-store made by all consumers living in the same locality in a month by the the total number of servings to obtain a common unit price. If the information to compute a unit price is missing, we replace it with the average across local markets within the same period. By constructing our price variable in this way, we are assuming that consumers have rational expectations. Due to data limitations, we do not account for manufacturers' nor stores' promotional activities or discounts of any kind.

We follow closely Dubois and Jódar-Rosell (2010) to compute distances. Data on stores location was obtained from *LSA/Atlas de la Distribution 2005*, which contains information on most french stores involved in groceries distribution. The information was merged with the household data using the name of the store, the zip code of the consumer's residence and the surface of the outlet. For each store, we found the closest outlet to the consumer thanks to zip codes and geographical data. Only one outlet per store chain was included in this set.

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