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

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

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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 continuously 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 preferences for the delisted brand. This suggests that retailers may be hurting themselves, and not only manufacturers, when they delist a product. However, when customers have strong preferences for the store such effects are lower, suggesting that inducing store loyalty in customers 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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1 Introduction

Recent decades have witnessed the consolidation of powerful large-scale supermarket chains and a shift in the balance of power from manufacturers to distributors. The modern grocery retail industry is now highly concentrated¹ and is characterized by: 1) the proliferation of superstores with huge floor areas (20,000+ sq. meters) that offer a large product range (200,000+ different brands) and parallel services² in an attempt to attract customers via one-stop shopping;³ 2) the promotion of private labels (PLs), which makes supermarkets less dependent on branded products (the so-called national brands (NBs)) 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 this context, the buying 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 Organization for Economic Cooperation and Development (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, threats of product delisting (or refusal to stock) appears to be widely used by distributors against manufacturers.^{7,8} According to the literature, a product (or supplier) is said to be delisted by a retailer when the volume of purchases is significantly reduced or the product (or range of products) is completely removed from the retail store’s shelves even though it continues to be sold by rival stores (Davies (1994); Davies and Treagold (1999)).

Delisting of products can happen purely for commercial reasons.⁹ However, a supermarket

¹For instance, in 13 member countries of the European Union (including France, the UK, Germany, Sweden, Finland, and the Netherlands), the five leading retailers in each country have a combined market share of more than 60% (European Commission, 2014)

²These services include shopping malls, beauty salons, restaurants, car wash facilities, gas stations, and playgrounds for children.

³In Europe, for instance, between 2000 and 2011, the number of hypermarket outlets increased by 72% and the sales area increased by 46%, while the corresponding figures for supermarket outlets were 10% and 26%, respectively (European Commission, 2014).

⁴Caprice and Rey (2010) provide some examples of retail chains that have formed buying alliances: in France, Système U and Leclerc in 1999, Système U and Casino in 2006, and Système U and Auchan in 2014, in Finland, Kesko and Tuko in 1996, and in the US, the Independent Grocers Association.

⁵The emergence and consolidation of hard-discount stores as a cheaper alternative, mostly in relation to basic products, is also an important feature of the modern grocery retail sector. In Europe, hard discounters experienced the greatest growth of all types of retailers in terms of sales area between 2000 and 2011 (81%), while the number of outlets increased by 47%.

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

⁷See the OECD paper (1998, p. 15), which states 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 levels, minimum advertising requirements, and sunk facility requirements.

⁹A store can decide to delist 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 other reasons (Davies, 1994).

with sufficient market power can threaten to delist a product as a way of obtaining a better deal from the manufacturer, or can even actually delist a product as a form of punishment. Even though the retailer might benefit from this practice, it also entails some risk, as consumers may be tempted to switch to rival supermarkets when a product they want is unavailable at their usual store. The objective of this paper is to empirically examine the effects of product delisting on consumer shopping behavior in the context of multiproduct retailing and multistop shopping.

Anecdotal evidence indicates that retailers use the threat of delisting as a bargaining strategy, and that the risk of a company going bankrupt if it is delisted by a large supermarket is real. For instance, in 2008, a large food supplier to the top four supermarket chains in the UK (Tesco, Asda, Sainsbury's, and WM Morrison) revealed that some retailers' negotiating strategies included delisting as the main threat.¹⁰ There are some remarkable cases of disputes between large retailers and suppliers involving refusal to stock products. In the US, Costco, one of the largest retail chains in that country, removed all Coca-Cola products from its shelves for about a month in 2009 after the two companies failed to reach agreement on prices.¹¹ In the same year in Belgium, a request for 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. Both parties ended up being hurt: Delhaize lost 31% of its customers to rivals and among those who remained, 47% substituted other brands for Unilever's products.¹² In the UK, a similar dispute between Tesco, the largest supermarket chain in the country, and *Premier Foods* resulted in the delisting of a number of the suppliers' products in 2011, resulting in a 1% fall in sales and an 18% fall in the value of Premier Foods' shares.¹³ In 2016, Tesco and Unilever engaged in a brief but bitter dispute that resulted in Tesco refusing to carry Unilever's products for about 24 hours.¹⁴

Similar cases have motivated policy interventions in the past. In France, the so-called "Galland Act"¹⁵ highlighted three practices related to product delisting that were considered to abuse the economic dependence of suppliers on retailers: abusive delistings, abusive threats to terminate commercial relations, and abusive termination of established commercial relationships.¹⁶

¹⁰According to the *Telegraph*, supermarkets use a broad range of "psychological and strategic manoeuvres" that can range from intentionally "misunderstanding a conversation or pleading poverty" to "physically disturbing the suppliers" to obtain the best deal 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 once being told 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.cnn.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>.

¹⁵Loi 96-588 du 1er juillet de 1996

¹⁶Although there has been an explicit prohibition of the abuse of "economic dependence" by the competition law since the 1980s, several cases alleging the abuse of dependent suppliers by supermarket buying groups were rejected on the basis that it was the supplier who was able to abuse 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 to prove adverse effects on competition, as was the case under the previous law (Dutilh, 2004).

In the UK, the Competition Commission issued the *Groceries Supply Code of Practice* in 2009, a set of obligations for big retailers to “fairly manage” their relationships with suppliers.¹⁷ According to the code, delisting may only be possible for “genuine commercial reasons” and prior to delisting the retailer must inform the supplier, in writing, of the reasons for delist the product or products it is carrying, and must also inform the supplier of the possibility of having the decision reviewed by a senior buyer.¹⁸ Moreover, the retailer must allow the supplier to discuss the delisting decision with its code compliance officer.¹⁹

The buying power of large retailers has been the subject of a substantial amount of academic research, especially during 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, few studies have focused on the implications of product delisting from a theoretical perspective (Inderst and Shaffer (2007), Inderst and Mazzarotto (2007), Caprice and Rey (2010), Johansen (2012)).²⁰ All of these papers have a common feature: the demand side is modeled by restricting consumers to one-stop shopping behavior. However, the evidence indicates that customers often visit multiple competing stores in a given shopping period. Figure 1 shows the average number of supermarkets visited per week using home scanner data relating to supermarket purchases by a representative sample of households in France. It can be seen that while nearly 60% of households only visit one supermarket per week, a significant proportion of households visit more than one supermarket. This evidence suggests that, some of the results presented in the existing literature may not hold. In particular, consumers need not leave their usual store when a desired product is no longer available at their usual store, but may simply make an additional stop at a competing store to buy that product, i.e. a retailer will not necessarily experience reduced demand for its entire product range if it decides to delist a specific product.²¹

This paper adds to the literature on multiproduct retailing, buyer power and vertical restraints imposed by retailers on suppliers, and consumer shopping behavior in two ways. First, we empirically examine the implications of product delisting on consumer shopping behavior

¹⁷The code is part of “The Groceries (Supply Chain Practices) Market Investigation Order 2009” and is addressed to the largest retailers in the UK: Asda, The Co-operative Group, Marks & Spencer, Morrisons, Sainsbury’s, Tesco, Waitrose, Aldi, Iceland, and Lidl. A designated ombudsman, known as the Groceries Code Adjudicator (GCA), was empowered to receive complaints and help enforce the code, and is able to impose penalties of up to 1% of the retailer’s annual UK turnover in cases involving a breach of the code. See <https://www.gov.uk/government/publications/groceries-supply-code-of-practice/groceries-supply-code-of-practice>.

¹⁸This is a retailer’s employee or group of employees who is in charge of the primary buyers dealing with a particular supplier.

¹⁹See <https://www.gov.uk/government/publications/groceries-supply-code-of-practice/groceries-supply-code-of-practice#duties-in-relation-to-de-listing>.

²⁰According to Inderst and Mazzarotto (2007), delisting has traditionally been treated as an off-equilibrium strategy or as a channel through which buyer power can be exerted.

²¹A model that allows consumers to visit multiple stores should consider several scenarios that could arise. For example, if the consumer is loyal to the store but not to the brand, she may either buy a substitute brand or decide not to buy that product at all. If the consumer is loyal to both the brand and the store, and has a low opportunity cost in terms of time spent visiting stores, she will purchase everything else she needs at the initial store and then travel to a competing store to obtain the missing product. Finally, if the consumer is loyal to the brand but not to the store, she might go to a competing store and purchase everything she needs there.

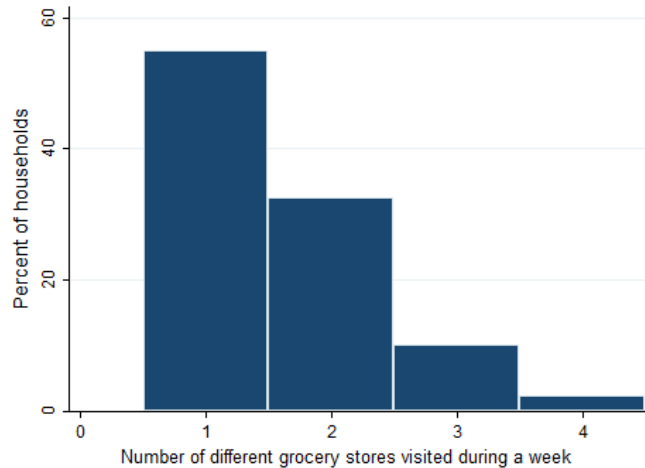


Figure 1: Distribution of households by average number of stores visited per week in 2005

Notes: The observed distribution has a longer tail than that displayed in the figure as some households visited up to nine separate stores per week. However, 99.4% of the observations involved between one and four stops.

Source: Kantar Worldpanel database 2005. Authors' calculations.

using a structural approach. To the best of our knowledge, this is the first attempt to provide empirical evidence in relation to this topic. We develop a multiple-discrete-choice model in the context of competition between multiproduct grocery retailing firms that offer the same product line to the same customers. Consumers can purchase baskets of products from either a single store or multiple stores during a given period. In other words, our model allows for not only the simultaneous choice of multiple products but also the simultaneous choice of multiple grocery stores.²² In our study, we observe that in a given week, some customers concentrate their purchases at a single store (*one-stop shopping*), whereas others visit multiple rival stores (*multistop shopping*)—see Figure 1. Our key modeling strategy is to explicitly account for this observed heterogeneity by introducing consumer transaction costs related to shopping, also known as *shopping costs*. Following Klemperer (1992), we define *shopping costs* in a comprehensive way as all of the consumer’s real or perceived costs of using a supplier.²³ These may include transportation costs and opportunity costs related to time spent parking, selecting the products in the store, and waiting in line at the checkout; they may as well account for the taste for shopping

²²Previous papers have developed demand models for multiple products. 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 the case of carbonated soft drinks given that, according to the evidence provided by the author, consumers commonly buy multiple alternatives on each shopping trip. Gentzkow (2007) develops a flexible framework in which similar products can be either substitutes or complements. None of these studies incorporate consumer transaction costs into the choice problem. Wildenbeest (2011) presents a search model 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 the products in the basket at a single store, i.e. consumers are not allowed to visit multiple stores, which makes it similar to a single-product discrete-choice model.

²³Klemperer (1992) distinguishes among consumer costs in the following way: “(...) a 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.

(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 on 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 magnitude of individual shopping costs. Consumers weigh up the extra benefits of dealing with an additional supplier against the additional costs involved. If benefits exceed costs, the individual will patronize an additional store. Otherwise, she will make all her purchases at 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. On every shopping trip, 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 the 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 cause individual costs to deviate from the average cost. Examples of these characteristics are individual valuations of time spent on transportation, parking, waiting in line, and the taste for shopping. Given the panel structure of our data, we can control for observed household characteristics that serve as a proxy for household time constraints. Having obtained estimates for the parameters of the model, we perform counterfactual experiments that serve two purposes. First, we assess the relative importance of accounting explicitly for shopping costs in predicting consumer behavior in a multistop shopping model by computing the predicted probabilities of visiting either one or several stores in the absence of shopping costs. Second, we assess how product delisting affects consumer shopping behavior.

Perhaps the biggest limitation of our approach is the dimensionality problem that arises when estimating demand for baskets of products. A common problem in the discrete-choice literature on 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 Industrial Organization literature by restricting the choice set to the leading brands based on market share. 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. For example, consider a market where three differentiated supermarkets offer an identical product line consisting of two products. The choice set of a consumer (unconditional on her shopping costs) who seeks to purchase both products

consists of 3^2 mutually exclusive baskets.²⁴ Adding another product increases the choice set exponentially. In our data set, some households are observed to purchase up to 275 different products from up to nine separate grocery suppliers in the same week.²⁵ Estimating a demand system with such a huge choice set is infeasible.

We deal with this dimensionality problem as follows. First, we model both brand- and basket-level utilities using a discrete-choice approach. Second, we restrict our focus 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) staple food items, which are generally not subject to temporary price reductions as a result of promotional activities, 2) frequently purchased, as these products are among the most popular items bought by French households, and 3) subject to 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 of “biscuit” or “dessert,” respectively. As for the yogurt category, we allow for two alternatives, namely, the leading NB in France in 2005, and a composite “brand” that includes all of the remaining brands (both other NBs and PLs). Therefore, consumers have a set of four products from which they can choose at most three: one of the two yogurt alternatives, biscuits, and desserts.²⁶ Finally, we focus on a reduced set of three supermarket chains that were the leading grocery retailers in France in 2005 based on market share. The remaining grocery stores in our data set, along with the no purchase of the included goods option are left as part of the outside option.²⁷

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,²⁸ 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 the search process, and our shopping cost estimates would capture search costs to some extent. In most contexts, it is unreasonable to assume that there is no information frictions. However, when consumers frequently visit stores to buy a basket of basic products, as is the case with routine grocery shopping, information frictions do not appear

²⁴Products A and B in supermarket 1; A and B in supermarket 2; A and 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.

²⁵On average, a household purchases baskets containing 24 different products from two separate stores each week.

²⁶The choice of yogurt as the category offering two alternatives is arbitrary. To check the robustness of our results, we calculate the estimation of our demand model several times, changing the category containing two options each time.

²⁷Of course, our data set indicates that consumers often purchase/visit more than the included products/stores. We take this into account in our empirical strategy. Following Gentzkow (2007), we assume that every basket includes a maximization over the included as well as the excluded (both observed and unobserved) products. 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 products she purchased, or it may be that she purchased additional products and visited stores other than those included. Regardless, we assume that the utility of baskets that contain inside products purchased from any of the included locations is greater than that of alternative baskets containing any other combination of inside products. However, it is important to note that labeling some products in the outside option does not change the interpretation of substitution patterns among baskets containing included products. See Section 5.4 for a detailed discussion.

²⁸See, for instance, Hortaçsu and Syverson (2014), and Dubois and Perrone (2015).

to be a primary concern.²⁹ The set of products we focus on is consistent with this observation.³⁰

We obtain several interesting results. First, from descriptive regressions, we find a significant relationship between the number of supermarkets visited by a household in a week and household characteristics that are a proxy for the opportunity cost of time. Second, our structural model allows us to retrieve consumer shopping costs, which we estimate to be 1.79 € per store visited, on average. This cost includes a fixed shopping cost, which we estimate to be 1.57 €, on average, and a transport cost of 21.6 euro cents per trip to the average store. Third, when we simulate the delisting of a product by one supermarket, we find that customers' probability of visiting that store decreases if it increases for competing stores. When consumers have strong preferences for the delisted product the supermarket that is removing the product faces a decrease in demand by 35%. However, when consumers have a strong preference for the store in question, the effects are lower: delisting a product only reduces the probability of being visited by less than 1%. Overall, our results suggest that retailers may be hurting themselves when they delist products. Inducing store loyalty in customers appears to reduce the cost a supermarket incurs when it delists products, which may play a role on vertical negotiations, as it enables the supermarket to deliver a more credible threat of delisting. Finally, our counterfactuals indicate that while in the absence of shopping costs all consumers would visit at least one store every week with positive probability, when shopping costs are accounted for, the predicted probabilities of both one- and multistop shopping are lower, and consumers are less likely to visit a supermarket on a week-to-week basis if doing so is relatively costly.

Related literature

Few papers have examined the effects of product delisting in grocery retailing, and all of them have focused on theoretical analyses. In a one-stop shopping model, if a retailer delists a strong product (i.e. a product for which demand is large) it can suffer a reduction in demand for its entire product range, as consumers can switch shopping locations looking for the missing product (Inderst and Mazzarotto, 2007). This does not apply in the case of a consolidated retailer, which can find it more profitable to move to a single-source relationship by delisting all but the most competitive supplier. Although this induces more aggressive competition among suppliers, total industry profits may decrease as a result of 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 the product of a strong manufacturer: a joint delisting decision by an alliance makes it less harmful for every group member because all of the other members of the alliance will also move to alternative suppliers (Caprice and Rey, 2010). Finally, in the context of one-stop shopping, where some

²⁹Based on the same observation, the main theoretical contributions to the shopping cost 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 a discussion.

³⁰We are not aware of the existence of a full model of consumer shopping behavior that accounts for search activities prior to the purchase of each product in the desired basket and allows us to differentiate between search, switching, and other costs. Such a model is beyond the scope of this paper, and is left for future research.

buyers seek to purchase a single product and others a basket of products, 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 in demand for the entire product range (Johansen, 2012).

Concerning consumer opportunity costs associated with shopping activities, there is a growing body of empirical literature that explicitly measures and includes these costs. This literature has focused on two types of costs, namely, search costs (e.g. Hortaçsu and Syverson (2014), Hong and Shum (2006), Koulayiev (2014), Moraga-Gonzalez and Wildenbeest (2013), Kim and Bronnenberg (2010), Wildenbeest (2011), De los Santos and Wildenbeest (2012), Hong and Shum (2014), and Dubois and Perrone (2015)) and switching costs (e.g. Shy (2002), Viard (2007), and Hong and Shum (2014)).³¹ Less attention has been paid to shopping costs. Brief (1967) models consumer shopping patterns in a Hotelling framework, and basically estimates transportation costs to account for consumer shopping costs.³² 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 incur a time cost that is explicitly accounted for.

In analyzing multiproduct and multistore choice with shopping costs, our paper is closely related to that of Schiraldi et al. (2016). They study pricing by grocery stores in the context of competition between specialized stores and multicategory grocery retailers (i.e. supermarkets). The latter internalize the effects that arise from selling multiple categories of products to customers interested in buying baskets of products. To do this, they develop a model of demand in which consumers make discrete–continuous choices: a discrete choice of which supermarket to visit by category and a continuous choice regarding the quantity of each category to be purchased. In their model, some consumers purchase from a single store, whereas others visit at most two stores in each period. To rationalize this heterogeneity, they introduce a choice-specific fixed cost to the utility function of a consumer.

Our approach, which we developed contemporaneously and independently, differs from theirs in several important ways. First, we are interested in a very different question, and our focus is on consumer behavior in the context of competition between powerful supermarket chains with similar characteristics. Second, our structural model is in keeping with the theoretical literature on this topic (see, in particular, Chen and Rey (2012, 2013)). Our key modeling feature is based on the view that heterogeneous shopping patterns stem from differences in shopping costs across consumers. In our setting, the number of stores visited by a consumer is endogenously determined by a stopping rule involving the extra utility and extra costs involved in visiting an additional store. This enables us to empirically identify the distribution of shopping costs. Last,

³¹As noted by Klemperer and Padilla (1997), shopping costs differ from switching costs in that the latter derive from the economies of scale from repeated purchases of a product while the former are associated with economies of scope through buying related products.

³²Brief (1967) claims that the final price paid by a consumer has two components, namely, the “pure” price of the product and the marginal cost of shopping for it. These shopping costs include both explicit costs, such as transportation costs, and implicit costs, such as the opportunity costs of shopping, which are related to the “purchaser’s valuation of time and inconvenience associated with the shopping trip.”

but not least, our empirical implementation differs from theirs in relation to several features including the categories of products that we focus on, our definition of the outside option, and our estimation method.

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 some other potential explanations for observed heterogeneity in shopping patterns and shows, using some descriptive regressions, that they 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 provides details of our counterfactual experiments and presents the results. Section 9 concludes and discusses possible 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 were obtained from the Kantar Worldpanel database. This is homescan data relating to grocery purchases made by a representative sample of 10,000 randomly selected households in France during 2005. These data were collected by household members using scanning devices.³³ The data set contains information on 352 grocery product categories from approximately 90 grocery stores including supermarket chains, hard discounters, and specialized stores. An entry in the data set records the purchase of a specific product from a given store on a particular date. Further, the data set includes information on household characteristics.

We supplement the homescan data with information on supermarket characteristics from the Atlas LSA 2005. This includes information by store format and type (regular and hard-discount stores) on aspects including the store's location, sales area, number of checkouts, and number

³³The Kantar Worldpanel is a continuous panel database that commenced in 1998. Most households that comprise the panel have been randomly sampled since 1998. Every year, new randomly selected households are added to the panel, either to replace other households that rarely report data or to increase the sample size.

of parking bays. We merge both data sets using household data, the name of the retailer, the zip code of the consumer’s residence, and the floor area of the outlet. Following Dubois and Jódar-Rosell (2010), we determine the outlet of each supermarket chain that is closest to the consumer’s dwelling using zip codes. We exclude from the consumers’ choice set all outlets located more than 20 kilometers from the city center.

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 age³⁴ 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 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: Kantar Worldpanel database 2005. Authors’ calculations.

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 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

³⁴By household head we mean the person mainly in charge of the household’s grocery shopping.

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: Source: Kantar Worldpanel database 2005. Authors' calculations.

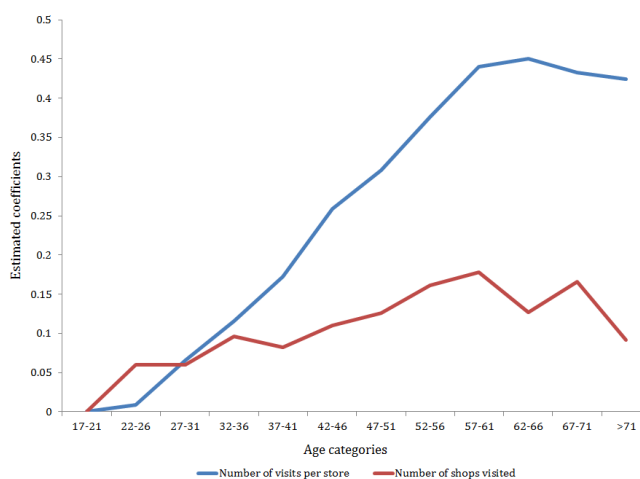
Age has been widely used in the literature as an indicator of opportunity cost of time. Aguiar and Hurst (2007) find that older people often pay lower prices because both their frequency of shop trips to the same store and the number of separate stores sourced, are larger relative to younger people. 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.³⁵ 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).

2.3 The nature of multistop shopping

Recall that shopping costs are defined as the costs of dealing with a store. This implies that multistop shopping, i.e. visiting several stores during a given shopping period, is expected to

³⁵In France, loyalty rewards have been mainly linked to repeat-purchasing.

Figure 2: Frequency of shopping by age ranges, 2005



Source: Kantar Worldpanel database 2005. Authors' calculations.

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.

be negatively correlated with consumers' real, as well as perceived, costs of shopping. Such a correlation would constitute key empirical evidence of the role played by shopping costs in consumer shopping behavior.

Following our definition of shopping patterns, and in line with theory, we measure multistop shopping in terms of the number of stores visited by a consumer per week. We regress this variable on a set of household characteristics that serve as a proxy for households' time costs to study the correlation between shopping costs and multistop shopping behavior. Further, we add some controls for household storage capacity (housing type, presence of a storage room and/or independent freezer, and the size of the largest freezer) that help to rationalize (at least in part) the frequency of shopping. Supermarket, region, and time dummies are included in all regressions. Table 3 shows the results. It can be seen that coefficients are basically of the expected sign and statistically significant.

We find evidence suggesting that a household's ability to patronize multiple stores is dependent on time constraints and distance to the stores. Interestingly, we find that larger households located in urban areas tend to favor multistop shopping, while higher-income households and those with babies visit less shops on average, presumably because of a greater opportunity cost of time. Internet access reduces the number of shops visited, as people can shop online and use home delivery services, which might involve savings in terms of both transport costs and time.

The coefficients for housing type, store format, and average distance to the store suggest some interesting patterns related to the physical structure of cities in France and store locations. In France, as a result of zoning regulations that limit store size, large-store formats are located out of the city centers. Hypermarkets, for instance, are often only reachable by car, which makes

it more costly to make top-up trips to this type of store. Conversely, convenience stores are widely located in the downtown areas and are easily reachable, but are generally small and only offer a limited range of products (mostly staples), which makes them suitable for top-up trips. Accordingly, our results show that people living in apartments, which are more likely to be in or closer to downtown areas, tend to visit a larger number of stores than those who live in a house. Meanwhile, those who live on farms visit less shops than families living in smaller types of accommodation. An alternative interpretation that is consistent with this result is related to household storage capacity. Households with lower storage capacity, i.e. those living in apartments, need to visit shops more often, and thus are more likely to be multistop shoppers.

Concerning store formats, stores are often present in various zones of a city in one of three formats: hypermarkets, which are the stores with the largest sales area and product range, supermarkets, which are medium-sized stores with a fairly varied assortment that are generally closer to the city center than hypermarkets, and convenience stores, which are small, downtown stores focused mainly on staples.³⁶ We included dummy variables for two of the three store formats, with hypermarkets and supermarkets each taking a value of 1 if they were the format visited. The coefficients obtained are negative and significant in both cases, and consistent with economic intuition: given that hypermarkets and supermarkets are larger than convenience stores and carry a larger product range, consumers who patronize them need to make less shopping trips than those patronizing convenience stores because the larger stores make bulk shopping possible. The coefficient of distance from the home location to the store shows a positive correlation with the number of stores visited in all regressions. We interpret this as people making top-up trips to convenience stores during the week, but going to a hypermarket or supermarket to do a bulk shop.

3 Sources of heterogeneity in consumer shopping patterns

In the previous section, we presented empirical evidence suggesting that household characteristics that illustrate members' time constraints help explain the observed dispersion across households of the number of stores visited in a week. Earlier, we noted that, according to theory, differences in consumer shopping patterns are the result of 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 used in the literature³⁷, which states that *shopping costs* are all of a consumer's real or perceived costs of dealing with a supplier, but interpret it in the broadest possible sense as referring to all transaction costs that consumers face during their shopping experience, including search and switching costs.

In this section, we attempt to provide evidence consistent with the view that when individuals

³⁶Officially, store formats are sorted according to their sales areas: hypermarkets have a sales area of 2500m² or more, supermarkets are between 400 m² and 2500 m², and convenience stores are less than 400 m²

³⁷See, for example, Brief (1967), Klemperer (1992), ?, Armstrong and Vickers (2010) and Chen and Rey (2012, 2013).

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)
Hardiscount (=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

Source: Kantar Worldpanel database 2005. Authors' calculations.

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.

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

make frequent repeat purchases of basic products such as staples, they are often well aware of prices and product characteristics, and hence search costs are not an issue. Based on this preliminary evidence, we develop a model in which customers are well aware of prices, and the overall price of the basket of products they wish to purchase is relevant in determining the optimal number of stores to visit.³⁸ As outlined below, our empirical strategy does not allow us to separately identify all consumer-related costs that can help to fully rationalize consumer shopping behavior. Consequently, our estimates of shopping costs may still capture some search and switching costs. However, we believe that this does not conflict with our definition of

³⁸This approach is supported by evidence. For instance, in a 2008 report on the supply of groceries in the UK, the Competition Commission stated that in relation to consumers' price comparisons across grocery retailers, the overall price of a basket of products matters Competition Commission (2008).

shopping costs.

3.1 Search costs

Even though the literature on price dispersion and search costs has extensively shown that consumers often lack information regarding key aspects of decision-making (such as price and quality of products), and may need to engage in costly searches to make better decisions,³⁹ the search costs story alone may not capture all of the factors leading consumers to favor multistop shopping. In contexts where information frictions are less relevant (and thus search costs are sufficiently small), consumers must still incur transaction costs of shopping (e.g. transportation, time spent collecting products at the store, and waiting in line at the checkout), hence there is still an observed heterogeneity in shopping patterns that needs to be accounted for. This has been widely analyzed by previous literature. ?, 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.

Alternative explanations need not exclude search activities prior to the actual purchase. However, developing a full model of consumer shopping behavior that explicitly incorporates search activities prior to the purchase of each product in the desired basket and then taking it to the data is a very challenging and cumbersome task. To the best of our knowledge, there is no paper in the literature that simultaneously addresses multiproduct search and multistop shopping behavior in an empirical context.⁴⁰ Given that our aim is to rationalize the observed heterogeneity across consumers related to one- and multistop shopping behavior rather than the observed dispersion of the prices of individual products or the total value of a basket of products, we develop a model that does not explicitly include search costs in optimal consumer decision-making. Furthermore, our empirical implementation relies on the selection of a basket of products that consumers purchase sufficiently frequently to ensure that they are reasonably aware of prices.

This does not mean that search costs play no role in observed shopping behavior. Indeed, the fact that our estimates of shopping costs may capture search costs should not be problematic *per se*. As 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.

Empirically, using search cost reasoning, we would expect prices to decrease with the number

³⁹See for example, ?, Hong and Shum (2006), ?, Koulayiev (2014), Moraga-Gonzalez and Wildenbeest (2013), Kim and Bronnenberg (2010), Wildenbeest (2011), De los Santos and Wildenbeest (2012), and Hong and Shum (2014).

⁴⁰Wildenbeest (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, neither study addresses the problem of multiproduct searching. Wildenbeest (2011) assumes that consumers are interested in buying a “representative” basket of 24 products, and compares the total value (price or utility) of identical baskets across stores, which is essentially a search for a single product, i.e. a fixed basket of products. Dubois and Perrone (2015) propose and test a search model using data on several food products, but proceed on a product-by-product basis, which makes their analysis a series of single-product searches.

of stores visited. Indeed, the negative correlation between the price of an item and the number of supermarkets visited has been used in the empirical search literature as reduced-form evidence of consumer searching.⁴¹ However, if consumers are reasonably 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 from the top 10 and top five 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 and the number of visits to the same store in that week, controlling for household characteristics, with proxies for household time costs, 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 search costs, we should observe that the price is lower on weekends than it is on weekdays. To capture this, we also include in our regressions a dummy that takes a value of 1 if the purchase was made on a weekend, and 0 otherwise. The results are displayed in Table 4, where the first column shows the price index for the 10 most frequently purchased non storable products, the second column shows the price index for the top five in that category, and the third column includes the three products we use in the empirical implementation below.⁴²

We find a significant positive relationship between the transaction price and the number of stores visited per week in the third regression, which suggests that, on average, consumers do not obtain cheaper baskets by visiting a larger number of stores. In the other two regressions, we find that this relationship is not statistically significant. This suggests that the search costs story according to which consumers visit numerous stores looking for lower prices, is not consistent with our results for non storable staple products. We do find a significant negative relationship (see columns one and three in the table) between the price index and the number of visits to the same supermarket chain. Households that frequently visit the same store pay lower prices, possibly because they are able to take advantage of sales and promotions (see Aguiar and Hurst (2007)) or obtain loyalty rewards more often than infrequent customers of that store. Interestingly, weekend purchases of the products under consideration do not seem to lead 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 searching is not an issue in this case.

3.2 Switching costs

Positive switching costs may be an additional way to (partially) rationalize the observed heterogeneity in consumer shopping patterns. In fact, one might be tempted to think of one-stop

⁴¹See, 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.

⁴²For details on how we construct price indices for the regressions, see the Data Appendix.

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: Kantar Worldpanel database 2005. Authors' calculations.

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

shopping behavior as being associated with large switching costs at the store level.⁴³ Although (artificial) switching costs are widespread 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. Conversely, shopping costs rationalize the use of one or several suppliers, even within a single period.⁴⁴ In other words, switching costs do not explain why a

⁴³Such as learning costs related to, for example, the store's layout and arrangement of products, and pricing and promotion policies, strong feelings of store loyalty, and non-price strategies used by stores to retain customers (e.g. loyalty programs).

⁴⁴Klemperer (1992) points out the importance of the temporal dimension and the choice of real versus perceived characteristics to differentiate between shopping and search costs: "The economies of scope of buying related prod-

shopper might find it optimal to simultaneously visit several stores.⁴⁵

In our data, we observe that almost all households undertake multistop shopping at some point. Even though, on average, there is a significant proportion of one-stop shopping in a given week (see 1), households often change their shopping patterns across weeks, and less than 6% of households are consistently week-to-week one-stop shoppers. This suggests that the kind of switching costs that lock consumers into a particular store do 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 store.

4 Consumer shopping behavior with shopping costs

4.1 General setup

There are I consumers in the market indexed by $i = 1, \dots, I$ with idiosyncratic valuations of 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 Customer i purchasing product k from store r in period t derives a net utility of \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 sufficiently small, otherwise she will optimally make her purchases from 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 as s_i . Transport costs, which are an important component of the total cost of shopping, are accounted for by including distance to stores as an additive term to the utility function of a basket of products (see below). Accordingly, shopping costs

ucts, 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 developed 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.

⁴⁵To understand 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 the 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 if we had observed her purchasing both products from a single store. Further, suppose we are able to observe that in the previous shopping period, she exhibited similar shopping behavior (product 1 from supermarket A and product 2 from supermarket B). Accordingly, she would not be a switcher, and yet she would be a multistop shopper, so it would be misleading to claim that multistop shopping is possible as a result of low switching costs.

⁴⁶Assuming that all consumers have access to the same product range might appear unreasonable. However, this helps us to reduce 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.

are assumed to be independent of store characteristics (e.g. size, facilities, location) and time invariant. Furthermore, we assume that s_i is randomly drawn from a continuous distribution function $G(\cdot)$ and positive density $g(\cdot)$ everywhere. Finally, we assume that consumers are well informed regarding prices and product characteristics. Therefore, consumers do not need to engage in costly search to gather information about prices and product quality.

Consumer i is supposed to exhibit optimal shopping behavior. This implies that she makes an optimal choice involving two elements: whether to be a one- or multistop shopper, and which stores to visit for each of the products she wants to buy. Roughly speaking, the choice set of consumer i will be restricted by the number of stores she can visit given her shopping costs, so that her choice will consist of selecting 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 select the best product–store combination from the three alternatives existing in the market within each category. A two-stop shopper will select the mix of two stores maximizing the utility of the desired basket from all possible product–store combinations. Her final basket will consist of the best of the 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 consumer i from his household location to store r 's location, and τ denote a parameter that captures the consumer's valuation of the physical and perceived costs of traveling that distance. We define the utility net of transport costs of a shopper who is able to visit 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, the net utility of a two-stop shopper is 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, the net utility of a consumer who is able to visit all three stores is given by

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

Note that the expressions in (1), (2), and (3) are particular cases of a more general utility function in which, conditional on shopping costs, an n -stop shopper is selecting 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 precisely the number of stores in the market, which is why she does not need to maximize subsets of suppliers.⁴⁸

Suppose $v_{it}^1 - s_i > 0$ such that all consumers will visit at least one supermarket in each period. To determine the number of stops to be made, consumer i weighs the extra utility of undertaking n -stop shopping with the extra costs involved, taking into account the fact that the total cost of shopping increases with the number of stores visited. A consumer will optimally decide to undertake three-stop shopping only if the net utility from visiting three stores is greater than that from either one- or two-stop shopping. 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 from visiting three stores rather than two, and $\Delta_{it}^3 \equiv v_{it}^3 - v_{it}^1$ be the additional utility from deciding to visit 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 undertake 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 from visiting two stores rather than one. Hence, consumer i will undertake two-stop shopping as long as

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

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

$$v_{it}^1 - s_i \geq \max\{v_{it}^2 - 2s_i, v_{it}^3 - 3s_i\}, \quad (6)$$

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

$$s_i > \max\left\{\delta_{it}^2, \frac{\Delta_{it}^3}{2}\right\}. \quad (7)$$

In general, the optimal stopping rule for consumer i indicates that she will choose the mix of stores that maximizes her utility conditional on the extra shopping cost being at most the extra utility obtained from visiting additional stores. Equations (4), (5), and (7) suggest that

⁴⁸The general expression of the utility and choices of an n -stop shopper are described in Appendix A.

we can derive critical cutoff points regarding the distribution of shopping costs. However, it is necessary to determine how δ_{it}^2 , δ_{it}^3 , and $\Delta_{it}^3/2$ are ordered. Of six possible orderings, only one survives,⁴⁹ namely,

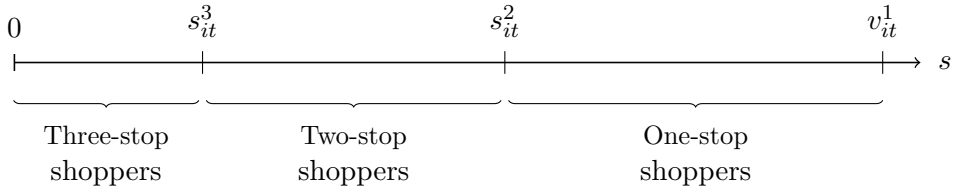
$$\delta_{it}^3 < \frac{\Delta_{it}^3}{2} < \delta_{it}^2. \quad (8)$$

Under this ordering, the highest possible shopping costs for any consumer able to undertake multistop shopping at either two or three stores, respectively, in equilibrium are given by the following critical cutoff points:

$$\begin{aligned} s_{it}^2 &= \delta_{it}^2, & \text{for two-stop shopping, and} \\ s_{it}^3 &= \delta_{it}^3, & \text{for three-stop shopping.} \end{aligned} \quad (9)$$

Note 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 for the distribution of shopping costs in (9) indicate that for given shopping costs, consumers only care about the marginal utility of visiting an additional store in making their final decision on how many stores they should visit. 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

$$\begin{aligned} q_{krt}(\mathbf{p}_t) &= \left[G(v_{it}^1(\mathbf{p}_t)) - G(s_{it}^2(\mathbf{p}_t)) \right] P_{it}^1(X_{\mathcal{B}}; \theta) \\ &+ \left[G(s_{it}^2(\mathbf{p}_t)) - G(s_{it}^3(\mathbf{p}_t)) \right] \prod_{\{b \in \mathcal{B}_2 \mid kr \in b\}} P_{it}^2(X_{\mathcal{B}}; \theta) \\ &+ G(s_{it}^3(\mathbf{p}_t)) \prod_{\{b \in \mathcal{B}_3 \mid kr \in b\}} P_{it}^3(X_{\mathcal{B}}; \theta), \end{aligned} \quad (10)$$

where P_{it}^1 is the probability that a one-stop shopper decides to shop at store r , P_{it}^2 is the probability that a two-stop shopper chooses store r as one of the two stores that she will visit,

⁴⁹We show why this is so in Appendix B.

⁵⁰Note that the kind of behavior according to which a shopper evaluates extreme choices such as visiting all shops rather than only one does not appear to be relevant here.

and P_{it}^3 is the probability that a three-stop shopper decides to select a basket b including product kr . All of these probabilities are known by shoppers.

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 cost cutoff values given that they depend on utilities. As a consequence, the distribution of shoppers between one-, two-, and three-stop shopping groups changes. In fact, an increase in product k 's price at store r reduces the indirect utility of consumer i visiting store r . Therefore, she may consider making less stops and purchasing a substitute for this product from a rival store, say h , as the gain in utility from visiting an additional store may not be sufficient to offset the extra shopping cost.

5 Empirical implementation

5.1 Shopping period

We define a shopping period as a week in which a household is recorded as making grocery purchases. During a week, a household that concentrates its purchases in a single supermarket chain can either make one visit to a store in the chain, make several visits to the same store, or it can visit several stores in the same chain or. Regardless, we define this household as a one-stop shopper as long as it is observed to only deal with a single supermarket chain during the week. Conversely, when we see the household purchasing products from stores in competing chains during the week, we define it as a multistop shopper.

5.2 Products and stores

Our demand model allows shoppers to buy several different products in the same week and assumes that shoppers are making a series of multiple-discrete decisions regarding 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 either one product or multiple products that can be purchased from either one store or several stores. When a household is observed to have made no purchases in a given shopping period, we define it as having opted for the outside option.

In our data set, households are observed to purchase up to 275 different products from up to 9 separate grocery suppliers during a given shopping period. On average, a household purchases baskets containing 24 products from two stores each week. Estimating a demand system for such a large choice set is infeasible. Thus, we focus on a reduced set of three product categories and three stores that represent the most frequently purchased products and stores most frequently visited by French households. In particular, we include yogurt, biscuits, and refrigerated desserts, given that they meet several criteria that make our empirical exercise consistent with our structural model (see Table 5). First, they are staples, because most French

households are heavy consumers of products from these categories (they are typically consumed every day by the average French household), and are not stored for very long, so stockpiling is not a first-order concern. Second, these categories are not close substitutes, which ensures that we can observe sufficient variation in shopping patterns, as consumers may tend to concentrate their purchases from the same category in a particular store, but might want to diversify purchases from other 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 of how we define servings).

Table 5: Characteristics of the selected categories

	Yogurt	Biscuits	Desserts
Position among 352 products ^a	2	3	6
Serving size (in grams) ^b	125	30	80
Mean price (euro cents/serving)	26.27	9.77	45.42
Mean consumption ^c	9	12	8
Days between purchase	8	10	10

Source: Kantar Worldpanel database 2005. Authors' calculations.

Notes: ^a Positions of the selected products in a ranking of the 352 products we observe, based on the number of purchases in 2005.

^b Servings are defined according to the most frequently purchased serving of each product.

^c Average number of servings purchased per household-week.

To capture consumers' responses when a product is delisted, we use two brands in the yogurt category, one being the leading NB in France in 2005 and the other being a composite "brand" that consists of the remaining brands (both other NBs and PLs) available in the market. Concerning the other two categories, in each case we treat purchases of all brands like they were purchases of a single general brand. Therefore, consumers face a set of four products from which they can choose at most three: one of the two yogurt alternatives, biscuits, and desserts.⁵¹

Regarding stores, we restrict our attention to the three leading supermarket chains in France based on national market share in 2005. These chains are present throughout the country and operate various store formats: hypermarkets, supermarkets, and convenience stores. The remaining stores observed in our data are included in the outside option along with the no purchase of the included goods option (the interpretation of the outside good in this context is discussed below). Thus, we have four *ex ante* homogeneous products that are available at three stores of similar size. This is consistent with our modeling framework of oligopolistic competition with differentiated product lines, where customers can visit multiple stores in the same shopping period to increase variety. In this context, a basket is a collection of product-store items, and given that there are four products, three stores, and baskets that can consist of one, two, or three items, we end up with a choice set of 112 mutually exclusive alternatives.

⁵¹The choice of yogurt as the category with two alternatives is arbitrary. To check the robustness of our results, we perform the estimation of our demand model by changing the category containing two options. The results are shown in Table D.1 in the Appendix.

5.3 Empirical specification of the utility

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

$$\bar{v}_{ikrt} = -\alpha_i p_{krt} + \mathbf{x}_k \boldsymbol{\beta}_1 + \mathbf{x}_r \boldsymbol{\beta}_2 + \xi_k + \xi_r + \phi_t, \quad (11)$$

where p_{krt} is the price of product k at store r , \mathbf{x}_k and \mathbf{x}_r are vectors of the observed product and store characteristics, respectively, ξ_k and ξ_r are vectors of the unobserved product and store characteristics, respectively, ϕ_t are time fixed effects, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are vectors of parameters, and α_i is an individual-specific coefficient that captures the valuation of the price.

The mean valuation of the observed product (store) characteristics is not identified separately from that of the unobserved characteristics. These are captured jointly by product (store) dummies included in the estimation of the model:

$$\delta_k = \mathbf{x}_k \boldsymbol{\beta}_1 + \xi_k, \quad \delta_r = \mathbf{x}_r \boldsymbol{\beta}_2 + \xi_r.$$

We model the distribution of consumers' tastes for prices as follows:

$$\alpha_i = \alpha + \mathbf{d}_i \boldsymbol{\pi} + \sigma^\alpha \nu_i, \quad \nu_i \sim N(0, 1), \quad (12)$$

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 that captures unobserved household attributes that influence consumer choices, and σ^α is a scaling parameter.

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 as a result of the need to engage in shopping, and an individual deviation from this mean, η_i , which rationalizes the individual heterogeneity in shopping costs. This yields

$$s_i = \varsigma + \sigma^s \eta_i, \quad \eta_i \sim N(0, 1), \quad (13)$$

where σ^s is a scaling parameter.

In line with our modeling framework, we empirically define the utility a n -stop shopper ($n \in \{1, 2, 3\}$) derives from purchasing basket b of products as

$$u_{ibt} = v_{ibt}^n - n s_i + \varepsilon_{ibt} \quad (14)$$

where v_{ibt}^n is the overall utility of basket b net of transport costs as defined by equations (1) through (3) above, s_i is the individual shopping cost, and ε_{ibt} is an idiosyncratic basket-level shock to utility.

Note that equation (14) along with equations (11) and (13) fully specify the utilities of one- and multistop shoppers as a function of price, product characteristics, distance to stores, and individual transaction costs of shopping. Thus, our utility accounts for both the vertical and horizontal dimensions of consumers' valuations of products. The vertical differentiation is captured by product-store characteristics, while the horizontal differentiation is captured by distance, which varies across store formats and zip codes, and shopping costs.

Finally, we normalize the utility net of shopping costs of the basket containing only excluded products (which we denote as basket $b = O$) to zero. Thus, it is modeled as a function of an individual random shock to utility, $u_{iOt} = \varepsilon_{iOt}$.

5.4 The outside option

Recall that to keep our problem involving multiproduct and multistore choices tractable, we restricted the choice set to all baskets resulting from the mix of up to three stores and up to three products from the four alternatives available (two brands of yogurt, biscuits, and refrigerated desserts). The three store chains that were selected shared nearly 60% of the French market (excluding hard discounters) in 2005. Recall also that with the exception of NB yogurt, the products we consider are in fact product categories. Hence, we take into account all other brands of yogurt and all brands of biscuits and refrigerated desserts purchased by consumers from the three chains. The remaining purchases of both included and excluded products at excluded stores and excluded products at included stores, as well as unobserved purchases and visits to unobserved sellers, are treated as outside products.

In this context, the interpretation of the outside option differs from that 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 choose multiple products simultaneously, every choice involves a maximization over all excluded alternatives, unlike the case of a standard multinomial model, where only the utility from good 'zero' is implicitly maximized over all excluded products.

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 by that household in that week, we would interpret the household as a two-stop shopper that purchased a basket of two 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 attainable through either of the two alternatives (one- and three-stop shopping). However, it may be that this household purchased yogurt and/or some excluded products at excluded stores, or that it also purchased some excluded products from the included stores. In any case, the interpretation is that this household was better off choosing a basket obtained by shopping at supermarkets A and C, and possibly an outside option, rather than choosing a basket obtained from any combination of products and stores that included supermarket B.

In line with this, we must include a caveat related to the interpretation of the shopping

patterns we observe in our final data set. If a consumer is observed to have made purchases at two of the three included stores, we interpret this as meaning that she was able to make two visits in addition to visits she might have made to any excluded stores. In this sense, the number of store visits by a household that possibly also purchased products at excluded stores is interpreted in the context of this paper as the number of additional visits the household made to included stores.

5.5 Identification

Equation (9) shows that we can identify critical cutoff points in 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 product-specific 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 involving alternative shopping patterns (either one- or three-stop shopping). To do this, we exploit the panel structure of our data. We observe sufficient cross-sectional and time variation in terms of choices of products and stores to allow 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 the price of the same product. Thus, the predicted probabilities vary as a result of this variation in prices, which generates sufficient moments for identification.

Fixed shopping costs are identified from the observed week-to-week variation in the shopping behavior of each household, e.g. a household undertaking one-stop shopping one week can be observed undertaking multistop shopping the following week. Week-to-week variation is necessary but not sufficient for identification; variation in terms of the set of products purchased from each store is also needed to enable the separation of shopping costs from mean product-store utility parameters. Further, to capture the component of shopping costs that varies with time and stores, we control for household characteristics that account for time constraints. As in Dubois and Jódar-Rosell (2010), we suppose that all households located in the same zip code have the same distance to travel to stores.⁵² The inclusion of distances to stores is useful for two reasons: they capture part of the horizontal dimension of consumers' preferences for product characteristics, and 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, which is consistent with our modeling framework.

Finally, the identification of aggregate demand requires the computation of the proportions of one-, two-, and three-stop shoppers, which in equation (10) are defined as the differences between the distribution of shopping costs $G(\cdot)$ evaluated at two different cutoff points. Given our setup, we are able to compute these values from the empirical distribution of one-, two-, and three-stop shoppers that we observe in our data.

⁵²Due to data limitations, we do not pinpoint the precise locations of either households or retailers, but merely use zip codes. As a consequence, we are not able to compute exact distances for each household.

5.6 Estimation

To estimate the parameters of our model, we use the data set described in Section 2. The sample we use consists of local areas where we observe households undertaking one-, two-, and three-stop shopping and purchasing at least one unit of one of the included products. Given that we allow for random coefficients of price and shopping costs, our choice probabilities do not have a closed-form solution. Thus, we use simulated methods to compute them. The details of the estimation method we use are as follows.

Let $\boldsymbol{\theta} = (\alpha, \boldsymbol{\beta}'_1, \boldsymbol{\beta}'_2, \tau, \boldsymbol{\pi}', \sigma_\alpha, \sigma_\eta, \varsigma)'$ be a vector containing all parameters to be estimated. A consumer who wishes to buy a basket of products, denoted as b , faces a choice set \mathcal{B} of mutually exclusive and exhaustive alternatives consisting of combinations of products and stores. The basket she chooses is such that she obtains the highest possible utility net of shopping costs. This maximizing behavior defines the set of unobservables leading to the choice of alternative b as

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

where n and m correspond to the number of stores visited to purchase basket b and basket j , respectively, v_{ibt}^n corresponds to the utility derived by consumer i from basket b at time t net of shopping costs. We assume that the random shocks to utility, ε_{ibt} , are distributed i.i.d. type I extreme value. Integrating over ε_{ibt} yields the closed-form choice probability of alternative b , at time t , as a function of the characteristics of products and retailers:

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

As each consumer makes a sequence of T choices, we index H as the set of all possible values our data takes, i.e. all sequence of baskets at 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} denotes 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, the integral over unobservables ν, η , does not have a closed-form solution. We use the Simulated Maximum Likelihood (SML) method (see Lerman and Manski (1981), and Pakes and Pollard (1989)) to overcome this problem. As the SML method requires the number of simulation draws, S , to approach infinity with $\sqrt{S/I} = O(1)$, we use 100 draws in our

simulations. The SML estimator is given by:

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

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 random 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.

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

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.

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 cost cutoffs, we find that a customer is able to visit at least one store per week if her shopping costs are less than 1.21€. Note that this figure is less than the average shopping cost calculated above, which means that, on average, not everyone can afford to visit even one store every week. This is consistent with the model's prediction that 66.9% of people are zero-stop shoppers. One-stop shoppers are those whose shopping costs lie between 7 euro cents and 1.21€, and comprise 31.7% of all customers. Finally, the shopping costs necessary to rationalize the low proportion of multistop shoppers who are able to visit either two (1.3%) or three (0.03%) stores every week are very small, even negative. A negative shopping cost is consistent with our model, as it accounts for a consumer's taste for shopping, i.e. a lower (even

negative) shopping cost means that the consumer derives has a stronger taste for shopping.

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

Total shopping costs	
Mean shopping cost (€)	1.57
Mean transport cost (€/km)	0.03
Average shopping cost cutoffs (€)	
Zero-one stop	1.21 [0.23, 2.87]
One-two stops	0.07 [-0.39, 0.06]
Two-three stops	-0.73 [-1.85, -0.37]
Distribution of shoppers (percentage of total)	
Zero-stop shoppers	66.92 [23.78, 94.42]
One-stop shoppers	31.73 [5.02, 68.16]
Two-stop shoppers	1.32 [0.13, 10.16]
Three-stop shoppers	0.03 [0.01, 1.40]

Notes: To translate estimates into euros, we divide the absolute value of each coefficient by the absolute value of the price coefficient. 95% confidence intervals are given in square brackets.

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 three 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 a 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 The effects of product delisting on consumer shopping behavior

Retail stores often use the threat of delisting either a product or a range of products to obtain better deals with manufacturers. If consumers find it very costly to visit alternative stores (e.g. because of strong feelings of loyalty, very large shopping costs, or head-to-head competition between stores), the delisting of a product will only hurt the manufacturer, making the threat of delisting an effective bargaining strategy for retailers. However, when consumers find it optimal to undertake multistop shopping, the delisting of a product can also hurt the delisting store as a result of a reduction in demand from shoppers who either continue to undertake one-stop shopping at a competing store or visit an additional store if their shopping costs are sufficiently low.

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 NB yogurt in supermarket 1 so that it becomes prohibitively expensive while keeping the price unchanged at the two competing stores.⁵³ We use our demand estimates to explore three situations: one in which, all else equal, Yogurt NB is delisted by supermarket 1. A second situation in which we apply a threefold increase to the coefficient of the dummy specific to the product that is being delisted by store 1 in the demand model without changing any other parameters. We interpret this as consumers having a strong preference for that product.⁵⁴ Finally, a third situation in which we

⁵³We believe that a situation in which a product 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.

⁵⁴Recall that each product is available at all stores. When we increase the coefficient of the dummy specific to

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 .

apply a threefold increase to the coefficient of the dummy specific to supermarket 1 without changing any other parameters. We interpret this as consumers having a strong preference for the store that is delisting the product.

Table 9 reports the probabilities of visiting each store. Columns 1, 2, and 3 show the probabilities obtained from our first, second, and third simulations, respectively. Panels A, B, and C report the probability of visiting stores 1, 2, and 3, respectively, under each scenario. There are three rows within each panel: row (a) corresponds to the baseline scenario, row (b) corresponds to the delisting scenario, and the third row shows the percentage difference between the predicted probabilities displayed in the preceding rows. Results show that when a store delists a product, the probability of being visited by consumers decreases, while it increases for rival stores.

A strong preference for the product reinforces this situation considerably: when customers have a higher valuation of the product being delisted relative to the baseline situation, the reduction in the probability of visiting store 1 decreases by about 35%, while the probability of visiting rivals increases in a range between 7.7% and 13.2%. This result is driven by the high proportion of one-stop shoppers in our sample, as they must find an alternative store where they can purchase all products. Delisting a product in the context of strong consumer preferences can be detrimental not only for the manufacturer, but also for the delisting store.⁵⁵

Alternatively, in a situation in which consumers place a higher valuation on store 1 relative to the baseline scenario, the delisting of a product appears to have a weaker effect. The probability of visiting store 1 decreases by less than 1%, which is a smaller decline than that seen in simulation 1. Consumers may find it optimal to substitute the missing product with an alternative product that is available at the same store rather than visiting a rival store. This result suggests that inducing consumer loyalty (e.g. through loyalty programs or strong PLs) can help a store chain to develop a stronger bargaining position *vis-à-vis* manufacturers, enabling it to deliver a threat of delisting more effectively.

Table 10 reports changes in weekly revenues for the three retailers resulting from the delisting of NB yogurt by supermarket 1 when prices are held fixed. In the three cases, removing one product from its shelves leads to a decrease in revenues while rivals' revenues increase. Supermarket 1 suffers most from delisting when consumers have strong preferences for the product: its revenues decrease by 18.8 million euros per week. By contrast, its rivals' revenues increase by 3.5 million euros for supermarket 2 and 4.8 million euros for supermarket 3.

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 of both products and stores. Of course, our analysis has a limitation stemming from our assumption that supermarkets do not react to the delisting of NB yogurt by supermarket 1 and

a product, the consumers' valuation of the product increases by the same proportion at every store.

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

Table 9: Predicted probability of visiting stores 1, 2, and 3 under different scenarios when supermarket 1 delists NB yogurt*

Scenario	Simulation 1	Simulation 2 Product 'loyalty'	Simulation 3 Store 'loyalty'
Panel A: Supermarket 1			
(a) Baseline	0.1460 [0.023, 0.277]	0.1874 [0.025, 0.359]	0.3316 [0.064, 0.540]
(b) Delisting	0.1438 [0.023, 0.270]	0.1215 [0.012, 0.246]	0.3290 [0.063, 0.539]
Difference (a-b)/a	-1.50%	-35.17%	-0.78%
Panel B: Supermarket 2			
(a) Baseline	0.1271 [0.022, 0.289]	0.1573 [0.026, 0.352]	0.1015 [0.017, 0.262]
(b) Delisting	0.1275 [0.022, 0.291]	0.1693 [0.026, 0.433]	0.1018 [0.017, 0.265]
Difference (a-b)/a	0.27%	7.65%	0.31%
Panel C: Supermarket 2			
(a) Baseline	0.1023 [0.014, 0.283]	0.1427 [0.020, 0.398]	0.0791 [0.009, 0.257]
(b) Delisting	0.1027 [0.014, 0.286]	0.1615 [0.020, 0.544]	0.0794 [0.009, 0.259]
Difference (a-b)/a	0.38%	13.18%	0.42%

Notes: *Supermarket 1 delists NB yogurt while its rivals continue to stock the product. 95% confidence intervals are given in square brackets.

Table 10: Change in weekly revenues under different scenarios when supermarket 1 delists NB yogurt (millions of euros)

Retailer	Simulation 1	Simulation 2 Product 'loyalty'	Simulation 3 Store 'loyalty'
Supermarket 1	-0.651	-18.841	-0.916
Supermarket 2	0.091	3.473	0.078
Supermarket 3	0.100	4.803	0.086

Notes: *Supermarket 1 delists NB yogurt while its rivals continue to stock the product. These numbers were obtained under the assumption that the market size for each product was equivalent to the average number of servings consumed by an individual in a week multiplied by the french population in 2005. According to our data, on average, an individual use to consume 3 servings of yogurt, 4 servings of biscuits and 3 servings of desserts in a week. 95% confidence intervals are given in square brackets.

hold their prices fixed. A complete study of the effects of product delisting would consider how rival stores and manufacturers optimally adjust prices. Nevertheless, our results are interesting and consistent with industry evidence.⁵⁶

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

8 The role of shopping costs

Do shopping costs matter when it comes to explaining consumer shopping behavior? We answer this question with the help of two exercises. On the one hand, we take our estimated model and simulate a scenario in which shopping costs fall to zero, i.e. we assume that consumers no longer incur positive shopping costs. On the other hand, we estimate an alternative specification of our structural model in which consumers do not incur any shopping costs, and compare the results with those obtained from our preferred specification with shopping costs.

In the first exercise, we compare the predicted probabilities of being a zero-, one-, or a multistop shopper obtained from our estimated model (baseline) with a counterfactual scenario in which all consumers face zero shopping costs. The results are reported in Table 11. In the absence of shopping costs, consumers choose the outside option with smaller probability. Shopping costs introduce frictions that deter consumers from purchasing the included products on a regular basis, which is consistent with the theory and shows the importance of accounting for such costs in a model of multistop shopping. Further, a scenario with zero shopping costs predicts a larger proportion of multistop shoppers, nearly 25% as opposed to 2% in our estimated model. Note that removing shopping costs need not translate into a situation in which all consumers are multistop shoppers. In fact, most shoppers optimally choose to visit a single store. This might be the result of unobserved idiosyncratic valuations of product-store combinations that yield a greater utility through concentrating purchases at a single store (and that are captured by the error term in the model).

Table 11: Probability of visiting a given number of stores with and without shopping costs^a

No. of stops ^b	Baseline	Zero shopping cost	Percentage change
0	0.6015 [0.238, 0.944]	0.0183 [0.002, 0.305]	-96.96%
1	0.3792 [0.050, 0.682]	0.7269 [0.600, 0.906]	91.69%
2	0.0187 [0.001, 0.102]	0.2458 [0.058, 0.255]	1214%
3	0.0005 [0.000, 0.014]	0.009 [0.001, 0.011]	1700%

Notes: ^a 95% confidence intervals are given in square brackets.

^b If the consumer visited stores other than the three included in our sample, the number of stops in this table should be interpreted as “additional” stops.

In the second exercise, we compare estimated substitution patterns from two alternative specifications. We take the semi-elasticities obtained under each model and compute the percentage change between the two as an indicator of estimation bias. Table 12 shows the average rates in two panels: the top panel presents the rates of within-retailer own- and cross-price semi-elasticities averaged across retailers, while the bottom panel shows the rates of inter-retailer

cross-price semi-elasticities averaged across supermarkets.⁵⁷

All of the entries on the main diagonal in Panel A are positive and greater than 100%, which means that the estimated own-price semi-elasticities under the no-shopping-costs scenario are more than twice as large than those obtained when shopping costs are accounted for. 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 at no additional costs. This suggests that a model of multistop shopping that does not account for shopping costs overestimates own-price elasticities.

Conversely, most cross-price semi-elasticities in both panels appear to be smaller under a model without shopping costs (percent changes being negative). This suggests that substitution between products is biased downwards when shopping costs are not accounted for in a model of multistop shopping. In particular, note that percentage changes in panel B are larger (in absolute value) relative to those in Panel A, which is indicative of customers being more willing to look for substitutes at an alternative store in the presence of shopping costs than without them. The rationale behind this is precisely given by the frictions introduced by shopping costs along with the large proportion of one-stop shoppers in our sample: once the price of a product rises, one-stop shoppers prefer to leave the store for a rival in order to find substitutes for all the desired products.

Table 12: Average rates of variation of own- and cross-price semi-elasticities estimated from two alternative models (percentages)^a

Product	Yogurt	Yogurt NB	Biscuits	Desserts
Panel A: within supermarket^b				
Yogurt	130	-68.1	38.7	-58.5
Yogurt NB	-73.8	108.1	37.7	-58.8
Biscuits	-36.9	-27.9	127.3	-63.3
Desserts	-26.1	-15.7	41.4	135.2
Panel B: across supermarkets^b				
Yogurt	-75.1	70.2	-112.4	-112.4
Yogurt NB	-75.2	-70.3	-113.4	-112.3
Biscuits	-107.1	-105.3	-45.7	-106.6
Desserts	-121.5	-117.0	-118.4	-86.2
Outside Good	22.6	50.7	185.2	-40.5

Notes: ^aRates are computed by taking the difference between the estimated semi-elasticity of the model without shopping costs with the corresponding semi-elasticity of the model with shopping costs, and then dividing it by the estimated semi-elasticity of the model with shopping costs.

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

⁵⁷Mean estimated own- and cross-price elasticities are available in the appendix. Table ?? shows the elasticities obtained from our preferred specification, and Table E.1 reports those numbers for the alternative specification of the demand model without shopping costs.

9 Concluding remarks

This study develops and estimates a model of multiproduct demand for groceries in which customers with different shopping costs can choose between visiting one store or multiple stores in a given 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 stores visited by a household per week and household characteristics that are a proxy for the opportunity cost of time. Second, our structural model allows us to retrieve consumer shopping costs, which we estimate as 1.79 € per store visited, on average. Finally, when we simulate the delisting of a product by one store, we find that the probability of customers visiting that store decreases, while the probability that they will visit competing stores increases. The reduction in demand is even greater when consumers have strong preferences for the delisted product. This suggests that retailers may be hurting not only the manufacturer, but also themselves when they delist products. However, when customers have strong preferences for the store, these effects are reduced. Therefore, inducing store loyalty in customers can potentially have an effect on vertical negotiations and, in particular, might enable powerful retailers to impose vertical restraints on manufacturers.

There are several avenues for further empirical research that can be addressed using our framework. The first is related to pricing by stores in the context of product delisting. Adding structure on the supply side to empirically assess how both retailers and manufacturers react to the delisting of a product by a store seems to be a natural step toward obtaining an overall 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 to offer 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 were eliminated would help to clarify this issue.

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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 (7) 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	Alternative samples		
	sample	(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.

E Own- and cross-price elasticities from an alternative specification

As a support for section 8 of this paper, and for the sake of comparison, we provide mean own- and cross-price Elasticities estimated from an alternative specification in which shopping costs are assumed to be zero for all consumers. Results are shown in Table E.1.

Table E.1: Mean own and cross-price elasticities from a model without 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	-4.20964	0.00532	-0.18644	-0.35751	0.05573	0.00452	0.00399	-0.01223	0.06062	0.00668	0.00092	-0.01119
Yogurt NB	0.06067	-3.86203	-0.18430	-0.34655	0.05567	0.00452	0.00411	-0.01216	0.06056	0.00668	0.00185	-0.01081
Biscuits	-0.25743	-0.02245	-1.47880	-0.29313	0.00098	0.00034	0.04261	-0.00170	-0.00010	0.00004	0.05852	-0.00062
Desserts	-0.33232	-0.02833	-0.19375	-6.99972	-0.01117	-0.00038	0.00213	0.05688	-0.01590	-0.00154	-0.00123	0.04902
Supermarket 2												
Yogurt	0.06023	0.00529	0.01008	-0.00094	-4.28082	0.00454	-0.18804	-0.32199	0.06082	0.00670	-0.01515	-0.03973
Yogurt NB	0.06024	0.00529	0.00793	-0.00438	0.05593	-4.34686	-0.18141	-0.32974	0.06071	0.00669	-0.01431	-0.03001
Biscuits	0.01137	0.00090	0.04518	0.00830	-0.25407	-0.01741	-1.49349	-0.27131	-0.01831	-0.00164	0.05855	-0.02285
Desserts	-0.00152	-0.00008	0.00818	0.05857	-0.31356	-0.02292	-0.19448	-7.11395	-0.03793	-0.00357	-0.01789	0.04969
Supermarket 3												
Yogurt	0.06034	0.00530	-0.00087	-0.01841	0.05598	0.00454	-0.00960	-0.03470	-4.74879	0.00671	-0.16645	-0.18331
Yogurt NB	0.06030	0.00529	-0.00097	-0.01581	0.05586	0.00453	-0.00973	-0.03456	0.06075	-4.07737	-0.16399	-0.17271
Biscuits	-0.00502	-0.00037	0.04518	-0.00487	-0.01587	-0.00092	0.04263	-0.02095	-0.16823	-0.01860	-1.65455	-0.14708
Desserts	-0.02132	-0.00202	-0.00111	0.05869	-0.04024	-0.00206	-0.01433	0.05744	-0.22648	-0.02391	-0.17829	-7.94753
Outside Good	0.06004	0.00528	0.04517	0.05809	0.05522	0.00448	0.04258	0.05544	0.05990	0.00662	0.05847	0.04797

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 .

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