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

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PARIS-JOURDAN SCIENCES ÉCONOMIQUES

48, Bd JOURDAN – E.N.S. – 75014 PARIS
TÉL. : 33(0) 1 43 13 63 00 – FAX : 33 (0) 1 43 13 63 10
www.pse.ens.fr

Multiproduct retailing and buyer power: The effects of product delisting on consumer shopping behavior

Jorge Florez-Acosta* Daniel Herrera-Araujo†

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Abstract

This paper empirically examines the effects of product delisting on consumer shopping behavior in a context of grocery retailing by large multiproduct supermarket chains. A product is said to be delisted when a supermarket stops supplying it while it continues being sold by competing stores. We develop a model of demand in which consumers can purchase multiple products in the same period. Consumers have heterogeneous shopping patterns: some find it optimal to concentrate purchases at a single store while others prefer sourcing several separate supermarkets. We account for this heterogeneity by introducing shopping costs, which are transaction costs of dealing with suppliers. Using scanner data on grocery purchases by French households in 2005, we estimate the parameters of the model and retrieve the distribution of shopping costs. We find a total shopping cost per store sourced of 1.79 € on average. When we simulate the delisting of a product by one supermarket, we find that customers' probability of sourcing that store decreases while the probability of sourcing competing stores increases. The reduction in demand is considerably larger when consumers have strong feelings of loyalty for the delisted brand. This suggests that retailers may be hurting themselves, and not only manufacturers, when they delist a product. However, when customers are loyal to the store, such effects are lower, suggesting that inducing store loyalty in customers (through strong private labels and loyalty programs, for example) appears to have an effect on vertical negotiations and, in particular, it enables powerful retailers to impose vertical restraints on manufacturers.

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*Universidad del Rosario, jorge.florez@urosario.edu.co

†Corresponding author. Hospinomics, Paris School of Economics, Assistance Publique des Hôpitaux de Paris, 1 Parvis Notre Dame, Bâtiment B, Étage 5, 75004, Paris, France. Phone: +33.(0)1.43.29.70.81. E-mail: daniel.herrera@psemail.eu.

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1 Introduction

The last decades have witnessed the consolidation of powerful great scale supermarket chains and a shift in the balance of power from manufacturers to distributors. The modern grocery retail industry is highly concentrated in a few large firms¹ and is mainly characterized by: 1) the proliferation of superstores with huge sales areas (20,000+ sq. meters) that offer a large product assortment (200,000+ different brands) and parallel services² as an attempt to attract customers through one-stop shopping;³ 2) the promotion of private labels (PL), which makes supermarkets less dependent on branded products (so-called national brands, NB), and induces consumer loyalty; and, 3) the formation of buying alliances between large supermarkets to increase bargaining power *vis-à-vis* manufacturers.^{4,5}

In such a context, the buyer power of supermarkets has become a central concern for policy makers and researchers, mainly because consolidated retailers often abuse market power by imposing vertical restraints on suppliers.⁶ In a 1997 research document the UK Office of Fair Trading (OFT) reported a “growth in vertical restraints of the sort imposed on manufacturers by retailers” (p. 47). Similarly, the OECD (1998) reported that “There is a growing list of complaints that competition agencies are hearing concerning the alleged abuse of retail buyer power...” (p. 15). Among these restraints, (the threat of) product delisting (or refusal to stock) appears to be widely used by distributors against manufactures.^{7,8} According to the literature, a product (or a supplier) is said to be delisted by a retailer when the volume of purchases is significantly reduced or the product (or set of products) is completely removed from the retailer stores’ shelves but it continues being sold by rival stores (Davies, 1994; Davies and Treagold, 1999; GCA, 2009).

The delisting of products can happen merely for commercial reasons.⁹ However, a super-

¹For instance, in 13 countries of the European Union (among which we have France, the UK, Germany, Sweden, Finland, and the Netherlands), the leading 5 retailers of each country concentrated a market share greater than 60% (European Commission, 2014)

²Such as shopping malls, beauty salons, restaurants, car wash, gas stations, and recreation grounds for kids.

³In Europe, for instance, hypermarkets increased the number of outlets in 72% between 2000 and 2011 and the sales area in 46% in the same period. The number of supermarket outlets increased by 10% and the sales area of this format raised by 26% (European Commission, 2014).

⁴Caprice and Rey (2015) provide some examples of retail chains that formed buying alliances: In France, Système U and Leclerc in 1999; Système U and Casino in 2006; Système U and Auchan in 2014. In Finland, Kesko and Tuko in 1996. In the US, the Independent Grocers Association.

⁵The emergence and consolidation of hard-discount stores as a cheaper alternative mostly on basic products, is also an important feature of the modern grocery retailing sector. In Europe, discounters experienced the greatest growth in sales area between 2000 and 2011 with 81% while the number of outlets of this retail form increased by 47%.

⁶Several policy papers discuss this and other related topics. See OFT (1997), OECD (1998, 2008), European Commission (1999), and FTC (2001).

⁷See OECD (1998), stating at p. 15 that “Some manufacturers say they are being forced to cave in to retailer demands because they fear being delisted or finding their products relegated to the lowest of the low shelves in important retail chains.”

⁸Other restraints listed in the OFT (1997) paper are: exclusive supply, minimum supply level, minimum advertising requirements, and sunk facility requirements.

⁹A retailer can decide to stop distributing a supplier’s products because of low gross and net profit margins, low sales volume, low customer flow, insufficient shelf space, high handling and storage costs, a large increase in the wholesale price, a reduction in the number of suppliers, or significant intrabrand competition, among others (Davies, 1994).

market with enough market power can use its ability to delist a product as a threat in order to obtain better terms of trade from manufacturers, or can actually delist a product as a punishment. Even though the retailer can benefit from this practice, it also faces some risk as consumers may be tempted to source rival supermarkets when a product they look for is missing at their preferred store. Consumers' reactions can be quite heterogeneous and depend, among other things, on the availability of substitutes, how costly is to deal with multiple stores, and the degree of store- and brand loyalty. The objective of this paper is to empirically examine the effects of product delisting on consumer shopping behavior, in a context of multiproduct retailing and multistop shopping.

Anecdotal evidence shows that retailers do use delisting as a bargaining strategy, and that the risk of a company going bankrupt if delisted by a large supermarket is real. For instance, in 2008 a large food supplier of the top four supermarkets in UK (Tesco, Asda, Sainsbury's and WM Morrison) revealed that some retailers' negotiation strategies included delisting as the main threat.¹⁰ There are some remarkable cases of disputes between large retailers and suppliers involving refusal to stock. In the US, Costco, one of the largest retail chains in that country, removed all Coca-Cola products from its shelves for about one month in 2009 after the two companies failed to agree on prices.¹¹ In the same year in Belgium, a request of a price rise by Unilever triggered the delisting of 300 of Unilever's products by Delhaize, one of the largest supermarket chains in that country. They ended up both hurt: Delhaize lost 31% of customers to rivals and among those who remained, 47% substituted Unilever's products with other brands.¹² In the UK, a similar dispute between Tesco, the largest supermarket chain in that country, and one of its main suppliers *Premier Foods* resulted in the delisting of a number of products in 2011, and a 1% fall in sales and 18% fall in shares' value.¹³ Last year, Tesco and Unilever experienced a short but remarkable dispute that led Tesco to stop carrying Unilever's products for about 24 hours.¹⁴

Similar cases have motivated some policy interventions in the past. In France, the so-called "Galland Act" (Loi 96-588 du 1er juillet de 1996) pointed out three practices concerning product delisting as abusive of economic dependence of suppliers on retailers: abusive delistings, abusive threats to terminate commercial relations, and abusive termination of established commercial relations.¹⁵ In the UK, the Competition Commission issued the *Groceries Supply Code of*

¹⁰According to the *Telegraph*, supermarkets use a broad range of "psychological and strategic manoeuvres", that can go from intentionally "misunderstanding a conversation or pleading poverty" to "physically disturbing the suppliers", to get the best terms of trade from manufacturers. The main threat that buyers use when bargaining with suppliers is that "they will de-list a supplier, a tactic commonly used if a producer is refusing to reduce prices or accede to other requests." A supplier reported being told once by a UK top four supermarket's representative that it was "on the 'Delinquent Customer List'", as a way of threatening that "delisting would be next.". See:

<http://www.telegraph.co.uk/finance/newsbysector/retailandconsumer/2789020/Supermarkets-and-suppliers-Inside-the-price-war.html>.

¹¹See: <http://www.cnbc.com/id/33994035>.

¹²See: <http://in.reuters.com/article/delhaize-unilever-idINLG51937220090216>.

¹³See: <http://www.telegraph.co.uk/finance/8684844/Premier-Foods-crumbled-by-Tesco-bust-up.html>.

¹⁴See: <https://www.theguardian.com/business/2016/oct/13/tesco-unilever-resolve-marmite-dispute-price-supermarket>.

¹⁵Although there was an explicit prohibition of the abuse of "economic dependence" by the competition law

Practice in 2009, a set of obligations for big retailers to “fairly manage” their relationships with suppliers.¹⁶ According to the Code, delisting may only be possible for “genuine commercial reasons” and prior delisting the retailer must inform the supplier, in a written way, the reasons to delist the product or products it is carrying, and will inform the supplier of the possibility it has to have the decision reviewed by a senior buyer.¹⁷ Moreover, the retailer must allow the supplier to discuss the delisting decision with its Code Compliance Officer.¹⁸

The buyer power of large retailers has been the subject of a substantial amount of academic work, especially in the last decade. In this literature it is widely recognized that powerful retailers can use delisting as a threat to enhance their bargaining position *vis-à-vis* suppliers. However, just a few works focus on the implications of product delisting from a theoretical perspective (Inderst and Mazzaroto, 2006; Inderst and Shaffer, 2007; Caprice and Rey, 2015; Johansen, 2012).¹⁹ All these papers have a common feature: demand side is modeled by restricting consumers to one-stop shopping behavior. However, evidence shows that customers often source multiple competing stores in the same shopping period. Figure 1 displays the distribution of the population by the average number of different supermarkets visited within a week, from home scanner data of supermarket purchases made by a representative sample of households in France. It shows that while barely 60% of households visited one supermarket per week, on average, a significant proportion of households used to visit more than one store in the same week. In such a context, some of the results from the existing literature may not hold. In particular, consumers need not switch stores when a desired product is missing at their preferred store, but may do an additional stop at a competing store to buy that product only, in which case, the retailer will not necessarily lose demand on its entire product range when it decides to delist a specific product.²⁰

This article adds to the literatures on multiproduct retailing, buyer power and vertical restraints (imposed by retailers on suppliers), and consumer shopping behavior in two ways. First,

since 80’s, several cases of abuse of supermarket buying groups against dependent suppliers were rejected under the idea that it was the supplier who was able to abuse of dependent retailers and not the reverse. The Galland Act basically recognized that retailers might use their power to abuse suppliers, and introduced flexibility to sanction retailers for their abusive behavior without the need of proving adverse effects on competition as it was under the precedent Law (Dutilh, 2004).

¹⁶The Code is part of “The Groceries (Supply Chain Practices) Market Investigation Order 2009”. It is addressed to the largest retailers in the UK: Asda, The Co-operative Group, Marks & Spencer, Wm Morrison, J Sainsbury, Tesco, Waitrose, Aldi, Iceland, and Lidl. A designated ombudsman, known as Groceries Code Adjudicator (GCA), was empowered to receive complaints and help enforce the Code. She has the ability to impose penalties of up to 1% of the retailer’s annual UK turnover in case of Code breach. See: <https://www.gov.uk/government/publications/groceries-supply-code-of-practice/groceries-supply-code-of-practice>.

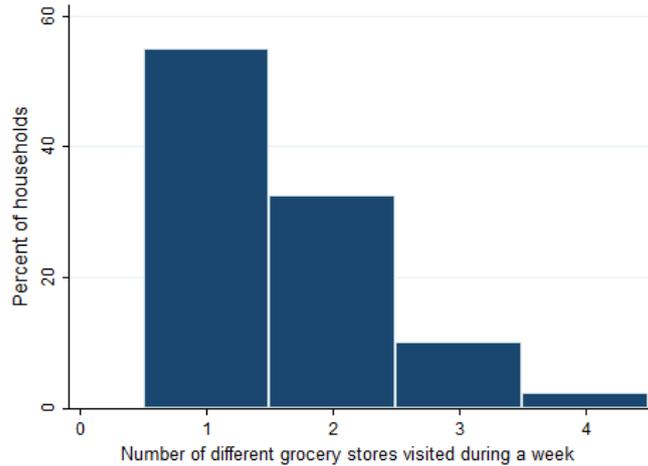
¹⁷A retailer’s employee or group of employees who is in charge of the primary buyers for a particular supplier.

¹⁸see <https://www.gov.uk/government/publications/groceries-supply-code-of-practice/groceries-supply-code-of-practice#duties-in-relation-to-de-listing>.

¹⁹According to Inderst and Shaffer (2007), delisting has traditionally been treated as an off-equilibrium strategy or as a channel through which buyer power can be exerted.

²⁰A model that allows consumers to source multiple stores, should consider several scenarios that can potentially arise. For example, if the consumer is loyal enough to the store but not to the brand, she may buy a substitute brand or may not buy that product at all. If the consumer is loyal to both the brand and the store, and has a low opportunity cost of time of visiting two separate stores, she will purchase the whole basket at the current location and will go to a competing store to get the missing product. Finally, if the consumer is loyal to the brand but not to the store, she can go to a competing store and purchase the whole basket there.

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 some households visiting up to 9 separate suppliers per week. However, 99.4% of the observations lie between 1 to 4 stops.

Source: TNS Worldpanel data base.

we empirically examine the implications of product delisting on consumer shopping behavior using a structural approach. To the best of our knowledge, this is the first attempt to provide evidence on a topic that to date has been empirically unexplored. We develop a multiple-discrete choice model in a context of competition between multiproduct grocery retailing firms that offer the same product line to the same customers. Consumers can purchase baskets of goods either from a single or from separate stores in the same period. In other words, our model not only allows for the simultaneous choice of multiple goods but also the simultaneous choice of multiple grocery stores.²¹ In our data we observe that in a given week, some customers concentrate purchases at a single store (*one-stop shopping*), whereas some others source multiple rival stores (*multistop shopping*) —see Figure 1 above. Our key modeling strategy is to explicitly account for this observed heterogeneity by introducing consumer transaction costs of shopping, also known as *shopping costs*. Following Klemperer (1992), we define *shopping costs* in a comprehensive way as all consumer’s real or perceived costs of using a supplier.²² These may include transportation costs, the opportunity cost of time of parking, selecting products at the store and

²¹Previous papers have developed demand models for multiple goods. Some examples are: Hendel (1999), who develops a multiple-discrete choice model in which consumers are allowed to choose more than one unit of each alternative of a product, to analyze the demand for personal computers by firms. Dubé (2004) applies Hendel’s model to study the case of carbonated soft drinks given that, according to the evidence provided by the author, consumers commonly buy multiple alternatives at each shopping occasion. Gentzkow (2007) develops a flexible framework in which similar goods can be either substitutes or complements. None of these works incorporates consumer transaction costs in the choice problem. Wildenbeest (2011) presents a model of search to explain price dispersion in grocery retailing markets. He considers the demand for a basket of products in which consumers care about the total price of the basket and must purchase all products at a single store, i.e. consumers are not allowed to source multiple stores, which makes it similar to a single-product discrete-choice model.

²²Klemperer (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.

waiting in line at the checkout; they may as well account for the taste for shopping (Chen and Rey, 2012).

A second innovation of our paper is precisely the identification of the distribution of shopping costs. The notion of consumer transaction costs of shopping as a rationale for heterogeneity in shopping patterns has been widely adopted in the literature of multiproduct demand and supply—see for example, Klemperer (1992), Klemperer and Padilla (1997), Armstrong and Vickers (2010) and Chen and Rey (2012, 2013). Therefore, the choice between one- and multistop shopping depends on the size of individual shopping costs. Consumers weigh the extra benefit of dealing with an additional supplier with costs. If benefits exceed shopping costs, the individual will patronize an additional store. Otherwise, she will concentrate purchases with a single store.

Our general empirical strategy is to estimate basket-level demand using standard techniques from the discrete choice literature along with simulated methods. We specify the utility of each product as a function of observed and unobserved product and store characteristics as well as parameters to be estimated. At every purchase occasion, each consumer faces idiosyncratic shopping costs that increase with the number of stores visited. The total utility of a basket of products is the sum of the product-specific utilities minus shopping costs. To consistently estimate the parameters of the model, we have to deal with a challenge: shopping costs vary across individuals and are unobserved (by the econometrician). We deal with this by decomposing shopping costs into two components: a mean shopping cost which is common to all consumers, and an idiosyncratic shock which is known to consumers and assumed to follow a known parametric distribution. This shock captures all individual (unobserved) characteristics that individual costs deviate from this average. Examples of these characteristics are individual valuation of time spent in transportation, parking, waiting in line, etc., and the taste for shopping. Given the panel structure of our data, we can control for observed household characteristics that proxy for household time constraints. Once we obtain estimates for the parameters of the model, we perform counterfactual experiments that serve two purposes. On the one hand, we attempt to assess the relative importance of accounting explicitly for shopping costs for predicting consumer behavior in a model of multistop shopping. To do that, we compute predicted probabilities of visiting one or several stores in absence of shopping costs. On the other hand, we attempt to assess how product delisting affect consumer shopping patterns.

Perhaps the biggest limitation of our approach is the dimensionality problem that arises when estimating demand for baskets of goods. A common problem in the discrete-choice literature of single product demand estimation concerns the number of varieties in the choice set: a large number of differentiated brands is difficult to deal with in the estimation process. This problem is commonly solved in the IO literature by restricting the choice set to the leading brands based on market shares. However, when the problem involves the choice of multiple product categories and multiple shopping locations, as in our case, the dimension of the choice set increases with both. Consider for example a market with 3 differentiated supermarkets offering identical product line consisting of two goods. The choice set of a consumer (unconditional on her shopping costs)

who seeks to purchase both goods consists of 3^2 mutually exclusive baskets.²³ Adding a new good to the problem will increase the choice set exponentially. In our data set, some households are observed to purchase up to 275 different products from up to 9 separate grocery suppliers in the same week.²⁴ Estimating a demand system with such a huge choice set (9^{275}) is infeasible.

We deal with this dimensionality problem as follows: first, we model both brand- and basket-level utilities following a discrete-choice approach. Second, we restrict attention to three categories of products (yogurt, biscuits, and refrigerated desserts) that meet the following conditions that make our empirical exercise consistent with our structural model: 1) staples, because these are generally not subject to temporary price reductions due to promotional activities, 2) frequently purchased, our products are among the most frequently bought by french households, and 3) of unit demand, as required by the discrete-choice method we use. We aggregate purchases by category for biscuits and desserts, i.e. all purchases of any brand in a given category are considered as purchases of a unique brand “biscuit” or “dessert”, respectively. As for the yogurt category, we allow for two alternatives, namely, the leading national brand of yogurt in France in 2005, and a composite brand of yogurt which gathers the remaining brands (both other NBs and PLs). Therefore, consumers have a set of four goods from which they pick at most three: at most one of the two alternatives of yogurt, biscuits and desserts.²⁵ Finally, we focus on a reduced set of three supermarket chains that are the leading grocery retailers in France in 2005 according to market shares. The remaining grocery stores observed in our data along with the no purchase of the included goods option are left as part of the outside option.²⁶

A caveat of our approach is that it does not explicitly model consumer search prior to the observed purchase. Even though our structural model is similar to non-sequential search models,²⁷ our objective is not to explain price or quality dispersion in a search market. If search costs are important in the markets we consider, then the differences between one- and multistop shopping might as well be driven by search and our shopping costs estimates would capture search costs to some extent. Assuming away any information friction is a strong and unreasonable assumption in most contexts. However, when consumers frequently visit stores to buy a basket of basic products, as is the case of routine grocery shopping, information frictions

²³Products A,B in supermarket 1; A,B in supermarket 2; A,B in supermarket 3; A in 1 and B in 2; A in 2 and B in 1; A in 1 and B in 3, and so on and so forth.

²⁴On average, a household purchases baskets containing 24 different products from 2 separate stores in a week.

²⁵The choice of yogurt as the category with two alternatives is arbitrary. In order to check the robustness of our results, we perform the estimation of our demand model several times changing the category containing two options.

²⁶Of course, in our data we observe that consumers often purchase/visit more than the three included goods/stores. We take account of this fact in our empirical strategy. Following Genztkow (2010), we assume that every basket includes a maximization over the included as well as the excluded (observed and unobserved) goods. In line with this, if a consumer is observed to have purchased two of the inside goods at the included supermarkets, it may be the case that those were the only goods she purchased, or it may as well be that she purchased additional products and visited other stores than those included. In any case, we will assume that the utility of baskets that contain the inside products purchased from any of the included locations is greater than the utility of alternative baskets that contain any other combination of inside goods. However, it is important to notice that leaving some goods as part of the outside option does not change the interpretation of substitution patterns among baskets containing inside goods. See Section 5.4 for a detailed discussion.

²⁷See, for instance, Hortaçsu and Syverson (2004), and Dubois and Perrone (2015).

do not appear to be a primary concern.²⁸ The set of products we focus on is consistent with this observation.²⁹

We obtain several interesting results. First, from descriptive regressions we find a significant relationship between the number of supermarkets sourced by a household in a week and household characteristics that proxy for opportunity cost of time. Households with higher income, a car and babies are less likely to be multistop shoppers. On the other hand, households with older leaders, of larger size, and living in urban areas are more likely to visit a larger number of stores in a week. Second, our structural model allows us to retrieve consumer shopping costs, which we estimate in 1.79 € per store sourced, on average. This cost includes a fixed shopping cost, which we estimate in 1.57 €, on average, and a transport cost of 21.6 cents on the euro, per trip to the average store. Third, our counterfactuals indicate that while in the absence of shopping costs all consumers would source at least one store every week with positive probability, when shopping costs are accounted for, predicted probabilities of (one and multistop) shopping are lower, and consumers are less likely to source a supermarket on a week-to-week basis provided that dealing with a store is costly. In other words, shopping costs discourages supermarket visits every week and give rise to a much lower proportion of multistop shoppers. Further, predicted shopping patterns would be biased in a model of demand that does not account for shopping costs. Finally, when we simulate the delisting of a product by one supermarket, we find that customers' probability of sourcing that store decreases by 3%, while the probability of sourcing competing stores increases by 1%. The reduction in demand is even larger when consumers have strong feelings of loyalty for the delisted brand: the probability of sourcing the store that stopped stocking that brand decreases by about 85%, while it rises for competing retailers by approximately 50%. This suggests that retailers may be hurting themselves, and not only manufacturers, when they delist products. However, when customers are loyal to the store, such effects are lower: delisting a product implies a decrease in the probability of being sourced of 2%. Therefore, inducing store loyalty in customers (through strong private labels and loyalty programs, for example) appears to have an effect on vertical negotiations and, in particular, it enables powerful retailers to impose vertical restraints on manufacturers.

Related literature

There are few papers studying the effects of product delisting in retailing. This literature has focused on theoretical analyses. In a model of one-stop shopping, if a retailer delists a strong brand (a brand for which demand is large) it can suffer from a reduction in demand of the whole product range as consumers can switch shopping locations looking for the missing product (Inderst and Mazzaroto, 2006). This is no longer the case in the presence of a consolidated retailer

²⁸Based on the very same observation, the main theoretical contributions on the shopping costs literature — Klemperer (1992), Klemperer and Padilla (1997) and Chen and Rey (2012, 2013), assume that consumers are reasonably aware of prices. See Brief (1967) and Chen and Rey (2012) for discussions on this.

²⁹We are not aware of the existence of a full model of consumer shopping behavior accounting for search activities prior to the purchase of each good of the desired basket and allowing to separately identify between search, switching, and other costs. Such a model is out of the scope of this paper and is left for future research.

(as a result of a downstream merger, for example), which can find it more profitable to turn to a single sourcing relationship by delisting all suppliers but the most competitive. Although this induces a more aggressive competition among suppliers, total profits of the industry may decrease due to the delisting of products that best fit the preferences of some consumers (Inderst and Shaffer, 2007). Buying alliances appear to be not only a good alternative to mergers, but also a way to soften the consequences of delisting a product of a strong manufacturer: a joint delisting decision by an alliance, makes it less harmful for every group member since all other members will turn to alternative suppliers as well (Caprice and Rey, 2015). Finally, in a context of one-stop shopping where some buyers seek to purchase a single product and some others a basket of goods, increasing the share of the latter raises the buyer power of the retailer; however, delisting a product becomes less convenient as consumers may be tempted to switch shopping locations, leading to a decrease of the demand for its whole product range (Johansen, 2012).

Concerning consumer opportunity costs associated to shopping activities, there is a growing empirical literature including or measuring explicitly these costs. This literature has focused on two types, namely, search costs —these include Hortagsu and Syverson (2004), Hong and Shum (2006), Chen, Hong and Shum (2007), Koulayiev (2014), Moraga-González, Sandor and Wildenbeest (2013), Kim, Albuquerque and Bronnenberg (2010), Wildenbeest (2011), De los Santos, Hortagsu and Wildenbeest (2012), Honka (2014), and Dubois and Perrone (2015); and switching costs —these include Dubé et al. (2010), Handel (2010), and Honka (2014).³⁰ Less attention has been placed on shopping costs. Brief (1967) models consumer shopping patterns in a Hotelling framework, and basically estimates transportation costs to account for consumer shopping costs.³¹ Aguiar and Hurst (2007) evaluate how households substitute time for money by optimally combining shopping activities with home production. Customers use different shopping technologies to reduce the price of the products they buy and pay a time cost which is explicitly accounted for.

In the analysis of multi-product and multi-store choice with shopping costs, our paper closely relates to Schiraldi, et al. (2015). They study pricing by grocery stores in a context of competition between specialized stores and multi-category grocery retailers (supermarkets). The latter internalize the effects that arise from selling multiple categories of goods to customers interested in buying baskets of products. To do this, they develop a model of demand in which consumers make discrete-continuous choices: discrete choice of the supermarket to source by category, and a continuous choice of the quantity of each category. In their model, some consumers purchase from a single store whereas others source at most two stores in each period. To rationalize this heterogeneity, they introduce a choice-specific fixed cost in the utility function of a consumer. Our approach differs from theirs in several important ways. First, we are interested in a very

³⁰As 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.

³¹Brief (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.”

different question and our focus is on consumer behavior in a context of competition between powerful supermarket chains of similar characteristics. Second, our structural model is in the spirit of the theoretical literature on this topic (in particular, Chen and Rey, 2012; 2013). We adopt the view that heterogeneous shopping patterns stem from differences in shopping costs across consumers as our key modeling feature. In our setting, the number of stores sourced by a consumer is endogenously determined by a stopping rule involving the extra utility and extra costs of sourcing an additional store. This enables us to empirically identify the distribution of shopping costs. Last, but not least, our empirical implementation differs from theirs in several features: the categories of products we focus on, the definition of the outside option, and the estimation method we rely on are some of them.

The rest of the paper is organized as follows. Section 2 presents the data and a preliminary analysis of consumer shopping behavior based on descriptive statistics and reduced-form regressions. Section 3 discusses other potential explanations to observed heterogeneity in shopping patterns and shows, using some descriptive regressions, that those are less appealing than the shopping costs reasoning adopted in this paper. Section 4 outlines the structural model of multiproduct demand and consumer shopping behavior in the presence of shopping costs. Section 5 describes our empirical strategy, discusses identification and details the estimation procedure. Section 6 reports the estimation results. Section 7 give details on our counterfactual experiments and presents the results. Finally, Section 8 concludes and discusses directions for further research. Robustness checks are reported in the Appendix.

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 in a context of competing retail stores supplying multiple products. For this purpose, we use data on the full set of products for which households in the sample reported purchases to derive some descriptive statistics. We exclude from this analysis households that did not report purchases for at least 8 months during 2005. In the empirical implementation of our structural model, we restrict the sample to a few products in order to deal with dimensionality issues.

2.1 Data overview

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 10,000 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, new randomly selected households are added to the panel either to replace other households

rarely reporting data or to increase sample size.

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. Concerning store formats, supermarket chains are often present in different zones of a city in three formats: hypermarkets (also known as big-box stores) which are stores with the largest sales areas and product range; supermarkets, which are medium-sized stores with a fairly varied assortment and closer to customers than big boxes; and convenience stores, which are small downtown stores focused mainly on staples.³² The data is reported at the purchase level, so we observe product characteristics such as total quantity, total expenditure, the store where it was purchased from, brand, etc. In addition, the data include a range of household characteristics such as household size, number of children, location, income, number of cars, internet access, storage capacity, among others.

We supplement the homescan data with information on supermarket characteristics coming from the Atlas LSA 2005. It includes information by store format and type (regular and hard-discount stores) on store's location, surface, number of checkouts, parking slots, etc. Following Dubois and Jodar-Rosell (2010), using household data, the name of the retailer, the zip code of the consumer's residence and the surface of the outlet we merge both data sets. For each supermarket chain, we attributed the closest outlet to the consumer's dwelling using zip codes. All outlets located at a distance greater than 20 kilometers from the city center were excluded from the consumers' choice set.

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 age³³ being 49 years old, with around 2,366 € monthly income and at least one car. Only half of the households in the sample reported having internet access at home which partially explains why internet purchases are not important in our data. As for storage capacity and home production, 77% of households have storage rooms at home and 67% an independent freezer in addition to a refrigerator. Further, about 36% of households reported producing vegetables at home which, along with the fact that nearly 30% of the households are located outside urban areas, can be a reason for the observed low frequency of shopping of some households.

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 tends to do between one and two trips per week to the same store. The average number of days between shopping occasions is 5 days. The preferred store type remains the regular supermarket over the hard-discounter: only a 18,6% of weekly visits to grocery stores are done to the latter type. Larger store formats are preferred by consumers: on average, the two

³²In France, store formats are sorted according to their sales areas: hypermarkets have a sales area of 2500m² and beyond, supermarkets between 400m² and 2500m², and convenience stores have sales area lower than 400m².

³³By household head we mean the person mainly in charge of the household's grocery shopping.

Table 1: Summary statistics for household characteristics

Variable	Mean	Median	Sd	Min	Max
Demographics Household size	3.00	3	1.39	1	9
Income (€/month)	2,366	2,100	1,115	150	7,000
Children under 15 (proportion of hh)	0.37	0	0.48	0	1
Household head's age	49.26	47	14.31	17	98
Lives in city	0.74	1	0.44	0	1
Car	1.55	2	0.80	0	8
Internet access at home	0.51	1	0.50	0	1
Storage capacity					
Independent freezer	0.67	1	0.47	0	1
Freezer capacity > 150L	0.57	1	0.50	0	1
Storage room at home	0.77	1	0.42	0	1
Vegetables production at home	0.36	0	0.48	0	1

Source: TNS Worldpanel data base.

most frequently visited store formats are Supermarkets and Hypermarkets with 54% and 42% share on total visits per week, respectively. Convenience stores, the smaller shops supplying a reduced product range generally at higher prices, receives the lower number of visitors per week with 3.9%. Although convenience stores have the advantage of being within walking distance from households location, as opposed to hypermarkets that are located far from city centers, the preference for larger store formats can be explained by several factors such as bulk shopping, lower prices, more intensive sales and promotional activities and a larger product range.

Table 2: Summary statistics for household shopping patterns

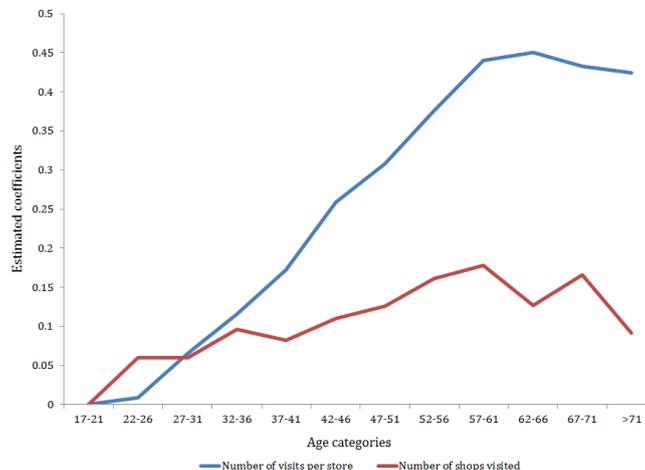
Variable	Mean	Median	Sd	Min	Max
No. Trips to same grocery store/week	1.41	1	0.76	1	7
No. separate grocery stores visited/week	1.65	1	0.83	1	9
Days between visits	5.40189	4	6.06834	1	188
Visits to Hard discounters (% of total/week)	18.58	0	38.89	0	100
Visits by format (% of total/week)					
Hypermarket	41.84	35.21	34.52	0	100
Supermarket	53.81	57.03	34.39	0	100
Convenience	3.92	0.00	12.90	0	100

Source: TNS Worldpanel data base.

Age has been widely used in the literature as an indicator of opportunity cost of time. Aguiar and Hurst (2007) find that older people often pay lower prices because both their frequency of shop trips to the same store and the number of separate stores sourced, are larger relative to younger people. They show that the cost of time decreases with age, so older customers can allocate more time to their shopping experiences. In our data we find a similar relationship between indicators of shopping intensity 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. However, while repeat-purchasing becomes much more important as consumers grow old, the number of shops visited increases with age

but not at the same rate as the number of visits to the same store. This evidence suggest that older people with lower opportunity cost of time repeat-purchase with more intensity in order to benefit from promotions and loyalty rewards.³⁴ Another consequence of the lower opportunity cost of time is the possibility of visiting a larger number of stores than their younger counterparts, although the economies of scale of repeat purchasing appear to dominate. An additional interpretation is that the increase in the shopping intensity motivated by more time devoted to search activities. However, this is a less appealing explanation as long as regular, repeat grocery shopping allows people to be reasonably well informed about prices and promotional activities which reduces the effects of information frictions on shopping behavior. Moreover, for some products that are not subject to promotions, such as staples, engaging in costly search may not be necessary (see a detailed discussion below).

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 The nature of multistop shopping

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, is expected to be negatively correlated with consumers' real as well as perceived costs. Such a correlation would constitute key empirical evidence of the role of shopping costs on consumer shopping behavior.

Following our definition of shopping patterns, and 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 a set of household characteristics that proxy for households' time costs, to study the correlation between shopping costs and multistop shopping behavior. Further, we add some

³⁴In France, loyalty rewards have been historically linked to repeat-purchasing, see Florez (2016).

controls for household storage capacity (housing type, presence of a storage room, independent freezer, and the size of the largest freezer at home) that help rationalize (at least in part) the frequency of shopping. Supermarket and time dummies are included gradually in order to assess their effect on the estimates. Finally, we allow region fixed-effects to enter all regressions. Table 3 shows the results. Coefficients are basically of the expected sign and statistically significant.

We find evidence suggesting that households' ability to patronize multiple stores depends on time constraints and how costly it will be in terms distance. Interestingly, we find that larger households living in urban areas tend to favor multistop shopping. On the other hand, higher income people as well as those having 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 some staples.

The coefficients on housing type, store format and average distance to store suggest some interesting patterns related to the physical structure of cities in France and store location. In France, as a result of zoning regulations that among others limit store size, large store formats are located out of city centers. Hypermarkets, for instance, are often reachable only by car which makes it more costly to do top-up trips to this type of stores. On the other hand, convenience stores are widely present in downtowns and easily reachable but are generally of small size and offer a limited assortment of products (mostly staples), which makes them suitable for top-up trips. Accordingly, our results show that people living in an apartment, which are more likely to be located at or closer to city downtowns, tend to source a larger number of stores as compared to those who live in a house. In contrast, those who live in farms, do less stops as compared to families living in smaller places. An alternative interpretation which is consistent with this result is related to households' storage capacity. Households with lower storage capacity, which is the case of those living in apartments, need to go more often to grocery stores and, consequently, are more likely to be multistop shoppers.

Concerning store formats, supermarket chains are often present in different zones of a city in three formats: hypermarkets (also known as big-box stores) the stores with the largest sales areas and product range, supermarkets that are medium sized stores with a fairly varied assortment and closer than big boxes, and convenience stores that are small downtown stores focused mainly on staples.³⁵ We included dummy variables for two out of three store formats: hypermarket and supermarket each taking on 1 if the store visited is the respective format. The coefficients obtained are negative and significant in both cases, and consistent with economic intuition: provided that super and hypermarkets are larger than convenience, and carry a larger product assortment, consumers that source one of those often need less additional stops than those going to a convenience, as it is possible the former make bulk shopping in big formats. The coefficient of distance from home location to stores exhibits a positive correlation with the number of stores

³⁵Officially, store formats are sorted according to their sales areas: hypermarkets have a sales area of 2500m² and beyond, supermarkets between 400m² and 2500m², and convenience stores have sales area lower than 400m²

visited in all regressions. We interpret this as people making top-up trips to closer smaller stores during the week, before going to a large supermarket to bulk shopping.

Table 3: Results for number of different stores visited per week^a

Variable	OLS		Poisson	
	(1)	(2)	(3)	(4)
Hypermarket ^b	-0.080*** (0.028)	-0.080*** (0.028)	-0.051*** (0.018)	-0.051*** (0.018)
Supermarket ^b	-0.056** (0.025)	-0.056** (0.025)	-0.034*** (0.015)	-0.034*** (0.015)
Harddiscount (=1 if yes)	0.197*** (0.024)	0.198*** (0.024)	0.130*** (0.016)	0.130*** (0.016)
HH head's age	0.003*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Log Income	-0.021* (0.012)	-0.021* (0.012)	-0.014*** (0.008)	-0.014*** (0.008)
HH size	0.061*** (0.006)	0.061*** (0.006)	0.041*** (0.004)	0.041*** (0.004)
Car (=1 if yes)	-0.021 (0.026)	-0.021 (0.026)	-0.014*** (0.018)	-0.014*** (0.018)
Lives in urban areas (=1 if yes)	0.064** (0.014)	0.064*** (0.014)	0.042*** (0.010)	0.042*** (0.010)
Lives in an apartment (=1 if yes)	0.035*** (0.016)	0.035** (0.016)	0.023*** (0.011)	0.023*** (0.011)
Lives in a farm (=1 if yes)	-0.102*** (0.038)	-0.102*** (0.038)	-0.072*** (0.028)	-0.072*** (0.028)
Baby (=1 if yes)	-0.065*** (0.016)	-0.065*** (0.016)	-0.044*** (0.011)	-0.043*** (0.011)
Internet access at home (=1 if yes)	-0.012 (0.013)	-0.012 (0.013)	-0.009*** (0.009)	-0.009*** (0.009)
Home production (=1 if yes) ^c	-0.017 (0.013)	-0.017*** (0.013)	-0.011*** (0.009)	-0.012*** (0.009)
Constant	1.376*** (0.114)	1.339*** (0.114)	0.315*** (0.077)	0.289*** (0.077)
Store FE	Yes	Yes	Yes	Yes
Week FE		Yes		Yes
R^2	0.0629	0.0641	0.0073	0.0074

Notes: ^aStandard errors in parenthesis are clustered by household. Regressions are based on 1.8 million observations. All specifications include the average of the distances between household location and stores visited in a week, as well as controls for household storage capacity and region fixed effects.

^b Proportion of visits to the respective store format on the total of visits to stores that week.

^c A household reports yes in this variable if it grows vegetables at home and zero otherwise.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3 Sources of heterogeneity in consumer shopping patterns

In the previous Section we provided some empirical evidence suggesting that household characteristics (such as age, income, number of cars, children, location, etc.) that are informative on its members' time constraints, help explain the observed dispersion across households of the number of stores visited in a week. Earlier we said that, according to theory, differences in consumer shopping patterns are due to heterogeneous shopping costs. Our preliminary evidence is

consistent with this view. In line with this, the concept of shopping costs has a precise meaning within the context of our empirical approach. We follow the widely adopted definition by the literature³⁶ according to which *shopping costs* are all consumer’s real or perceived costs of dealing with a supplier, but interpret it in the broadest possible sense as all transaction costs consumers face in their shopping experience. In particular, they may include search and switching costs.

However, the same empirical results may well support an alternative story according to which the dispersion in the number of supermarkets visited is due to heterogeneous search costs: those customers with lower search costs, are able to search at more places (according to a given search rule) than those with higher search costs. However, the fact that we observe purchases of subsets of products at different shopping locations rises questions about the nature of the search process. Why are consumers actually making separate purchases at several shopping locations during the process of information acquisition? Are they quoting the total price of a bundle of products or are they searching separately for each product they desire to buy? Are there products that are more important than others? Do households have different stopping rules for different products?

In this Section, we attempt to show that when individuals repeat and frequently purchase some basic products (such as staples), they are often well aware of prices and product characteristics, and hence, search costs need not be an issue. To do this, we provide some empirical evidence suggesting that search costs is not the main driver of the preference of some consumers for sourcing several supermarkets in the same week. As it will become apparent below, we develop a model where customers are well aware of prices and where the overall value of the basket of products is relevant to determine the optimal number of stores to be sourced.³⁷ However, our empirical strategy does not allow us to separately identify all consumer-related costs that can help fully rationalize consumer shopping behavior, for which our estimates of shopping costs may still capture some search and switching costs. We claim that these are not conflicting with our shopping costs definition.

3.1 Search costs

Even though the literature on price dispersion and search costs has extensively shown that consumers often lack information about key aspects for decision-making (such as the price and quality of some products), and may need to engage in costly search in order to make a better choice,³⁸ the search costs story alone may not capture all factors that motivate consumers to favor multistop shopping. On the other hand, alternative explanations need not exclude search activities prior to the actual purchase occasion.

In contexts in which information frictions are less relevant (so that search costs are small

³⁶See for example, Brief (1967), Klemperer (1992), Klemperer and Padilla (1997), Armstrong and Vickers (2010) and Chen and Rey (2012, 2013).

³⁷This approach is supported by evidence. For instance, in a 2008 report of the supply of groceries in the UK, the Competition Commission states that in consumers’ price comparisons across grocery retailers the price of the basket of products matter.

³⁸See for example, Hortagsu and Syverson (2004), Hong and Shum (2006), Chen, Hong and Shum (2007), Koulayiev (2014), Moraga-González, Sandor and Wildenbeest (2013), Kim, Albuquerque and Bronnenberg (2010), Wildenbeest (2011), De los Santos, Hortagsu and Wildenbeest (2012), and Honka (2014).

enough), consumers must still incur transaction costs of shopping (e.g. transportation, time spent collecting products at the store, waiting in line for checking out, or just because some do not enjoy shopping at all, etc.) so there is still an observed heterogeneity in shopping patterns that needs to be accounted for. This is precisely the case that has been widely analyzed by the literature so far. Klemprer (1992), Klemperer and Padilla (1997), Armstrong and Vickers (2010) and Chen and Rey (2012, 2013), all develop models in which fully informed consumers incur idiosyncratic shopping costs and, consequently, heterogeneous shopping patterns arise in equilibrium.

Empirically, developing a full model of consumer shopping behavior that explicitly incorporates search prior to the purchase of each good of the desired basket, and then taking it to the data is (if at all possible) a very challenging and cumbersome task. To the best of our knowledge, there is no paper in the literature addressing simultaneously multiproduct search and multistop shopping behavior in an empirical context.³⁹ Our paper is not the exception. Provided that our aim is to rationalize the observed heterogeneity across consumers related to one- and multistop shopping behavior rather than observed dispersion in prices of individual products or in the total value of a basket of products, we develop a model that does not explicitly include search costs in consumer optimal decision making. Furthermore, our empirical implementation relies on the selection of a set of products that consumers purchase frequently enough so that they are reasonably well aware of prices.

This need not mean that search costs play no important role in observed shopping behavior. Actually, the fact that our estimates of shopping costs may capture search costs should not be problematic *per se*. As we previously pointed out, those two concepts are not conflicting and in a broad sense search costs can be an important component of the transaction costs a consumer incurs when shopping, which is consistent with our definition of shopping costs. A problem would rather be that the observed heterogeneity in consumer shopping patterns is best explained by a search costs technology, leaving little explanatory power to other sources of costs of shopping, which we believe is not the case when consumers are reasonably well aware of prices.

Search and shopping costs are similar in many ways. A widely used approximation to assess their size is the number of stores visited (or prices quoted)/sourced, respectively.⁴⁰ But according to the literatures, they designate distinct phenomena. Search costs are related to the time spent in acquiring information to pay lower prices (or buy higher quality products).⁴¹ Shopping costs

³⁹Wildenbeest (2011) and Dubois and Perrone (2015) are the only papers that we are aware of that have considered multiple products in search costs models of demand. However, none of them addresses the problem of multiproduct search. Wildenbeest (2011) assumes consumers are interested in buying a “representative” basket of 24 products and compare the total value (price or utility) of identical baskets across stores, which is essentially a model of search for a single product (the product being here a basket of goods). On the other hand, Dubois and Perrone (2015) propose and estimate a model of search using data on several food products, but perform the estimation on a product-by-product basis which makes their analysis a collection of single-product searches.

⁴⁰For instance, in his 1961 seminal paper on information frictions and search, Stigler refers to search costs in the following way: “The cost of search, for a consumer, may be taken as approximately proportional to the number of (identified) sellers approached, for the chief cost is time.”

⁴¹According to Baye and Morgan (2006) search costs “consist of consumers’ opportunity cost of time in searching for lower prices, plus other costs associated with obtaining price quotes from competing firms (such as the incremental cost of the postage stamps or phone calls used in acquiring price information from firms)”.

are transaction costs (both real and perceived) of dealing with a supplier. These may include transportation costs (the cost of gas for a private car or a trip fee for public transports, the price of a parking slot, the time spent on a trip to the supermarket, the effort made to reach that place, etc.), and all other costs related to the shopping experience. Search costs can be thought of as being part of those transaction costs incurred in a shopping occasion. Whenever consumer decisions are affected by information frictions, engaging in information gathering activities is possible at a cost. Alternatively, when consumers are well informed, shopping costs would still be positive reflecting other transaction costs consumers incur when shopping, as well as accounting for their taste for shopping.

Empirically, under a search costs reasoning, one should expect that prices decrease with the number of stores visited. Actually, the negative correlation between the transaction price of an item and the number of supermarkets visited has been used in the empirical search literature as reduced-form evidence of consumer search.⁴² However, if consumers are reasonably well aware of prices, we should not observe this relationship. We believe that this is the case for frequently-purchased non-storable products. To verify this in our context, we take two subsamples of the (top 10 and top 5) most frequently-purchased non-storable product categories in our data set and regress a category-specific price index on the number of separate stores visited as well as the number of visits to the same supermarket in that week, and controls for household's characteristics, proxies for household's time cost, product, supermarket chain, and time fixed-effects, and dummies for store characteristics that vary across stores within the same supermarket chain and are not captured by chain fixed effects (such as store format). If consumers have more time on weekends and, as a consequence, incur lower costs of search, we should observe that the transaction price paid is lower on weekends relative to that on week days. To capture this, we also include in our regressions a dummy which takes on one if the purchase was made on a weekend. Results are displayed in Table 4. There are three columns: the first corresponds to the price index of the top ten most-frequently-purchased non-storable products, the second is for the top 5 of that class, and the last includes the three products we use in our empirical implementation below.⁴³

We find a positive and significant relationship of the transaction price and the number of separate stores visited per week in the third regression, which suggests that, on average, consumers do not get cheaper baskets by sourcing a larger number of separate stores. In the two other regressions, we find that this relationship is not statistically significant. This suggests that the search costs story according to which consumers source different stores in order to find lower prices is not consistent with our results for non-storable staple products. We do find a negative and significant relationship (in columns one and three) of the price index with the number of visits to the same supermarket chain. Households that go frequently to the same store pay lower prices possibly because they can take advantage of sales and promotions (see Aguiar and Hurst,

⁴²See, for example, Dubois and Perrone, 2015, who perform reduced-form regressions using a subsample of purchases of a selected set of storable products: Beer, Coffee, Cola, and Whisky.

⁴³For details on how we construct price indices for the regressions, see the Data appendix.

2007), or get loyalty rewards more often than infrequent buyers.

Interestingly, purchases of the products we consider on weekends does not seem to be leading to lower prices. We find a statistically insignificant relationship between the purchase-on-weekend dummy and the price index in the three regressions. This indicates that households are not necessarily paying lower prices for non-storable staple products when they have more time, suggesting that search is not an issue in this case. Coefficients of store and household characteristics are significant and basically of the expected sign. Prices paid at larger store formats are lower as compared to convenience stores. Similarly, transaction prices at hard-discount stores are lower than those of regular supermarket chains. Income, household head's age and living in urban areas are positively correlated with the price paid. By contrast, larger households tend to pay lower prices.

3.2 Switching costs

Positive switching costs may be an additional way to (partially) rationalize the observed heterogeneity in consumer shopping patterns.⁴⁴ In fact, one might be tempted to think of one-stop shopping behavior as being associated with large switching costs at the store level such as learning costs (related to stores' structure and arrangement of products in-store, pricing and promotion policies, etc.), strong feelings of store loyalty, supermarket non-price strategies to retain consumers (e.g. loyalty programs), and so on, which makes it very costly to substitute stores or even purchase part of the desired basket at another shopping location. Although (artificial) switching costs are widely present in the grocery retailing sector, the switching costs story makes sense when we look at shopping patterns from a dynamic perspective rather than in the same shopping period. Shopping costs, on the other hand, rationalizes the use of one or several suppliers even in a single period.⁴⁵ On the other hand, switching costs do not offer a convincing explanation as to why a shopper might find it optimal to source simultaneously several grocery stores. To see why, consider the case of a multistop shopper who, in a given week, is interested in buying a basket of two products and decides to purchase product 1 from supermarket A and product 2 from supermarket B. Without further information about past behavior of the consumer, we cannot say anything about her switching behavior. What we can say with certainty is that this consumer has lower transaction costs of shopping (or larger taste for shopping) than she would have had we observed her shopping the two products at a single store that week. Further, suppose we are able to observe that in the previous shopping period she had a similar shopping behavior (1 from A and 2 from B). Accordingly, she would not be a switcher, yet she

⁴⁴Switching costs arise from "... consumers using a brand develop 'user skills' that may not be transferable to *ex ante* identical alternative brands" (Klemperer, 1992, citing Wernerfelt, 1985,1989).

⁴⁵Klemperer (1992) points out the importance of the temporal dimension and the choice of real vs. perceived characteristics to differentiate between shopping and search costs in the following sentence: "The economies of scope of buying related products, arising from these 'shopping costs' are similar to the economies of scale in repeat-purchasing a product that are discussed in the 'switching costs' literature... Thus, this [switching costs] literature has already develop economic reasons for (and implications of) 'brand loyalty', but it has concentrated on intertemporal issues and has said little about the choice of 'real' product characteristics (as distinct from perceived or nonfunctional characteristics that exist purely to affect compatibility across suppliers)." p. 741.

Table 4: Results for the log of household weekly expenditure^a

Variable	Top 10 ^b	Top 5 ^b	Three selected ^c
No. Stores visited/week	-0.0020 (0.0023)	-0.0020 (0.0033)	0.0045* (0.0027)
No. Visits to each store/week	-0.0052** (0.0025)	-0.0038 (0.0031)	-0.0063** (0.0031)
Purchase on Weekend (=1 if yes)	-0.0001 (0.0031)	0.0018 (0.0043)	-0.0007 (0.0043)
Average distance	-0.0005* (0.0003)	-0.0005 (0.0004)	-0.0005 (0.0004)
Hypermarket	-0.0416*** (0.0070)	-0.0509*** (0.0093)	-0.0243** (0.0096)
Convenience	0.0239*** (0.0086)	0.0280** (0.0115)	0.0226* (0.0133)
Hard-discount	-0.2780*** (0.0116)	-0.3190*** (0.0155)	-0.2660*** (0.0165)
HH head's age	0.0025*** (0.0002)	0.0029*** (0.0003)	0.0017*** (0.0003)
Log of Income	0.1210*** (0.0055)	0.1460*** (0.0072)	0.1320*** (0.0078)
HH size	-0.0542*** (0.0020)	-0.0687*** (0.0026)	-0.0655*** (0.0028)
Baby	0.0118** (0.0060)	0.0138* (0.0077)	-0.0157* (0.0084)
Lives in urban areas	0.0197*** (0.0055)	0.0275*** (0.0073)	0.0340*** (0.0079)
Constant	0.3260*** (0.0413)	0.1930*** (0.0548)	0.3170*** (0.0583)
Controls for hh storage capacity	Y	Y	Y
Other household characteristics	Y	Y	Y
Category FE	Y	Y	Y
Store FE	Y	Y	Y
Week FE	Y	Y	Y
R^2	0.064	0.055	0.116
Observations	1,423,528	804,904	509,291

Source: TNS Worldpanel data base.

Notes: ^aAsymptotically robust s.e. are reported in parentheses.

^b These are the most frequently purchased among the non-storable products, from a ranking of 344 products that registered purchases by french households in our data base.

^cThese are: Yogurts, refrigerated desserts and biscuits, selected for the empirical implementation of our model (see below). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

would be a multistop shopper, so it would be misleading to claim that multistop shopping is possible due to low switching costs.

In our data we observe that almost all households do multistop shopping at some point. Even though, on average, we have an important proportion of one stop shopping in a week (see 1), households often change shopping patterns across weeks and only less than 6% of households are consistently week-to-week one-stop shoppers. This number suggests that the kind of switching

costs that make consumers be locked in a particular store does not seem to be important in this case. However, we do not claim that this is evidence that switching costs do not exist in the sector, the classical economies of scale of repeat-purchasing at the product level may still be present here, but not necessarily linked to a particular shop.

4 Consumer shopping behavior with shopping costs

In this Section, we introduce a model of demand for multiple grocery products and multiple stores. Our structural model allows for consumer heterogeneity in two dimensions, namely, in the valuation for products and in shopping costs. To keep exposition simple and without loss of generality, we present a model of three grocery stores that offer a product line consisting of three (categories of) products. We believe this is enough to capture the basic intuition of one- and multistop shopping behavior and the role of shopping costs.

4.1 General set-up

There are I consumers in the market indexed by $i = 1, \dots, I$ with idiosyncratic valuations for grocery products indexed by $k = 1, 2, 3$. Suppose there are three store chains in the market indexed by $r \in \{A, B, C\}$ that supply the same products to all consumers.⁴⁶ A customer i purchasing product k from store r at period t derives a net utility \bar{v}_{ikrt} .⁴⁷

Consumers have unit demand for each product class and can purchase one, two or three products in the same period. Let \mathcal{B} be the set of all exclusive and exhaustive baskets. Baskets with multiple products may be purchased from a single store (*one-stop shopping*) or from multiple stores (*multistop shopping*). A consumer favors multistop shopping if her shopping costs are small enough, otherwise she will optimally concentrate all her purchases with a single store.

In the formulation of the model, we focus on the fixed component of the total shopping costs that may account for the consumer’s taste for shopping. From now on, we will refer to this fixed cost as “shopping costs” and denote it s_i . Transport costs, which is an important component of the total cost of shopping, is accounted for by including distances to stores as an additive term entering the utility function of a basket of products (see below). 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, consumers do not need to engage in costly search to gather information about prices, qualities and the like.

A consumer i is supposed to have an optimal shopping behavior. This implies she optimally makes a choice that involves two elements: being a one- or a multistop shopper, and which

⁴⁶Assuming all consumers have access to the same product range might appear strong. However, this helps us reducing dimensionality issues in the estimation of the model. An extension of the model would be to relax this assumption and allow for heterogeneous choice sets.

⁴⁷For now, we do not specify a functional form for the utility as it is not necessary for setting out the model. We will assume a parametric specification at the empirical implementation stage in Section 5.

stores to source for each of the products she desires to buy. 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 and stores that maximize the overall value of the desired basket. In line with this, a three-stop shopper who can visit all stores and wants the three products, will pick the best product-store combination from the three alternatives existing in the market within each category. A two-stop shopper will pick the mix of two stores maximizing the utility of the desired basket from all the combinations of products-stores possible. Her final basket will consist of the best products 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 basket of products.

Formally, let D_{ir} , for all $r \in \{A, B, C\}$ denote the distance traveled by a consumer i from his household location to store r 's location, and τ a parameter that captures consumer's valuation of the physical and perceived costs of traveling that distance. Define the total utility net of transport costs of a shopper who is able to source only one of the three stores in the market as follows:

$$v_{it}^1 = \max \left\{ \sum_{k=1}^3 \bar{v}_{ikAt} - \tau D_{iA}, \sum_{k=1}^3 \bar{v}_{ikBt} - \tau D_{iB}, \sum_{k=1}^3 \bar{v}_{ikCt} - \tau D_{iC} \right\}. \quad (1)$$

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

$$v_{it}^2 = \max \left\{ \sum_{k=1}^3 \max\{\bar{v}_{ikAt}, \bar{v}_{ikBt}\} - \tau(D_{iA} + D_{iB}), \sum_{k=1}^3 \max\{\bar{v}_{ikAt}, \bar{v}_{ikCt}\} - \tau(D_{iA} + D_{iC}), \sum_{k=1}^3 \max\{\bar{v}_{ikBt}, \bar{v}_{ikCt}\} - \tau(D_{iB} + D_{iC}) \right\}. \quad (2)$$

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

$$v_{it}^3 = \sum_{k=1}^3 \max\{\bar{v}_{ikAt}, \bar{v}_{ikBt}, \bar{v}_{ikCt}\} - \sum_{r \in \{A, B, C\}} \tau D_{ir}. \quad (3)$$

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 maximizes the overall utility of her desired basket. 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 subsets of suppliers.⁴⁸

Suppose $v_{it}^1 - s_i > 0$ so that all consumers will source at least one supermarket each period. To determine the number of stops to be made, consumer i weighs the extra utility of doing n -stop shopping with the extra costs, taking into account that the total cost of shopping increases

⁴⁸The general expression of the utility, and the choice of a n -stop shopper are described in Appendix A.

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,

$$v_{it}^3 - 3s_i \geq \max\{v_{it}^2 - 2s_i, v_{it}^1 - s_i\}$$

Let $\delta_{it}^3 \equiv v_{it}^3 - v_{it}^2$ be the incremental utility of visiting three stores rather than two, and $\Delta_{it}^3 \equiv v_{it}^3 - v_{it}^1$ be the extra utility of deciding to source either one or three stores. The optimal stopping rule for a three-stop shopper is given by

$$s_i \leq \min\left\{\delta_{it}^3, \frac{\Delta_{it}^3}{2}\right\} \quad (4)$$

A consumer optimally decides to do two-stop shopping if and only if

$$v_{it}^2 - 2s_i \geq \max\{v_{it}^1 - s_i, v_{it}^3 - 3s_i\}$$

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

$$\delta_{it}^3 < s_i \leq \delta_{it}^2 \quad (5)$$

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

$$v_{it}^1 - s_i \geq \max\{v_{it}^2 - 2s_i, v_{it}^3 - 3s_i\}$$

from which we can derive the optimal stopping rule for a one-stop shopper as

$$s_i > \max\left\{\delta_{it}^2, \frac{\Delta_{it}^3}{2}\right\} \quad (6)$$

In general, the optimal stopping rule for consumer i indicates that she will choose the mix of suppliers to maximize her utility, conditional on the extra shopping cost being at most the extra utility obtained from sourcing additional stores. 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_{it}^2 , δ_{it}^3 and $\Delta_{it}^3/2$ ordered. From six possible orderings only one survives,⁴⁹ namely,

$$\delta_{it}^3 < \frac{\Delta_{it}^3}{2} < \delta_{it}^2, \quad (7)$$

Under this ordering, 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

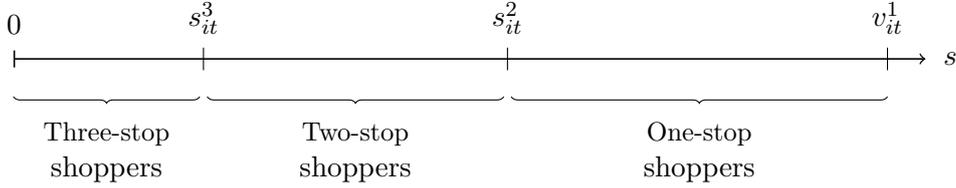
⁴⁹We show why this is so in Appendix B.

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 these cutoff points depend on the period of purchase —the subscript t was added— because it depends on utilities that may vary with time. The derived cutoffs of the distribution of shopping costs in (8) indicate 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 in equilibrium and will be defined over the entire support of $G(\cdot)$ —see Figure 3.⁵⁰

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



4.2 Aggregate demand

Let $\mathcal{B}_2, \mathcal{B}_3 \in \mathcal{B}$ be subsets of baskets involving two- and three-stop shopping, respectively. The aggregate demand for product k supplied by store r is given by

$$\begin{aligned} q_{krt}(\mathbf{p}_t) &= \left[G(v_{it}^1(\mathbf{p}_t)) - G(s_{it}^2(\mathbf{p}_t)) \right] P_{it}^1(X_{\mathcal{B}}; \theta) \\ &+ \left[G(s_{it}^2(\mathbf{p}_t)) - G(s_{it}^3(\mathbf{p}_t)) \right] \prod_{\{b \in \mathcal{B}_2 \mid kr \in b\}} P_{it}^2(X_{\mathcal{B}}; \theta) \\ &+ G(s_{it}^3(\mathbf{p}_t)) \prod_{\{b \in \mathcal{B}_3 \mid kr \in b\}} P_{it}^3(X_{\mathcal{B}}; \theta), \end{aligned} \tag{9}$$

where P_{it}^1 is the probability that a one-stop shopper decides to stop at r , P_{it}^2 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_{it}^3 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 $\eta_{krht} = \frac{\partial q_{krt}}{\partial p_{jht}} \frac{p_{jht}}{q_{krt}}$, for all $j \in \{1, 2, 3\}$, $h \in \{A, B, C\}$. 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 they depend on utilities. As a consequence, the distribution of shoppers between one-, two- and three-stop 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

⁵⁰Notice 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.

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.

5 Empirical implementation

In this section we provide details on how we take our model to data, how we define the consumers' choice set, the empirical specification of the utility function, and how we deal with estimation challenges.

5.1 Shopping period

We define a shopping period as a week in which the household is recorded making grocery purchases. In a week, a household can concentrate purchases in a single store chain but may visit several of its branches or may make several visits to the same place. In any case, we say this household is a one-stop shopper as long as it is observed to deal with a single supermarket chain during the same week. Alternatively, when we observe the household purchasing at several competing stores in the same week, we say it is a multistop shopper. Further, our demand model allows consumers to buy several distinct products in the same week and assumes consumers are making a series of multiple discrete decisions over which products to buy, as part of a desired basket of products from a set of mutually exclusive and exhaustive alternatives. This choice set includes baskets of one and multiple products, and when a household is not observed to have made purchases in a given shopping period, we say it opted for the outside option.

5.2 Products and stores

The consumer choice set consists of baskets of products that can be purchased from one or several separate stores. Accordingly, if we observe purchases of K different products from R separate stores, the size of the choice set for each individual would be R^K mutually exclusive and exhaustive baskets, which grows exponentially as R or K increases. In our data set, households are observed to purchase up to 275 different products from up to 9 separate grocery suppliers in the same shopping period.⁵¹ Estimating a demand system with such a huge choice set (9^{275}) is infeasible. We focus on a reduced set of three product categories and three grocery stores that are on the top of most frequently purchased products/stores sourced by french households. In particular, we include yogurt, biscuits, and refrigerated desserts, provided that they meet several criteria that make our empirical exercise consistent with our structural model (see Table 5). These criteria are: first, they are staples, most french households are heavy consumers of products from those categories (they are typically consumed everyday by an average french household), and cannot be stored for very long, so stockpiling is not a concern. Second, these categories are not close substitutes, which ensures we can observe enough variation in shopping patterns as consumers may tend to concentrate purchases of the same category in a particular

⁵¹On average, a household purchases baskets containing 24 different products from 2 separate stores in a week.

store but might want to diversify categories across stores. Finally, customers tend to consume one serving of a product from these categories at a time, which makes it convenient for a demand model that relies on a unit demand assumption (see Table 5 for details on how we define servings).

Table 5: Characteristics of the selected categories

Product	Serving (in grams)	Consumers (% of pop.) ^a	Position among 352 products ^b	Days between purchase
Yogurt	125	90.7	2	8
Refrigerated desserts	80	76	3	10
Biscuits	30	57	4	10

Notes: ^aSource: Étude Inca (Afssa) 2006-2007 by *Agence Française de Sécurité Sanitaire des Aliments*. Yogurt appears in the Inca study as part of a broader category that includes other similar dairy products. 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 products for which we observe purchases in our data set, TNS Worldpanel 2005 by frequency of purchase.

The question we aim to answer in this paper requires a choice set with at least two alternatives in the same product category, to capture consumers’ reactions when when one of them is delisted. We then allow two brands in the yogurt category: one being the leading national brand of yogurt in France in 2005 and, on the other hand, a “generic” brand of yogurt which consists of the remaining brands (both other national brands and private labels) available in the market. Concerning the other two categories, purchases of all brands in each case are treated as purchases of a single generic product. Therefore, consumers face a set of four goods from which they pick at most three: at most one of the two alternative yogurt, biscuits and desserts.⁵²

Concerning grocery stores, we restrict attention to the three leading supermarket chains in France according to their national market share in 2005. They are the largest chain stores in France and are widely present along the country through the various store formats: hypermarkets (outside downtown boundaries), supermarkets, and convenience stores (generally located in downtowns). The remaining grocery stores observed in our data are included in the outside option along with the no purchase of the included goods option, and the no shopping (at all) option (the interpretation of the outside good in this context is discussed below). In other words, consumers have three alternative stores in their choice set plus an outside option. We believe this is good enough to describe one- and multistop shopping behavior and to estimate shopping costs cutoffs.

We end up having four products that are *ex ante* homogeneous and available at three alternative stores of similar size. This is consistent with our modeling framework of oligopolistic competition with differentiated product lines, where customers can source multiple stores in the same shopping period to increase variety. In this context, a basket is collection of product-store items, and with four products and three stores supplying them, and baskets that can consist of one, two or three product-store combinations, we end up with a choice set of 120 mutually

⁵²The choice of yogurt as the category with two alternatives is arbitrary. In order to check the robustness of our results, we perform the estimation of our demand model by changing the category containing two options. Results are shown in Table D.1 in the appendix

exclusive and exhaustive alternatives.

5.3 Empirical specification of the utility

We empirically specify the per-product utility as a function of observed product-store characteristics, and consumer valuation of unobserved product-store characteristics as well as time fixed effects. We allow consumer heterogeneity enter the utility function through the price coefficient which is a function of observed and unobserved household characteristics. Formally, let the utility of consumer i from purchasing good k from store r at time t be given by

$$\bar{v}_{ikrt} = -\alpha_i p_{krt} + \mathbf{x}_k \boldsymbol{\beta}_1 + \mathbf{x}_r \boldsymbol{\beta}_2 + \xi_k + \xi_r + \phi_t + \varepsilon_{ikrt}, \quad (10)$$

where, p_{krt} is the price of good k at store r , \mathbf{x}_{kr} is a vector of product-store observed characteristics, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ is a vector of product and store coefficients, that capture consumer mean valuation of product-store characteristics, ξ_k are product unobserved characteristics, ξ_r are store unobserved characteristics, ϕ_t are time fixed effects, and ε_{ikrt} is an idiosyncratic shock to utility which rationalizes all remaining week-to-week individual variation in choices. Because the consumer observed mean valuation of product-store characteristics will not be separately identified from the unobserved product-store characteristics, we replace the following terms by a single constant term:

$$\delta_k = \mathbf{x}_k \boldsymbol{\beta} + \xi_k, \quad (11)$$

and,

$$\delta_r = \mathbf{x}_r \boldsymbol{\beta} + \xi_r. \quad (12)$$

We model the distribution of consumer tastes for price as follows:

$$\alpha_i = \alpha + \mathbf{d}_i \boldsymbol{\pi} + \sigma^\alpha \nu_i, \quad \nu_i \sim N(0, 1) \quad (13)$$

where α captures the mean (across consumers) valuation for price, \mathbf{d}_i is a vector of observable household characteristics, $\boldsymbol{\pi}$ is a vector of coefficients measuring the change in tastes with household characteristics, ν_i is a random variable distributed standard normal, that capture unobserved household attributes that influence consumer choice and σ^α is a scaling parameter.

When consumers are observed not to purchase any of the included products-store goods included in our analysis, we say they opted for the outside good. We normalize the mean utility of the outside good to zero, and thus, its utility is modeled as a function of a random shock, $\bar{v}_{i0t} = \varepsilon_{i0t}$.

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

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 engaging in costly shopping, and an individual deviation from this mean η_i , which rationalizes the individual heterogeneity in shopping costs, this yields

$$s_i = \varsigma + \sigma^s \eta_i, \quad \eta_i \sim N(0, 1). \quad (14)$$

where σ^s is a scaling parameter.

Remark that even though the choice set for all consumers is the same (i.e. all products from all retailers are available for purchase to everyone), consumers with large 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.

5.4 The outside option

Recall that to keep our problem of multiproduct and multistore choice tractable, we restricted the choice set to all exhaustive and exclusive baskets resulting from the mix of up to three store chains and up to four separate products (two brands of yogurt, biscuits, and refrigerated desserts). The selected three supermarket chains concentrated a share of near 60% of the national market of supermarket sales in France (excluding hard-discounters) in 2005. Recall also that with the exception of Yogurt NB, the products we consider are in fact product categories. Hence, we take account of any other brand of yogurt, and all brands of biscuits and refrigerated desserts purchased by consumers from the three included store chains. The remaining observed purchases of both included and excluded products at excluded stores, of excluded products at included stores, as well as unobserved purchases and visits to unobserved sellers are left as part of the outside good.

In such a context, the interpretation of the outside option is not the same as in a standard discrete choice model of demand for a single product. As pointed out by Gentzkow (2007), in a model that allows consumers to pick multiple goods simultaneously, every choice involves a maximization over all excluded alternatives, unlike in a standard multinomial model where only the utility for good ‘zero’ is implicitly maximized over all excluded goods.

To see what this means in our case, take for instance a household that registered purchases of biscuits and desserts from two of the included supermarkets (say, A and C) in a given week. If this was the only grocery shopping activity of that household that week, we would interpret it as a two-stop shopper that purchased a basket of three products in two separate shopping locations and conclude, according to our structural model, that its overall utility net of shopping costs was larger than that of the two alternatives (one- and three-stop shopping). However, it may be that this household purchased yogurt and/or other excluded products at excluded stores, or that it made purchases of excluded products at the included stores. In any case, the interpretation is that this household was better off by choosing a basket including stops at supermarkets A and C and (possibly) the outside option rather than any other combination including supermarket B.

In line with this, we have to make a caveat related to the interpretation of the shopping patterns we observe in our final data set. In fact, if a consumer is observed to have made purchases at two stores out of the three included, we would interpret that she was able to make two stops in addition to other she could have made (or not) to any other excluded shop. In this sense, the number of stops of a household that possibly made purchases at excluded shopping locations is interpreted in the context of this paper as the number of additional stops the household made to included stores.

5.5 Identification

Equation (8) shows 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- and multistop shoppers and identify the parameters of the per product utilities involved in the computation of the n th cutoff point. For each individual we need to identify both the utility of her actual choice, say a basket implying two stops, and the utility she would have derived had she chosen any basket implying alternative shopping patterns (either one- or three-stop shopping). To do this, we exploit the panel structure of our data. We observe enough cross-section and time variation in choices of products and stores, which allows us to identify the mean utility parameters. In particular, we are able to separately identify the price coefficient from the mean utility thanks to the observed variation in prices of the same product. The predicted probabilities will vary due to this variation in prices, which generates enough moments for identification.

Fixed shopping costs are identified from the observed week-to-week variation in the shopping patterns of each household, i.e. a household making one-stop shopping at a given week can be observed doing multistop shopping the following week. Week-to-week variation is necessary but not sufficient for identification, variation in the set of products purchased from each store is needed as well to separately identify shopping costs from product-store mean utility parameters.

We allow shopping costs to be heterogeneous across individuals, while remaining fixed for each individual, by including household characteristics that account for time constraints, as well as other sources of time costs that may vary across retailers and/or periods. We control for household income, number of cars, household size, household's head age, and distances from household location designated by postal codes to stores. As in Dubois and Jódar-Rosell (2010), all households located at a same postal code have the same distance to stores.⁵³ The inclusion of distances to stores is useful for two purposes: they capture part of the horizontal dimension of consumers' preferences for product characteristics and, on the other hand, they allow us 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 and time periods, consistent with our set up.

Finally, the identification of aggregate demand requires the computation of the mass of

⁵³Due 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 for each household.

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.

5.6 Estimation

In this section we present details on how we estimate the utility parameters, and the coefficients of the shopping costs distribution. Given that we use a flexible model of demand for each product, allowing for random coefficients on price and shopping costs, our choice probabilities do not have a closed-form solution. We use simulated methods to compute them. To implement the estimation, we use the data set described in Section 2. The final sample we use consists of local areas where we observe households doing one-, two- and three-stop shopping and purchasing at least one unit of one of the products considered in our sample. We explain details of the estimation method we use in the following.

A consumer who wishes to buy a set of products, faces a choice set \mathcal{B} of mutually exclusive and exhaustive alternatives consisting of combinations of products and stores available in the market. She will purchase a basket consisting of a combination of products $\{1, 2, 3\}$ and stores $\{A, B, C\}$, call it basket $b \in \mathcal{B} = \{1, \dots, 112\}$, such that she can obtain the highest utility net of shopping costs. Let $\boldsymbol{\theta} = (\alpha, \phi_t, \tau, \sigma_\alpha, \sigma_\eta, \varsigma)'$ be a vector containing all parameters to be estimated. This maximizing behavior defines the set of unobservables leading to the choice of alternative b as

$$A_{ibt}(\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i; \boldsymbol{\theta}) = \left\{ (\boldsymbol{\epsilon}_{it}, \nu_i, \eta_i) \mid v_{ibt}^n - ns_i > v_{ijt}^m - ms_i \forall m \in \{1, 2, 3\}, j \in \mathcal{B} \right\},$$

where n and m corresponds to the number of stores visited in basket b and j , respectively; v_{ibt}^n corresponds to the net utility derived by consumer i from basket b at choice occasion t before incurring n -times the shopping costs. Integrating over the $\boldsymbol{\epsilon}_{it}$ yields closed-form choice probability of alternative b , at choice occasion t , as a function of characteristics of products and retailers, conditional on observable and other unobservables:

$$Q_{bt}(\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i, \boldsymbol{\eta}, \boldsymbol{\nu}; \boldsymbol{\theta}) = \frac{\exp(v_{ibt}^n - ns_i)}{1 + \sum_{j \in \mathcal{B}-1} \exp(v_{ijt}^m - ms_i)}. \quad (15)$$

As each consumer makes a sequence of T choices, we index H as the set of all possible values our data takes - all sequence of baskets across all choice occasions during our period of observation. The probability of observing consumer i making a sequence of choices $h \in H$ is:

$$P_h(\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i, \boldsymbol{\eta}, \boldsymbol{\nu}; \boldsymbol{\theta}) = \prod_{t=1}^T Q_{\hat{b}_t}(\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i, \boldsymbol{\eta}, \boldsymbol{\nu}; \boldsymbol{\theta}), \quad (16)$$

where \hat{b}_t denote the actual basket chosen at each corresponding choice occasion. Given the matrix of observable characteristics $\mathbf{X} (= \{\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i\})$, and the T -dimensional vector of observed choices

for each consumer, \mathbf{h} , a natural way to estimate $\boldsymbol{\theta}$ is by maximizing the log-likelihood function:

$$L(\mathbf{X}, \mathbf{h}; \boldsymbol{\theta}) = \sum_i \ln \int_{\nu, \eta} P_h(\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i, \boldsymbol{\eta}, \boldsymbol{\nu}; \boldsymbol{\theta}) dF(\boldsymbol{\eta}, \boldsymbol{\nu}; \boldsymbol{\theta}). \quad (17)$$

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. Simulated methods help overcome this problem by simulating a sample of choice probabilities and replacing the original unknown probabilities by the empirical mean of the simulated statistics. We use the Simulated Maximum Likelihood (SML) –see Lerman and Manski (1981), and Pakes and Pollard (1989). We assume the basket-level shocks follow an extreme value distribution. As SML requires the number of simulation draws, S , to approach infinity with $\sqrt{S/T} = O(1)$, we use 100 draws in our simulation. The SML estimator is given by:

$$\hat{\boldsymbol{\theta}}_{SML} = \arg \max_{\boldsymbol{\theta}} \left\{ \sum_i \ln \left[\frac{1}{S} \sum_s P_h^s(\boldsymbol{\delta}, \mathbf{p}, \mathbf{d}_i, \boldsymbol{\eta}, \boldsymbol{\nu}; \boldsymbol{\theta}) \right] \right\}.$$

6 Results

Table 6 displays SML estimates of the utility parameters, distance and shopping costs, according to four specifications. The first and second columns correspond to a Multinomial Logit specification of our model, which does not allow random coefficients to enter the utility function. As a consequence, these two columns give estimates for the common valuation of product characteristics, and average shopping cost. Unlike the specification in column (1), in the second we allow for observed household characteristics to enter the utility model through interactions with the number of stores visited in a week. Columns (3) and (4) correspond to a more flexible specification (Mixed Logit) that allows random coefficients for price and shopping costs. Similarly, the difference between specifications (3) and (4) are interactions between households characteristics and the number of visited stores. All regressions include product, store and time fixed-effects.

All taste coefficients are significant, and results are as expected: demands are downward sloping and the estimate for the distance shows that the mean valuation of a basket of products is lower the farther a store is from customers' location. The estimate for the shopping costs is negative and statistically significant, which we interpret as consumers facing, on average, a positive fixed-cost of dealing with suppliers. Moreover, the estimates for the standard deviations of the coefficients of price and shopping costs, displayed in the last two columns are significant and larger than one in both cases. This indicates that unobserved household characteristics are important in explaining observed heterogeneity in household choices and shopping patterns.

Finally, the estimates of the interactions of the number of different stores visited in a week with observed household characteristics (that we believe contain information on shopping costs) are significant in the multinomial Logit specification in column 3, but become statistically insignificant once we allow unobserved household characteristics to enter the model through ran-

dom coefficients in column 4. Estimated coefficients of household characteristics in column 2 show some interesting findings. Higher income households prefer dealing with less stores presumably because higher income people have a higher opportunity cost of time as compared to lower income people. Further, older people prefer visiting less stores than their younger counterparts, probably because repeat purchase and loyalty to the same store chain may give them advantages in terms of prices and promotions. This is consistent to what we showed in Figure 2, about older people strongly preferring loyalty over multistop shopping. The number of cars as well as the number of members in a household appear to make people more likely to patronize a larger number of stores in the same week.

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

Covariate	Multinomial Logit		Mixed Logit	
	(1)	(2)	(3)	(4)
Price (€/basket ^b)	-2.522*** (0.214)	-2.008*** (0.211)	-2.999*** (0.698)	-2.565*** (0.707)
Shopping costs	-3.262*** (0.066)	-3.175*** (0.066)	-4.480*** (0.280)	-4.039*** (0.270)
Distance	-0.063*** (0.003)	-0.067*** (0.003)	-0.076*** (0.015)	-0.076*** (0.014)
No. visited stores × Log Income		-0.271*** (0.038)		0.307 (0.717)
No. visited stores × Age		-0.005*** (0.001)		0.010 (0.010)
No. visited stores × No. Cars		1.099*** (0.064)		0.819 (0.710)
No. visited stores × hh size ^c		0.058*** (0.015)		-0.162 (0.163)
Constant	1.107*** (0.088)	1.023*** (0.089)	2.414*** (0.209)	2.381*** (0.218)
Standard deviations (σ's)				
Price			2.834*** (0.627)	3.191*** (0.252)
Shopping cost			1.934*** (0.121)	2.022*** (0.156)
Observations	1,635,424	1,635,424	1,638,448	1,635,424

Notes: ^aRobust standard errors are in parenthesis. All regressions include product, store and time (months) fixed effects. ***, **, *: significant at 1, 5 and 10% confidence levels, respectively.

^bA basket can consist of unit servings of one, two or three products: dessert (80g), biscuit (30g) and, yogurt (125g). For multistop shoppers, each product may be purchased from different stores. Therefore, the choice set contains 112 mutually exclusive and exhaustive alternative baskets.

^c'hh' stands for household.

We use the results of the full model (column (4) of Table 6) to obtain measures in euros of average shopping and transport costs, and shopping costs cutoffs (moments of the distribution of shopping costs). Table 7 displays the results. The average fixed shopping cost is 1.57 € per trip to a store. It was computed using the estimate in Table 5 divided by the price coefficient. The average transport cost is 3 cents on the euro per km. This number was obtained by translating the disutility of distance into euros using the price estimate in Table 6. The average distance

between the mean consumer's dwelling to a store is 7.2 km, which multiplied by the transport cost per km gives a total transport cost of 21.6 cents on the euro per trip to the average store. Summing up, the total shopping costs (fixed shopping costs plus transport costs) the mean consumer incurs for a trip to a store located at an average distance is 1.79 €.

Concerning shopping costs cutoffs, we find that a customer is able to visit at least one store in a week if her shopping costs lie below 1.21€. Notice that this value is lower than the average shopping costs, which means that, on average, not everyone affords to visit one supermarket every week. This is consistent with the model's prediction of 66.9% being zero-stop shoppers. One-stop shoppers are those whose shopping costs lie between 7 cents on the euro and 1.21€, this is 31.7% of customers. Finally, the shopping costs necessary to rationalize the low proportion of multistop shoppers able to visit either two (1.3%) or three stores (0.03%) every week are very small, even negative. A negative shopping costs is consistent with our model as they account for consumer's taste for shopping. In line with this, a smaller (negative) shopping cost means that the consumer has a stronger taste for shopping.

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

Total shopping costs	
Mean shopping cost (€)	1.57
Mean transport cost (€/km)	0.03
Average shopping costs cutoffs (€)	
Zero-one stop	1.21
One-two stops	0.07
Two-three stops	-0.73
Distribution of shoppers (% of total)	
Zero-stop shoppers	66.92
One-stop shoppers	31.73
Two-stop shoppers	1.32
Three-stop shoppers	0.03

Notes: To translate estimates into euros, we divide the absolute value of each coefficient by the absolute value of the price coefficient.

Table 8 shows mean own- and cross-price elasticities. Each entry i, j , where i indexes rows and j columns, gives the average elasticity of product category i with respect to a change in price of j . For the three store chains we consider in our analysis, average estimated elasticities show similar patterns. As expected, we obtain negative own-price elasticities and of similar magnitudes. In the case of yogurts, both the composite and the NB have near 1 (in absolute value) mean own-price elasticities. For the Biscuits category we obtained smaller elasticities and, on average, the own-price elasticity is approximately 0.4 in absolute value, which indicates that the demand for this category is inelastic, on average. We found the opposite in the case of Desserts: mean own-price elasticities lie between 1.89 and 2 (in absolute value) for the tree

retailers considered, which indicate that the demand for this category is, on average, the more elastic among the three categories considered. On the other hand, we obtain positive cross-price elasticities for the same category across retailers. This captures an expected effect: given that all the supermarkets supply the same product line, consumers are willing to substitute retailers when the price of a particular product increases in one supermarket. Notice that the only category that allows intrastore as well as interstore substitution is Yogurts, provided we allowed for two alternative brands in this category available at each store. When the price of, say, Yogurt NB rises, the demand of the composite Yogurt increases in both the store where the price raised and the two competing stores.

An interesting effect captured by our elasticities is the complementarity between categories in the same store. When the price of a product increases, the demand of all categories in that store decrease, while the demand for all products at competing stores rises. We interpret this result as being the consequence of two things: the large number of consumers who are observed to purchase the three categories in the same week, and the larger proportion of one-stop shoppers in our data. Consider, for example, an increase in the price of the yogurt NB in store 1. Given that all baskets containing that product in store 1 are more expensive now, demand of all consumers who desire to purchase that product will decrease. Some consumers will find it optimal to substitute Yogurt NB for its alternative and some others will prefer to source another store in order to purchase the Yogurt NB. In particular, if a one-stop shopper prefers the inter-store substitution of Yogurt NB, she must purchase all products at another supermarket as her shopping costs do not allow her to do multistop shopping. As a consequence, demand for all products (but the alternative yogurt) decreases at store 1 and increases at the rival stores.

7 Countefactual experiments

In this section we present the results of a series of counterfactual experiments that allow us to assess how consumer shopping behavior is affected by the presence of shopping costs and, on the other hand, how consumers react when a product is delisted by a particular supermarket while its rivals continue supplying that product. To do this, we use the results of the full random-coefficients model (column 4 in Table 6).

7.1 The role of shopping costs

In order to assess the role of shopping costs in consumers' shopping patterns, we compare two situations: a status-quo scenario, in which consumers face shopping costs when dealing with stores, and a "zero-shopping costs" scenario, in which all consumers can decide whether to deal with one or multiple suppliers at no cost. In a first exercise, we check how are estimated elasticities in the baseline scenario with respect to those that would be obtained from a model without shopping costs. We take semi-elasticities obtained under each scenario and compute a ratio with the semi-elasticity of the baseline scenario in the denominator. Table 9 displays average ratios in two panels: the top panel shows ratios of within retailer own- and cross-price

Table 8: Mean own and cross-price elasticities with shopping costs (averages across periods and consumers)

Brand	Supermarket 1				Supermarket 2				Supermarket 3			
	Yogurt	Yogurt NB	Biscuits	Desserts	Yogurt	Yogurt NB	Biscuits	Desserts	Yogurt	Yogurt NB	Biscuits	Desserts
Supermarket 1												
Yogurt	-1.03821	0.01495	-0.11056	-0.36500	0.13682	0.00979	0.03601	0.11531	0.18250	0.02444	0.03725	0.12328
Yogurt NB	0.15574	-1.05293	-0.11014	-0.35918	0.13702	0.00981	0.03608	0.11562	0.18279	0.02448	0.03730	0.12361
Biscuits	-0.37514	-0.03588	-0.38361	-0.35135	0.11382	0.00815	0.04537	0.11496	0.14736	0.01973	0.04696	0.12114
Desserts	-0.39070	-0.03688	-0.11076	-1.89345	0.11173	0.00800	0.03520	0.14898	0.14435	0.01937	0.03597	0.15999
Supermarket 2												
Yogurt	0.15624	0.01502	0.03759	0.11633	-1.06844	0.00974	-0.09668	-0.33357	0.18260	0.02445	0.03529	0.11739
Yogurt NB	0.15627	0.01503	0.03759	0.11629	0.13621	-1.21024	-0.09656	-0.33312	0.18268	0.02446	0.03531	0.11752
Biscuits	0.12607	0.01213	0.04760	0.11405	-0.29995	-0.02137	-0.40984	-0.31487	0.13613	0.01822	0.04745	0.11353
Desserts	0.12204	0.01175	0.03572	0.14957	-0.31272	-0.02228	-0.09508	-1.90188	0.13194	0.01770	0.03324	0.16285
Supermarket 3												
Yogurt	0.15645	0.01504	0.03674	0.11375	0.13708	0.00981	0.03302	0.10604	-1.12866	0.02452	-0.08395	-0.30623
Yogurt NB	0.15677	0.01507	0.03684	0.11433	0.13740	0.00984	0.03309	0.10657	0.18357	-1.08881	-0.08341	-0.29809
Biscuits	0.12594	0.01212	0.04701	0.11271	0.10616	0.00761	0.04524	0.10619	-0.33527	-0.04453	-0.42189	-0.29237
Desserts	0.12182	0.01173	0.03510	0.14746	0.10319	0.00740	0.03200	0.14932	-0.35269	-0.04588	-0.08427	-2.00119
Outside Good	0.05741	0.00550	0.01659	0.05286	0.04922	0.00352	0.01538	0.05107	0.06551	0.00873	0.01631	0.05610

Notes: Each entry i, j , where i indexes rows and j columns, gives the percentage change of demand for product category i with respect to a percentage change in price of j .

semi-elasticities averaged across supermarkets; and the bottom panel shows the ratios computed with inter-retailer cross-price semi-elasticities averaged across supermarkets.

In both panels all entries in the main diagonals are larger than 1 which means that estimated semi-elasticities under the no-shopping-costs scenario are larger than those obtained when shopping costs are accounted for in the model. Our interpretation of this result is that in the absence of shopping costs, consumers are more sensitive to a price change as they are able to substitute products across stores without incurring any additional costs. At the estimation level, a model of multistop shopping that does not account for consumer shopping costs gives biased estimates for the demand elasticities: own-price elasticities as well as inter-store cross-price elasticities are overestimated, whereas intra-store cross-price elasticities are underestimated.

Table 9: Average ratios of own- and cross-price semi-elasticities^a

		Yogurt	Yogurt NB	Biscuits	Desserts
Within ^b	Yogurt	2.36	4.23	0.57	0.63
	Yogurt NB	4.23	2.64	0.56	0.60
	Biscuits	0.57	0.57	2.61	0.63
	Desserts	0.62	0.60	0.62	2.74
Across ^b	Yogurt	4.34	4.36	2.01	1.94
	Yogurt NB	4.36	4.37	2.00	1.96
	Biscuits	2.00	2.02	5.07	2.06
	Desserts	1.93	1.96	2.05	5.31
Outside Good		0.13	0.14	0.15	0.15

Notes: ^aRatios are computed by dividing the estimated semi-elasticity of a model without shopping costs over the corresponding semi-elasticity of a model with shopping costs.

^bAn entry in the panel “Within” corresponds to the average across supermarkets of intra-store own- and cross-price semi-elasticity ratios. An entry in the sub-panel “Across” corresponds to the average across retailers of inter-store cross-price semi-elasticity ratios.

In a second exercise, we compare predicted probabilities of being a zero-, one-or multistop shopper under the two scenarios. Results are reported in Table 10. In the absence of shopping costs, consumers choose the outside option with smaller probability. Shopping costs introduces frictions that deter consumers from purchasing the included goods, which is consistent with theory and shows the importance of accounting for such costs in a model of multistop shopping. Further, a model with zero shopping costs predicts a larger proportion of multistop shoppers, barely 25% against 2% in the baseline model. Notice that removing shopping costs need not translate into all consumers being multistop shoppers, but most optimally choose to source a single store. This result might be due to unobserved idiosyncratic valuations of product-store combinations that yield a larger utility of concentrating purchases at a single store (and that are captured by the error term of the model).

Table 10: Probability of visiting a given number of stores with and without shopping costs

No. of stops ^a	Baseline prob.	No Shopping Costs prob.
0	0.6015	0.0183
1	0.3792	0.7269
2	0.0187	0.2458
3	0.0005	0.0090

Notes: ^aIf the consumer sourced other stores different to the three included in our sample, the number of stops in this table should be read as “additional” stops.

7.2 The effects of product delisting on consumer shopping behavior

Retail stores often use the (threat of) delisting of a (set of) product(s) or a supplier in order to get better terms of trade from manufacturers. If consumers find it very costly to source alternative stores (because of strong feelings of loyalty, very large shopping costs or head-to-head competition between stores, for example), the actual delisting of a product would only hurt the manufacturer, and this practice would be an effective bargaining strategy for supermarkets. However, we showed that consumers often source multiple stores. When consumers find it optimal to do multistop shopping, the actual delisting of a product can also hurt the delisting supermarket due to a reduction in demand from all those who either substitute stores and continue doing one-stop shopping at a competing supermarket, or source an additional supplier given that they have low enough shopping costs.

To assess the effects of product delisting on consumer shopping behavior, we perform counterfactual experiments in which we simulate a large increase in the price of the yogurt NB at supermarket 1, so that it becomes prohibitively costly, while we keep unchanged the price for the same brand at the two competing stores. Although the product is not actually taken away from the store’s shelves, we believe a situation in which a good is so expensive that nobody can afford to buy it is equivalent to a situation in which the product is no longer available at that store. Using our demand estimates, we compute the probability of sourcing each store under two scenarios: a baseline scenario which gives the predicted probability by our model, and a delisting scenario. Provided that the net effect of product delisting may depend on the consumer valuation of the product to be stocked out, and the store delisting it, we perform three simulations in which we manipulate the estimated mean valuations for the product and the store. Results are displayed in Table 11. Panels A, B and C of the Table report probabilities of sourcing stores 1, 2 and 3, respectively, under each scenario. Within each panel, there are three rows: row *a* corresponds to the baseline scenario, row *b* concerns the delisting scenario, and the last row gives the percentage difference between predicted probabilities displayed in the previous rows. Columns 1, 2 and 3 of the Table report these probabilities obtained from our first, second and third simulations, respectively. The first column reports the results of the predicted probabilities from the original model with a larger price for Yogurt NB at supermarket 1.

The second column shows these probabilities when we directly increase threefold the coefficient of the dummy specific to the product which is being delisted at store 1 in the demand model without changing other parameters. We interpret this as consumers experiencing strong feelings of loyalty for this product.⁵⁴ Finally, the third column reports predicted probabilities from the original demand model when we increase threefold the coefficient of the dummy specific to supermarket 1 without changing other parameters. We interpret this as consumers having strong feelings of loyalty for the store delisting the product.

Our simulations show that when a store delists a product, the probability of being sourced by consumers decreases while it increases for rival stores. Consumers appear to be more sensitive to product delisting once we increase the mean valuation for the product being removed. On the other hand, consumers appear to be less sensitive to product delisting once we increase the mean valuation for the store delisting the products.

Table 11: Predicted probabilities of sourcing stores 1, 2 and 3 under different scenarios when supermarket 1 delists Yogurt NB*

Scenario	Simulation 1	Simulation 2 (Product Loyalty)	Simulation 3 (Store Loyalty)
Panel A: Supermarket 1			
(a) Baseline	0.1397	0.3261	0.3521
(b) Delisting	0.1351	0.0501	0.3445
Difference (a-b)/a	-3.30%	-84.63%	-2.16%
Panel B: Supermarket 2			
(a) Baseline	0.0956	0.2063	0.0619
(b) Delisting	0.0965	0.3061	0.0630
Difference (a-b)/a	0.94%	48.40%	1.78%
Panel A: Supermarket 3			
(a) Baseline	0.0702	0.1748	0.0452
(b) Delisting	0.0709	0.2640	0.0461
Difference (a-b)/a	0.97%	51.03%	1.79%

Notes: *Supermarket 1 delists Yogurt NB from its stores while its rivals keep supplying that product.

The first counterfactual simulation results in a reduction in the probability of sourcing store 1 by 3.3%, while the probability of sourcing competing stores rises by about 1%. Product loyalty reinforces this situation considerably: when customers have a larger valuation for the product being delisted (relative to the baseline situation), the reduction in the probability of sourcing store 1 decreases by about 85% and, on the other hand, rivals' probabilities of being sourced increase by 50%. This result is due to the larger proportion of one-stop shoppers in our sample: once a product is removed from store 1, those customers who desire to purchase it and cannot source multiple stores in the same period, have to find a competing supplier where to buy the product missing at their preferred shopping location. Delisting a product in a context of strong

⁵⁴Recall that each product is available at all supermarkets. When we increase the coefficient for the dummy specific to a product, consumers' valuation for it increase at every shopping location in the same proportion.

feelings of loyalty by customers can be detrimental not only for the manufacturer, but also for the supermarket. Further, if consumers can readily find an alternative store supplying the missing product, the supermarket will possibly suffer most from its own strategic decision.⁵⁵

Alternatively, in a situation in which consumers have a larger valuation for store 1 (relative to the baseline situation), the delisting of a product appears to have weaker effects than those obtained in simulations 1 and 2. The probability of sourcing store 1 decreases by about 2.2%, a lower effect than that obtained in simulation 1. Consumers may find it optimal to substitute the missing product by an alternative available at the same store rather than leaving for a rival store. This results suggests that inducing consumer loyalty (through loyalty programs or strong private labels, for instance) may help a supermarket chain to have a stronger bargaining position *vis-à-vis* manufactures, and enable it to deliver a threat of delisting more effectively.

The net effect of imposing vertical restraints on manufacturers, such as product delisting, appears to depend not only on the size and power of the retailer but also on consumers' valuations for both product and stores. Of course, our analysis assumes pricing as exogenous, which limits the scope of our results. A complete study of the effects of product delisting would consider how rival stores and manufacturers react in terms of prices. Yet, our results are interesting and consistent with industry evidence.⁵⁶

8 Concluding remarks

This paper presents and estimates a model of multiproduct demand for groceries in which customers, that differ in shopping costs, can choose between sourcing one or multiple supermarkets in the same shopping period, to empirically examine the effects of product delisting on consumer shopping behavior.

We obtain several interesting results. First, from descriptive regressions we find a significant relationship between the number of supermarkets sourced by a household in a week and household characteristics that proxy for opportunity cost of time. Households with higher income, a car and babies are less likely to be multistop shoppers. On the other hand, households with older leaders, of larger size, and living in urban areas are more likely to visit a larger number of stores in a week. Second, our structural model allows us to retrieve consumer shopping costs, which we estimate in 1.79 € per store sourced, on average. This cost includes a fixed shopping cost, which we estimate in 1.57 €, on average, and a transport cost of 21.6 cents on the euro, per trip to the average store. Third, our counterfactuals indicate that while in the absence of shopping costs all consumers would source at least one store every week with positive probability, when shopping costs are accounted for, predicted probabilities of (one and multistop) shopping are lower, and consumers are less likely to source a supermarket on a week-to-week basis provided

⁵⁵This simulation is similar to what happened in 2009 between Costco and Coca-Cola. After a dispute in prices, Costco decided to stop stocking Coca-Cola products. Given the importance of Coca-Cola in many US markets, Costco might have suffer most (<http://www.reuters.com/article/cocacola-costco-idUSN1020190520091210>).

⁵⁶In 2009 Delhaize, a large supermarket chain in Belgium, decided to stop stocking about 300 Unilever products over a price dispute. As a consequence, Delhaize lost 31% of its customers to rivals (<http://in.reuters.com/article/delhaize-unilever-idINLG51937220090216>).

that dealing with a store is costly. In other words, shopping costs discourages supermarket visits every week and give rise to a much lower proportion of multistop shoppers. Further, predicted shopping patterns would be biased in a model of demand that does not account for shopping costs. Finally, when we simulate the delisting of a product by one supermarket, we find that customers' probability of sourcing that store decreases by 3%, while the probability of sourcing competing stores increases by 1%. The reduction in demand is even larger when consumers have strong feelings of loyalty for the delisted brand: the probability of sourcing the store that stopped stocking that brand decreases by about 85%, while it rises for competing retailers by approximately 50%. This suggests that retailers may be hurting themselves, and not only manufacturers, when they delist products. However, when customers are loyal to the store, such effects are lower: delisting a product implies a decrease in the probability of being sourced of 2%. Therefore, inducing store loyalty in customers (through strong private labels and loyalty programs, for example) might potentially have an effect on vertical negotiations and, in particular, it might enable powerful retailers to impose vertical restraints on manufacturers.

There are several avenues for further research that can be empirically addressed using our framework. A first avenue is related to pricing by supermarkets in a context of product delisting. Adding structure on the supply side to empirically assess how both competing supermarkets and manufacturers react to the delisting of a product by a store seems to be a natural step to have the whole picture of the effects of product delisting. A second avenue relates 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.

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, $n \in N = \{1, \dots, R_i\}$, $R_i \leq R$, 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 $j \in \{1, \dots, J_i^n\}$, 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

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

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 she is not maximizing over several subsets of stores in equation (3).

B Possible orderings for extra utilities

As stated in Section 4, 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:

$$\delta_{it}^2 > \frac{\Delta_{it}^3}{2} > \delta_{it}^3, \quad (B1) \qquad \delta_{it}^3 > \frac{\Delta_{it}^3}{2} > \delta_{it}^2, \quad (B2)$$

$$\frac{\Delta_{it}^3}{2} > \delta_{it}^3 > \delta_{it}^2, \quad (B3) \qquad \frac{\Delta_{it}^3}{2} > \delta_{it}^2 > \delta_{it}^3, \quad (B4)$$

$$\delta_{it}^3 > \delta_{it}^2 > \frac{\Delta_{it}^3}{2}, \quad (B5) \qquad \delta_{it}^2 > \delta_{it}^3 > \frac{\Delta_{it}^3}{2}, \quad (B6)$$

From the six cases above, only (B1) survives, the remaining are contradictory. To see why, notice that the incremental utility of sourcing two additional stores, $\Delta_{it}^3 := v_{it}^3 - v_{it}^1$, 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: $\Delta_{it}^3 = \delta_{it}^2 + \delta_{it}^3$. Therefore, if we assume, for instance, that $\frac{\Delta_{it}^3}{2} > \delta_{it}^3$ as in (B3), then

$$\frac{v_{it}^3 - v_{it}^2}{2} + \frac{v_{it}^2 - v_{it}^1}{2} > v_{it}^2 - v_{it}^1 \equiv \delta_{it}^3,$$

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

C Data

Three products are taken into the analysis, fresh desserts, yogurt and biscuits, which are among the most purchased products by french households. It is often the case that people do not only buy one brand, or even one unit of the same brand at a time but several varieties to have different choices at home (different flavors, fruit contents, etc.). However, following Nevo (2001), we claim that an individual normally consumes one unit of either product at a time: yogurt (125 grams per portion), biscuits (30 grams per serving), and one serving of dessert (28 grams per serving), 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.

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 local markets (defined by zip codes), month, and stores and number of servings of each product purchased by each consumer. Then, we divide the total expenditure on a given product-store made by all consumers living in the same zip code in a month by the the total number of servings to obtain a common unit price. In case we do not observe all the information necessary to compute the unit price of a product, we average unit prices of that product across local markets within the same period and use it. By constructing our price variable this way, we are assuming that consumers have rational expectations. Due to data limitations, we do not account for neither manufacturers' nor stores' promotional activities of any kind.

Finally, in Table 3 in Section 3 we used a category-specific price index as the dependent variable in each regression. We followed Aguiar and Hurst (2007) and construct a price index per household that indicates how much more or less that household spent on that category of products relative to the average expenditure. To do that, we computed an average price at the product category level per week as the sum across households and supermarkets of expenditures on all brands within that category, and divided it by the sum across households and supermarkets of the quantities purchased of those goods that week. With this average price in hand, we computed two measures of household expenditure at the category-week level: the total expenditure of a household at actual prices, and the total expenditure of a household had it paid the average price. The final per household category-specific price index is the ratio of these two expenditures.

D Robustness checks

In this section we show estimation results of our model using alternative samples. Overall, results are similar to those in Table 6 above, which suggests that our results are robust to sample selection. Results are displayed in Table of Table D.1. The first column corresponds to the estimates obtained from the full model(column 4 of Table 6 above). The next three columns of the Table show the results of the same demand model estimated using alternative samples. Column (1) contains the estimates using the second leading national brand of yogurt as fourth product along with other yogurts, biscuits and desserts. Estimation in column (2) was obtained using this time the category Desserts was decomposed in two alternatives, while yogurt and biscuits categories were treated as if all brands were the same. Finally, the latter column shows the results when we consider two alternative brands (a leading NB and a composite brand) for the biscuits category.

All taste coefficients are similar to the main results in sign, magnitude and significance. The interactions with demographics are basically insignificant in all regressions with few exceptions. The estimated standard deviations are all statistically significant and greater than one, although magnitudes vary more between columns relative to other estimates. This is not surprising as these coefficients capture dispersion in individual tastes for product characteristics, and in each case the set of products is changing. Overall, results are robust to product selection.

Table D.1: Estimates for the utility parameters and shopping costs using alternative products^a

Covariate	Final sample	Alternative samples		
		(1)	(2)	(3)
Price (€/basket ^b)	-2.565*** (0.707)	-2.538*** (0.573)	-2.678*** (0.660)	-2.59*** (0.584)
Shopping costs	-4.039*** (0.270)	-4.352*** (0.379)	-4.601*** (0.189)	-4.208*** (0.284)
Distance	-0.0758*** (0.0144)	-0.116*** (0.0131)	-0.102*** (0.0119)	-0.104*** (0.0188)
No. visited stores× Log Income	0.307 (0.717)	-0.387 (0.255)	-1.09*** (0.186)	-0.160 (0.414)
No. visited stores× Age	0.00956 (0.0101)	0.00364 (0.00760)	-0.00477 (0.00559)	-0.00396 (0.0150)
No. visited stores× No. Cars	0.819 (0.710)	0.568** (0.263)	1.30*** (0.254)	1.849*** (0.456)
No. visited stores× hh size	-0.162 (0.163)	-0.00684 (0.0816)	0.141 (0.126)	0.0260 (0.0921)
Constant	2.381*** (0.218)	2.286*** (0.273)	2.962*** (0.193)	2.419*** (0.226)
Standard deviations (σ's)				
Price	3.191*** (0.252)	2.76*** (0.288)	3.231*** (0.380)	2.638*** (0.237)
Shopping cost	2.022*** (0.156)	1.920*** (0.113)	1.593*** (0.0899)	1.904*** (0.154)
Observations	1,635,424	1,411,760	1,573,152	1,656,704

Notes: ^a Robust standard errors are in parenthesis. All regressions include product, store and time (months) fixed effects. All coefficients are significant at 2% confidence level, except the coefficient of the interaction with 'Age' in column (4) which is significant at 6% level.

^b A basket consists of unit servings of one, two or three products: dessert (80g), biscuit (30g) and, yogurt (125g). For multistop shoppers, each product may be purchased from different stores. Therefore, the choice set contains 100 mutually exclusive and exhaustive alternative baskets.

^c 'hh' stands for household.

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