Consideration Sets in Storable Goods Markets*

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Abstract

In markets with frequent price fluctuations, costly price search makes it necessary for consumers to choose an optimal subset of products to search before making a final purchase decision. I refer to this subset as the consideration set. Consideration sets are usually not observed, which creates econometric challenges. I show that in storable goods markets it is possible to exploit a new source of variation to identify consideration sets. I study the importance of consideration sets in these markets and evaluate potential biases created by assuming full information and no search costs. To perform the analysis, I estimate a dynamic choice model with consideration sets. Consumers' consideration sets are derived from an optimization model under imperfect information and costly search. Choice is modeled as a two-stage process where consumers first choose the products to search and then decide whether to purchase one of them. The model is estimated using data on purchases of liquid laundry detergent.

My estimates show that consumers incur significant costs to collect information. These costs are lower when products are displayed or featured. I find that the probability of searching and the expected number of searched products decrease with inventory levels. My results demonstrate that ignoring consideration sets and demand accumulation overestimates the own-price elasticity for products that are more often present in consideration sets and underestimates the own-price elasticity for products that are less often present in consideration sets.

Firms employ marketing devices to influence consideration sets. These devices have direct and strategic effects, which I explore using the estimates of the model. I show that if such devices were not available, the revenues of some products would increase due to identical search costs, even though the revenues for most of the products would fall. I find that using marketing devices to reduce a product search cost during a price promotion has modest effects on the overall category revenues, and decreases the revenues of some products.

1 Introduction

Many markets are characterized by stable product lines but frequent price fluctuations. In these markets, costly price search makes it necessary for consumers to form consideration sets[1] before making a final purchase decision. Traditional discrete choice models assume consumers have full information and consider all available products when they choose which one to buy. Ignoring consideration sets in the estimation of discrete choice models is likely to mismeasure key parameter estimates and lead to incorrect conclusions regarding the intensity of competition. In

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[1] I refer to a consideration set as the optimal subset of products searched by a consumer and within which the consumer makes an explicit utility comparison before choosing the product to purchase.

fact, consideration sets may explain part of the variation in consumers' choices. It is thus important to allow for consideration sets in the estimation of choice models.

I study the formation of consideration sets in storable goods markets, which is relevant for three reasons. First, many researchers believe consideration sets are important in the consumer decision-making process (Manski, 1977; Hauser and Wernerfelt, 1990; Goeree, 2008). However, it is extremely difficult to test for the presence of consideration sets using purchase data alone because the search process is usually not observed. Demand accumulation provides a way of testing the existence of consideration sets due to the relationship between consumer inventory and consideration sets. If consideration sets are formed through consumer optimization (Mehta, Rajiv and Srinivasan, 2003; Honka, 2010), one expects a negative correlation between consumer inventory and the number of products in the consideration set because the benefits of searching a product decrease with higher inventory. This negative correlation allows to test whether consumers' choices are made through a consideration set. The aforementioned correlation also provides a new source of variation to identify consideration sets and search costs.

Second, consideration sets and demand accumulation have effects on demand estimates and consumers choices. These effects are often in different directions and so, to correctly assess consumer behavior, it is important to evaluate and quantify the specific effects of consideration sets on demand estimates in storable goods markets. For instance, the effect on price elasticities of ignoring the coexistence of consideration sets and demand accumulation is ambiguous, even without a relation between consideration sets and inventory holdings. On one hand, ignoring consideration sets tends to overestimate own-price elasticities of products that are normally in the consideration set and to underestimate the responses for products that are not in the consideration set. On the other hand, Hendel and Nevo (2006) showed that static demand estimates without demand accumulation overestimate own-price elasticities and underestimate cross-price elasticities. Furthermore, inventory holdings may have effects on the composition and size of consideration sets, so ignoring that relation could also bias demand estimates.

Finally, consideration sets have effects on the intensity of competition and are sensitive to strategies such as price promotions and marketing devices (e.g., product display, feature ads) because firms compete through prices within the consideration set and through marketing devices to influence consideration sets (Eliaz and Spiegler, 2011). Some of these effects are specific to storable goods markets. For instance, in storable goods markets, periodic price promotions may reduce consideration-set size and increase the market power of some products. Likewise, sellers and producers of storable goods may have specific incentives to create search costs (or avoid their reduction) to change the competitive market structure and avoid the cannibalization of sister-brands.

To motivate the modeling exercise that follows, I start by providing evidence for the relevance of consideration sets in a storable goods market. In particular, using data for liquid laundry detergent, I find that the likelihood of households choosing their favorite brand (defined as the most frequently purchased brand in the sample) conditional on buying detergent decreases with the time elapsed since the last purchase. This correlation is consistent with the existence of consideration sets in storable goods markets because it is expected that the favorite brand is often in the consideration set and faces less competition with a short amount of time elapsed due to the smaller size of the consideration set. I show that under some assumptions we can use the correlation between the likelihood of choosing the favorite brand conditional on buying detergent and inventory holdings to distinguish a model with consideration sets from alternative models. I find positive effects of non-detergent expenditures and the time elapsed since the last purchase on the likelihood of purchasing detergent. Conversely, the quantity bought during the last purchase and the likelihood of purchasing detergent are negatively correlated. Those effects are consistent with costly search, demand accumulation, and storage costs.

Next, I propose a structural model to evaluate the effects of consideration sets and demand accumulation on demand estimates and firms' decisions. In my model, consumers have imperfect information about the prices and the realization of the random shocks associated with each product but they can engage in costly search to collect this information. Choice is modeled as a two-stage process where consumers first choose the products to search, and then, after searching, decide whether to purchase one of the searched products or not to purchase any product. The optimal consideration set is arrived at by making an explicit trade-off between the benefits and costs of searching an additional product. I assume consumers are forward looking and the quantity not consumed is stored as inventory. The model is applied to liquid laundry detergent using scanner panel data on all purchases made by households over a six-year period.

I compare the demand estimates from my model with those of alternative models in order to evaluate the effects of ignoring consideration sets in storable goods markets. The estimated model is used to construct some counterfactual exercises where I evaluate the strategic effects that arise from the existence of consideration sets and from the possibility of firms employing marketing devices to influence consideration sets.

My estimates show that consumers incur significant search costs to collect information. Those costs are considerably lower when products are displayed or featured. I find that the incentives to search are sensitive to inventory: the probability of searching and the expected number of products in the consideration set are negatively correlated with inventory levels.

My results suggest that ignoring consideration sets and demand accumulation overestimates the own-price elasticity for products that are more often present in consideration sets and underestimates the own-price elasticity for products that are less often present in consideration sets. Most of the cross-price elasticities are underestimated in a static model without consideration sets. Hence, assuming full information and a static model leads to incorrect conclusions regarding the intensity of competition.

The estimates of the model show that firms can use marketing devices (e.g., product display, feature ads) to influence consideration sets. These devices normally also inform consumers about a product's posted price. The use of these devices can therefore have different effects. A counterfactual exercise shows that if there were no marketing devices (i.e., product display, feature ads) to influence consideration sets, the revenues for most of the products would fall due to the high cost of searching. Nevertheless, the absence of these devices is positive for some products since it narrows the differences in the marginal cost of searching. Keeping high search costs can also be positive for some products because it prevents large competition within the consideration set by ensuring that consideration sets are small. In my empirical application the number of searched products is always small, and thus the latter potential positive effect is irrelevant. The absence of marketing devices is negative for consumers because it increases search frictions.

In another counterfactual I study the interaction between pricing and search costs. I find that lowering a product search cost during a price promotion has positive effects on market shares but modest or even negative effects on revenues. This strategy increases the likelihood of searching a product on promotion, which reduces the probability of missing a price promotion. In my model, however, this strategy also steals consumers away from other products and purchases during other shopping trips. The product switching and the purchase acceleration usually imply a substitution towards products at lower prices, explaining the modest effects of this strategy on revenues.

Finally, I analyze the implications of physical and economic constraints on the number of products that can employ marketing devices to influence consideration sets. I show that those constraints create strategic effects associated with the use of marketing devices. For instance, the display of one product can foreclose the display of other products, which creates a competitive advantage during consideration-set formation, reduces competition within the consideration set, and eliminates negative externalities from other products.

My paper is related to several streams in the economics and marketing literatures, particularly those on consideration sets, imperfect information, costly search and demand accumulation.

The concept of consideration sets was initially introduced by Howard and Sheth (1969) but some of the ideas were already present in Stigler's (1961) seminal paper. Stigler (1961) showed that rational consumers do not search all the products in the market. In his model the expected utility of further search decreases as more products are examined while search costs stay constant. Those ideas were supported by survey-based research that provided extensive evidence that consumers created such restricted subsets of alternatives (Hauser and Wernerfelt, 1990; Roberts and Lattin, 1991). The evidence is particularly stronger for low-involvement categories where consumer brand choice decision does not involve a full search, evaluation and price comparison of all brands available at the point of purchase. This literature has shown that consideration sets can be justified by consumers facing an overwhelmingly large variety of products and thus often using screening criteria to reduce the number of "relevant" alternatives (Hoyer, 1984).[2] In subsequent work, Mehta, Rajiv and Srinivasan (2003), Draganska and

[2] As pointed out by Hoyer (1984), in situations that involve repeated purchases over time and which can typically be considered as low in importance or involvement, *"the major goal is not to make an 'optimal' choice but, rather, to make a satisfactory choice while minimizing cognitive effort."*

Klapper (2010), and Kim, Albuquerque and Bronnenberg (2010) analyzed the role of consideration sets on demand estimation and their implications on marketing strategies. Eliaz and Spiegler (2011) proposed a model in which firms use costly marketing devices to influence consideration sets.

My paper is closely related to the literature on costly search that analyzes the importance of imperfect information and search costs in the estimation and identification of consumer demand.[3] Goeree (2008), Moraga-Gonzalez, Sandor and Wildenbeest (2009), Koulayev (2009), and Gentry (2011) demonstrated that imperfect information has an effect on demand estimates and allowing for limited information increases the predictive power of the choice model. Other papers, such as Hortaçsu and Syverson (2004), Hong and Shum (2006), Honka (2010), De los Santos, Hortaçsu and Wildenbeest (2012), and Seiler (2011) quantified the effects of imperfect information by evaluating the magnitude of search costs. In a paper close to mine, Seiler (2011) proposed a structural model with imperfect information where consumers engage in costly search. He considered a two-stage model where consumers first decide whether to search, and if they decide to do so, they then choose which brand to purchase. In his model the search decision is integrated into a dynamic demand framework for a storable product and search is modeled jointly with the purchase decision in order to fully capture consumer behavior in a structural way. In contrast to my paper, Seiler (2011) assumed the consumer includes either all the products in the choice set or none. Thus, in the first stage, rather than choosing a consideration set, the consumer only chooses whether to search or not.

Demand accumulation and its implications were documented by several papers (e.g., Boizot et al., 2001; Pesendorfer, 2002; Hendel and Nevo, 2006a)[4]. Erdem , Imai and Keane (2003) and Hendel and Nevo (2006b) proposed structural models with a storable good and forward-looking consumers to evaluate the implications of demand accumulation on demand estimates. Hendel and Nevo (2011) studied intertemporal price discrimination with demand accumulation and found that storability creates incentives for consumers to strategically time their purchases in order to benefit from the promotional prices.

The paper is organized as follows. Section 2 describes the data and Section 3 reports household purchasing patterns that suggest the presence of consideration sets in a storable good market. Section 4 describes the model. Sections 5 and 6 discuss the empirical strategy and the identification of the parameters of the model. Section 7 analyzes the results and Section 8 evaluates the effects that arise from the existence of consideration sets and from the possibility of employing marketing devices to influence them. Section 9 concludes the paper.

[3]See Baye, Morgan and Scholten (2007) for an overview of the literature on consumer costly search.
[4]See Blattberg and Neslin (1990) for a survey of the literature on demand accumulation.

2 Data

The data for this project are movement data for 50 IRI markets[5] and panel data for two behavior scan markets (Eau Claire, Wisconsin and Pittsfield, Massachusetts) obtained from the IRI Marketing data set. The data cover six years (313 weeks), beginning January 1, 2001. Both the movement and the panel data cover 30 product categories, however I restrict the analysis to the liquid laundry detergent category[6].

The IRI movement data contain store level movement data based on a weekly dataset. From the store-level data I observe the average price charged, the aggregate quantity sold, and the promotional activities for each universal product code (upc) in each store in each week. The data record two types of promotional activities: feature and display. The feature variable measures whether the product was advertised by the retailer. The display variable captures whether the product was displayed differently than usual within the store that week. The store-level data is used to obtain the weekly prices and point-of-purchase marketing variables for each of the available products during a given shopping trip.

The panel data are provided for the two behavior scan markets using a yearly static sample (i.e., for any given year, only households that have maintained in the panel for the entire 12 months are included). Panel recruitment and attrition are thus confined to the end-of-year time periods. The panel data contain information for all shopping trips of each household in the panel, regardless of the product bought and the store visited. The panel data also contain the complete purchase history for each product category with detailed information about the characteristics of each purchase occasion, including the upc code of the product bought, the number of units bought, and the amount of dollars spent.

To obtain a sample suitable for estimation, I undertook several procedures to clean the raw data (see Appendix B). An observation in the final sample is the purchases of a particular household at a particular store in a particular week. Therefore, the data also contain when a household went shopping without buying any liquid laundry detergent, as long as at least one item was purchased during the trip. By data construction in each observation there is at most one brand of liquid laundry detergent purchased.

The final sample consists of 225,597 observations. It contains 704 households, 23 stores, and 366 upc´s, aggregated into 37 brands from 17 different manufacturers. The sample covers 300 weeks. I observe 24,796 trips with purchases of liquid laundry detergent, associated with the purchase of 31,979 units with a value of 154,191 dollars.

Table 1 displays some descriptive statistics for the final sample. The mean price of the brands available in the

[5] An IRI market is a geographic unit typically defined as an agglomeration of counties, usually covering a major metropolitan area but sometimes covering a part of a region. Markets with the highest retailer concentration (markets in which the top grocery chain has more than fifty percent) are not included, as these markets may reveal information about retailer chain names and information regarding their operations (Bronnenberg, Kruger and Mela, 2008).

[6] As pointed out by Seiler (2011), liquid laundry detergent is a suitable product category choice given my goals because it is storable and purchased infrequently. Thus, consumer search behavior is likely to be important and it is not expected an huge impact of promotions on weekly consumption. Laundry detergent comes in two main forms: liquid and powder. Most of the quantity sold is from liquid laundry detergent. By this reason I restrict the analysis to the liquid form.

store in each purchase occasion is, on average, 1.019 dollars per pound[7]. The average duration between trips is 5 days and the time elapsed since the last purchase of liquid laundry detergent is nearly 6 weeks. The average expenditure per trip is 62.99 dollars ($62.31 excluding detergent) and 95 percent of the trips occur in stores known by the household (i.e., stores where the time elapsed since the last visit is less than 12 weeks). The time elapsed since the last purchase of detergent, total expenditure, and likelihood of visiting a known store are higher in shopping trips with a purchase of liquid laundry detergent. Conditional on buying liquid detergent, the choice of the most frequently purchased brand occurs when the time elapsed since the last purchase is shorter. Those differences on the distribution of the time elapsed since the last purchase are illustrated in figures 1 and 2.

The typical (median) household has total income of $50,000 and is composed by 2 members. A household, on average, made nearly 337 shopping trips over the six-year period, spending around 72.80 dollars. In 38 of those trips the typical household purchased liquid laundry detergent. The average paid price was 0.745. A household purchased, on average, nearly 45 units of liquid laundry detergent and 6 different brands. The market for liquid laundry detergent is very concentrated at the household level as shown by the Herfindahl indexes which are around 0.5 for the brand and 0.58 for the manufacturers. Therefore, the purchases are concentrated at two main brands and two main manufacturers. Households usually visit a small number of stores and only buy liquid laundry detergent in a smaller subset of those stores. Households go shopping once or twice a week and, on average, the time elapsed since the last purchase of liquid laundry detergent is nearly 7 weeks.

On average, each brand includes nearly 10 upc's and the average price is 0.83. The brands' market shares range from 0.003 percent to 20.6 percent with an average of 2.7 percent. The market for liquid laundry detergent is very concentrated as shown by my data where the Herfindahl index is 0.11 and 8 brands (Tide, Dynamo, Xtra, Purex, All, Arm&Hammer, Era, Wisk) make up about 86 percent of the purchases, with all the other brands having substantially lower market shares. Nevertheless, the market is not as concentrated at the brand level as at the household level because preferred brands differ by household. The market is controlled by three manufacturers: Procter&Gamble, Church&Dwight and Lever Brothers. Each of them owns 2 out of the 8 brands with the highest market shares. Together these three manufacturers account for roughly two thirds of the quantity sold. There is a large heterogeneity of prices across the top 8 brands with average prices that range from 0.37 for Xtra to 1.25 for Tide. In my data, the proportion of display is very similar among the top brands with values between 5.1 percent and 6.1 percent. In contrast, there is some heterogeneity among those brands with regard to feature ads.

Figure 3 displays the evolution of prices for 4 different products at a specific store. The figure reveals large price variation across products and over time within the same products. This price variation is important to justify the relevance of imperfect information. If prices had small variation, imperfect information about actual prices would not be a main concern because information from previous prices would enable precise estimates of actual prices.

[7] All prices from this point on are in dollars per pound.

The week-to-week price variation creates a natural economic motive to search.

3 Preliminary Analysis

In this section I analyze household purchasing patterns. My goal is to determine whether those patterns suggest the presence of consideration sets in storable goods markets. The empirical evidence presented here will be used to construct the structural model described in the following sections.

Table 3 illustrates the impact of shopping-trip characteristics on the purchase of liquid laundry detergent. Each column of the table reports the coefficients from regressing a dummy variable equal to 1 for the purchase of liquid detergent on a set of control variables. This table reveals that the effect of the price of the most frequently purchased brand by the household is highly significant and has a large negative effect on the likelihood of purchasing liquid laundry detergent. In contrast, the effect of the mean price of the brands available in the store is positive but only significant when one does not include all the controls.

Table 3 shows that the likelihood of purchasing liquid laundry detergent is higher when the non-detergent expenditure is larger and when the shopping trip takes place in a store that was visited in the last 12 weeks. These results show that the non-detergent expenditure and knowledge of the store do matter substantially for the purchase probability. I expect that these two variables have effects on search costs but I do not expect that they have effects on the preferences for consuming or purchasing detergent. Therefore, the observed correlation is consistent with costly search and with the hypothesis that the non-detergent expenditure and knowledge of the store have an effect on search costs. I believe these variables essentially affect the cost of going to the detergent aisle and thus will affect the fixed cost of searching.

Columns 2 to 4 report the effects of the characteristics of the last purchase of liquid laundry detergent on the likelihood of buying liquid laundry detergent during the actual shopping trip. Those columns reveal that the likelihood of purchasing detergent increases with the time elapsed since the last purchase and decreases with the quantity bought during the last purchase. I expect that the time elapsed since the last purchase of detergent and the quantity bought during that last purchase are good proxies for inventory, and I do not expect that these variables directly affect preferences. In the presence of demand accumulation and storage costs, the value of buying detergent is negatively correlated with inventory levels. The observed effects of the time elapsed since the last purchase and the quantity bought during the last purchase on the likelihood of buying detergent are consistent with that negative correlation.

In table 4, I analyze the likelihood of choosing the most frequently purchased brand conditional on buying liquid laundry detergent. This table reports the results from regressing a dummy variable equal to 1 for the choice of the most frequently purchased brand on a set of control variables. In those regressions I only consider shopping trips with purchases. Neither a standard discrete choice model nor a model with demand accumulation but without consideration sets predicts an effect of inventory holdings on the choice of the brand to buy conditional on purchasing detergent.[8] In contrast, a correlation between inventory holdings and the likelihood of buying a given brand conditional on purchasing liquid laundry detergent is expected in a model with demand accumulation and consideration sets. In particular, if consumers' consideration sets are derived from an optimization model, a negative correlation between inventory and the number of products in the consideration set is expected. This negative correlation is due to the lower incentives to buy a product when inventory is high and the consequent lower incentives to search.

Table 4 shows that the likelihood of choosing the most frequently purchased brand conditional on buying liquid detergent decreases with the time elapsed since the last purchase. It is expected that the time elapsed since the last purchase is negatively correlated with inventory. Therefore, the correlation found in table 4 can be explained by the proposed relationship between consideration-set formation and inventory. According to that relationship, with a short amount of time elapsed since the last purchase, the consideration set includes few brands. Thus, conditional on buying detergent, the likelihood of choosing the most frequently purchased brand is higher when the time elapsed since the last purchase is shorter because the most frequently purchased brand is often in the consideration set and faces fewer competitors in this situation. The results in table 4 suggest that the quantity bought during the last purchase does not have a significant effect on the likelihood of buying the most frequently purchased brand.

Overall, the relationship between the time elapsed since the last purchase and the likelihood of choosing the most frequently purchased brand conditional on buying detergent reveals evidence for consideration sets in storable goods markets. The observed evidence would be sufficient to guarantee the existence of consideration sets only if one could rule out a relation between inventory and consideration sets for all the alternative hypotheses. Nevertheless, the observed evidence is always a necessary condition if the true model contains consideration sets and demand accumulation.

In the appendix I propose a formal test for the presence of consideration sets based on the correlation between the time elapsed since the last purchase and the likelihood of buying the most frequently purchased brand. This test is useful because it allows us to evaluate for the presence of consideration sets in storable goods markets using scanner panel data alone. Due to the extreme difficulty of testing for consideration sets without survey data, the test shows the importance of studying consideration sets with storable goods. In section 6, I show that the correlation found in table 4 is also relevant for the identification of the parameters of my model.

[8] I restrict my attention to models with demand accumulation where products are perfect substitutes in consumption and the random shocks to consumer choices are independent (see appendix for specific assumptions). In a standard discrete choice model, preferences are not affected by inventory, so the choice of the product is always independent of inventory. Hendel and Nevo (2006b) showed that in their model if products are perfect substitutes in consumption and the random shocks to consumer choices are independent and identically distributed extreme value type I, the probability of choosing a brand conditional on size is independent of inventory (see Hendel and Nevo, 2006b, for a discussion). In the appendix I discuss how this result can be extended under different assumptions.

4 Model

This section presents a model of consumer choice that nests the possibility of consideration sets and demand accumulation.

4.1 Setup

I model choice as a two-stage process. In the first-stage, the consumer knows the products available but does not know the price or the realization of the random shocks associated with each product. At this stage, the consumer decides whether to search or not. If the consumer does not search, she does not have to make another decision in the current time period. If the consumer searches, she will choose the set of products to search. The consumer pays a fixed cost $\bar{S}$ to search and pays a cost sc_{jxt} to collect the information about the price and realization of the random shocks for a specific brand j of size x.[9] In the second stage, the consumer observes the prices and the random shocks for the products searched and then chooses whether to purchase one of the options in the consideration set or not to purchase any product. In this stage, the consumer also chooses how much to consume and to store at the current period. I will refer to the first stage as the "search stage" and I will refer to the second stage as the "purchase stage".

Consideration sets are chosen to balance the benefit and cost of searching. I consider a simultaneous search process where consumers commit to a fixed number of searches before the beginning of the actual search. In this process the search only finishes after the consumer searched the number of products she committed to, even if she gets a good search outcome early on.[10]

I define a product as a brand/pack-size combination. Let Ω_{sxt} be the set of brands of size x available in store s at period t and let Λ_{sxt} be the powerset of Ω_{sxt} excluding the empty set (the choice of not searching). Define $\Lambda_{st} \equiv \cup_x \Lambda_{sxt}$. In each purchase occasion a consumer can buy at most one product. The value obtained by consumer i in period t from purchasing brand j with size x is given by

$$\begin{aligned} U_{ijxt} &= \alpha_i p_{jxt} + \gamma_i a_{jxt} + \xi_{ijx} + \epsilon_{ijxt} \\ &= \delta_{ijxt} + \epsilon_{ijxt} \end{aligned}$$

where p_{jxt} is the price of alternative j with size x at time t, a_{jxt} are nonprice observed attributes of alternative j with size x at time t, ξ_{ijx} is an idiosyncratic taste for brand j with size x that could be a function of brand-size

[9] My definition of search costs includes the cost of including a product at any given purchase occasion and an evaluation cost (see Hauser and Wernerfelt, 1990). The cost of searching includes, among others, the time spent to find and collect information about a product, mental storage and processing costs (e.g., reading ingredients).

[10] See Honka (2010) and De los Santos, Hortacsu and Wildenbeest (2012) for a discussion about the sequential and simultaneous search processes.

characteristics and varies across consumers, and ϵ_{ijxt} is a random shock to consumer choice.[11] The value associated with a no purchase is

$$U_{i0t} = \epsilon_{i0t}$$

Consumer i obtains per period utility of consumption $u_i\left(C_{it}\right)$, where C_{it} is the quantity consumed of the good in question. C_{it} is defined as the sum of consumption of all varieties in period t and I assume that all varieties provide the same utility (i.e., products are perfect substitutes in consumption). The previous assumptions imply that product differentiation takes place at the moment of purchase but not at the moment of consumption.[12]

The product is storable, so the quantity not consumed is stored as inventory. Since consumption is not affected by which brand is in storage, I can define inventory I_{it} as the total quantity stored of the good in question. The evolution of inventory is described by

$$I_{it} = I_{it-1} + x_{it} - C_{it}$$

where I_{it-1} is the current inventory and x_{it} is the size of the alternative purchased at period t. Consumer pays a storage cost $T_i\left(I_{it}\right)$ to store quantity I_{it} of the good.

My framework does not attempt to model store choice. The timing and incidence of shopping trips to the supermarket are exogenous[13]. The search process is modeled as a decision to search or not within each store for an exogenously given sequence of shopping trips, as in Seiler (2011) and Hartman and Nair (2010).

Let d_t^{ps} and d_t^{ss} describe, respectively, consumer's choice in the purchase stage and in the search stage. Define $d_t^{ss} = \phi$ if the consumer chooses not to search and $d_t^{ss} = K$ if the consumer chooses the consideration set K in the search stage. Let $d_{ijxt}^{ps} = 1$ if consumer chooses brand j of size x in the purchase stage and $d_{ijxt}^{ps} = 0$ otherwise. Define $d_{ijt}^{ps} = \sum_x d_{ijxt}^{ps}$ and $d_{ixt}^{ps} = \sum_j d_{ijxt}^{ps}$.

In the next lines I define the flow utilities[14] in each stage of the model. To simplify the notation, I omit the subscript i from now on.

The flow utility from not purchasing is

$$\begin{aligned} u_{0t}^{ps} &= u\left(C_t\right) - T\left(I_t\right) + \epsilon_{0t} \\ &= \tilde{u}_{0t}^{ps} + \epsilon_{0t} \end{aligned}$$

[11] The prices and the nonprice attributes are store specific. The idiosyncratic tastes and the random shocks can also be store specific. I only omit the store subscript from those variables to simplify the notation. Likewise, in the specification of search costs, the display and feature ads variables are store specific but the subscript for the store is omitted.

[12] See Hendel and Nevo (2006b) for a discussion of these assumptions.

[13] This assumption implies that the intention to purchase detergent does not cause consumers to go shopping. This assumption is supported by the evidence that consumer decision making usually occurs in store (Hoch and Deighton, 1989, Dreze, Hoch and Purk, 1994). According to Seiler (2011), this assumption is also reasonable because detergents are a small fraction of the total expenditure on the typical shopping trip and there are small effects, if any, of store-traffic promotions on individual items.

[14] The flow utility is defined as the utility in a particular time period and choice stage.

and the flow utility from purchasing brand j of size x is

$$\begin{aligned} u^{ps}_{jxt} &= u\left(C_t\right) - T\left(I_t\right) + \alpha p_{jxt} + \gamma a_{jxt} + \xi_{jx} + \epsilon_{jxt} \\ &= \tilde{u}^{ps}_{jxt} + \epsilon_{jxt} \end{aligned}$$

In the search stage the utility obtained from not searching is

$$\begin{aligned} u^{ss}_{iNSt} &= u\left(C_t\right) - T\left(I_t\right) + \bar{\epsilon}_{NSt} \\ &= \tilde{u}^{ps}_{0t} + \bar{\epsilon}_{NSt} \end{aligned}$$

The one-period flow utility from searching and choosing the consideration set K is

$$\begin{aligned} u^{ss}_{Kt} &= -SC_{Kt} + \bar{\epsilon}_{Kt} \\ &= \tilde{u}^{ss}_{Kt} + \bar{\epsilon}_{Kt} \end{aligned}$$

where $\bar{\epsilon}_{Kt}$ is a random shock to consideration set choice[15] and SC_{Kt} is the cost of searching consideration set K at period t. The search costs include a fixed component $\bar{S}$ and a specific cost sc of searching each product in the consideration set. That is,

$$SC_{Kt} = \bar{S} + \sum_{l \in K} sc_l$$

4.2 Dynamic Problem

Consumers are forward looking and maximize the present expected value of future utility flows[16]. Let s_t be the state variables and μ be an infinite sequence of decision rules $\mu_t = \left\{d^{ss}_t, d^{ps}_{t|K}\right\}$ with $d^{ps}_{t|K} = (d^{ps}_t | d^{ss}_t = K)$. The process governing (s_t, μ_t) is the solution to the following problem

$$V_\theta\left(s_t\right) = \max_{\mu} E\left[\sum_{\tau=1}^{\infty} \beta^{\tau - t} f\left(s_t, \mu_t, \theta\right) \middle| s_t\right]$$

The function $V_\theta\left(s_t\right)$ is the value function and is the unique solution to the Bellman equation given by

$$V_\theta\left(s_t\right) = \max_{d^{ss}_t} \left\{ \sum_{k \in \Lambda \cup \{\phi\}} d^{ss}_k \left[v^{ss}_k\left(s_t\right) + \bar{\epsilon}_{kt}\right] \right\}$$

[15] See De los Santos, Hortacsu and Wildenbeest (2012) for a discussion of possible interpretations of the random shock $\bar{\epsilon}$.

[16] As pointed out by Hauser and Wernerfelt (1990), I do not assume that in each shopping trip consumers are calculating the solution of the problem described. I assume only that the problem described is a good representation of individual-specific and situation-specific judgements.

where v_k^{ss} is the choice-specific value function in the search stage net of the error terms.

Let s_t^{ss} and s_t^{ps} denote, respectively, the state variables in the search and in the purchase stage. The choice-specific value function in the search stage if the consumer chooses not to search is

$$v_{NS}^{ss}\left(s_t^{ss}\right) = \tilde{u}_{NS,t}^{ss} + \beta E\left[\max_{k\in\Lambda\cup\{\phi\}}\left\{v_k^{ss}\left(s_{t+1}^{ss}|x_t, d_t^{ss}=NS\right)+\tilde{\epsilon}_{kt+1}\right\}\right]$$

and the choice-specific value function in the search stage when consumer chooses the consideration set K is

$$v_K^{ss}\left(s_t^{ss}\right) = E\left[\max_{(j,x)\in K}\left\{v_{jx}^{ps}\left(s_t^{ps}\right)+\epsilon_{jxt}\right\}\right] - SC_{Kt}$$

where v_{jx}^{ps} denotes the choice-specific value function in the purchase stage net of the error terms.

The choice-specific value function in the purchase stage net of the error terms can be written as

$$\begin{aligned} v_{jx}^{ps}\left(s_t^{ps}\right) &= \tilde{u}_{jxt}^{ps} + \beta E\left[\max_{k\in\Lambda\cup\{\phi\}}\left\{v_k^{ss}\left(s_{t+1}^{ss}|s_t, d_t^{ps}=(j,x)\right)+\tilde{\epsilon}_{kt+1}\right\}\right] \\ &= \alpha p_{jxt} + \gamma a_{jxt} + \xi_{jx} + M\left(s_t, j, x\right) \end{aligned}$$

where

$$M\left(s_t, j, x\right) = u\left(C_t\right) - T\left(I_t\right) + \beta E\left[\max_{k\in\Lambda\cup\{\phi\}}\left\{v_k^{ss}\left(s_{t+1}^{ss}|s_t, d_t^{ps}=(j,x)\right)+\tilde{\epsilon}_{kt+1}\right\}\right]$$

Thus, the value function for the search stage is

$$V^{ss}\left(s_t^{ss}, \bar{\epsilon}_t\right) = \max_{k\in\Lambda\cup\{\phi\}}\left\{v_k^{ss}\left(s_t^{ss}\right)+\bar{\epsilon}_{kt}\right\}$$

and the value function for the purchase stage is

$$V^{ps}\left(s_t^{ps}, \epsilon_t\right) = \max_{(j,x)\in K}\left\{v_{jx}^{ps}\left(s_t^{ps}\right)+\epsilon_{jxt}\right\}$$

where K is the consideration set for the purchase stage.

The state variables for the search stage include the current inventory, the search costs, the household price expectations, $\bar{\epsilon}_t$, and the expectation about ϵ_t. The state variables for the purchase stage include the current inventory, the prices, the consideration set, and ϵ_t.

In the search stage consumers face uncertainty about the actual prices and the random shocks to consumer choices. I make the following assumptions about the distribution of those variables. Households price expectations in the search stage are independent over products and over time (i.e., price expectations are not influenced by past realizations of prices) and they do not depend on other state variables. I assume that households price expectations correspond to the observed average prices. Households expectations about ϵ_t assume that those variables are independent and identically distributed extreme value type I.

In the search stage the random shocks $\bar{\epsilon}$ are observed by the consumer but not by the researcher. I assume $\{\bar{\epsilon}_t\}_{t=0}^{\infty}$ are independent and identically distributed extreme value type I. Conditional on the current values of the decision and the observed state variables, the next period observed state variables do not depend on $\bar{\epsilon}_t$. Finally, I assume the search costs are independent over time and do not depend on other state variables.

Let $V^{ps,k}(I_t, p_t, \epsilon_t)$ be the value function for the purchase stage conditional on choosing the consideration set k at time t. The previous assumptions imply that the expectations of V^{ss} and $V^{ps,k}$ given the state and current behavior are functions of end-of-period inventories. Let me denote such function as $V^e_{ss}(I_t)$ and $V^e_{ps,k}(I_t)$. My assumptions imply that the solution of the dynamic problem can be fully characterized by these functions:

$$\begin{aligned}
V^e_{ss}(I_t) &= \int \log \sum_{k \in \Lambda \cup \{\phi\}} \exp\left[v^{ss}_k(s_t)\right] dF_{SC} \\
V^e_{ps,k}(I_t) &= \int \log \sum_{jx \in k} \exp\left[\tilde{u}^{ps}_{jxt} + \beta V^e_{ss}(I_{t+1})\right] dF_p
\end{aligned}$$

4.3 Choice Probabilities

For the purpose of estimation I have to compute the unconditional probability of choosing brand j of size x given by

$$P(d_{jxt}|s_t) = \sum_{K \in \Lambda} P\left(d^{ps}_{jxt}\middle| s_t, K\right) P\left(d^{ss}_t = K|s_t\right)$$

The probability of not purchasing is

$$P(d_{0t}|s_t) = P\left(d^{ss}_t = \phi|s_t\right) + \sum_{K \in \Lambda} P\left(d^{ps}_{0t}\middle| s_t, K\right) P\left(d^{ss}_t = K|s_t\right)$$

The probability of choosing the brand j of size x conditional on choosing consideration set K is

$$P(d_{jxt}|s_t, K) = \frac{\exp\left[M(s_t, j, x) + \delta_{jxt}\right]}{\exp\left[M(s_t, 0)\right] + \sum_{(m,z) \in K \setminus \{0\}} \exp\left[M(s_t, m, z) + \delta_{mzt}\right]}$$

The probability of not searching is

$$P(\phi|s_t) = \frac{\exp\left[M(s_t, 0)\right]}{\exp\left[M(s_t, 0)\right] + \sum_{L \in \Lambda} \exp\left[E_p \log\left\{\exp\left[M(s_t, 0)\right] + \sum_{(m,z) \in L \setminus \{0\}} \exp\left[M(s_t, m, z)\right] + \delta_{mzt}\right\} - SC_{Lt}\right]}$$

and

$$P\left(K|s_t\right)=\frac{\exp\left[v_K^{ss}\left(s_t^{ss}\right)\right]}{\sum_{L\in\Lambda\cup\{\phi\}}\exp\left[v_L^{ss}\left(s_t^{ss}\right)\right]}$$

$$=\frac{\exp\left[E_p\log\left\{\exp\left[M\left(s_t,0\right)\right]+\sum_{j\in K_x\setminus\{0\}}\exp\left[M\left(s_t,j,x\right)+\delta_{jxt}\right]\right\}-SC_{Kt}\right]}{\exp\left[M\left(s_t,0\right)\right]+\sum_{L\in\Lambda}\exp\left[E_p\log\left\{\exp\left[M\left(s_t,0\right)\right]+\sum_{(m,z)\in L\setminus\{0\}}\exp\left[M\left(s_t,m,z\right)+\delta_{mzt}\right]\right\}-SC_{Lt}\right]}$$

5 Estimation

In the estimation of the structural model I consider an adapted version of the nested algorithm proposed by Rust (1987). In the algorithm, the solution of the dynamic programming problem is nested within the parameter search of the estimation. The parameters of the model are estimated by maximizing the likelihood of observed choices. This likelihood is characterized by

$$\log L=\sum_{i,j,x}d_{ijxt}\ln P\left(d_{ijxt}^{ps}\middle|\,s_t\right)$$

The computation of the likelihood is nested into the search of those parameters. The algorithm consists of two loops: an outer loop that searches over parameter values, and an inner loop that, for a given set of parameters, solves the dynamic programming problem and matches predicted choices using the likelihood of observed choices. The numerical solution is obtained by value function iteration using a discrete approximation.

One of the challenges in implementing the algorithm is that I do not observe the products considered by the household, and hence I need to integrate over all possible consideration sets. With a large number of products, this strategy creates a complex combinatorial problem. To make the problem tractable, I make the following assumptions. First, households do not include in their consideration sets brands that they did not buy in my sample. Second, products can be aggregated into ten brands: Tide, Xtra, Dynamo, Purex, All, Arm&Hammer, Era, Wisk, a Private Label, and a composite brand that includes all the other brands. This simplification drastically reduces the number of possible consideration sets, which reduces the computational burden. Third, each product can be assigned to one of three sizes: small, medium and large[17]. Finally, consideration sets only include products of the same size.

In my data, I also do not observe inventory or consumption decisions. The estimation of inventory holdings follows Hendel and Nevo (2006). For each household, I start with an initial guess for inventories and then calculate the inventory in each week using the observed purchases and the estimated consumption. To reduce the impact of the initial guess, the first 8 visits of each household are used to simulate the distribution of inventories but are not considered in the estimation of the likelihood.

To simplify the estimation procedure, I assume that households are consuming detergent at a constant rate γ

[17] Products with size greater than 0 and lower than 4lb were assigned to the small size, products with size greater than 4lb and lower than 8lb were assigned to the medium size, and products with size greater than 8lb were assigned to the large size.

until they run out. I can recover the rate of consumption because I observe households over a long period of time. The rate of consumption for each household is the ratio of the total amount purchased to the overall time in the sample. One of the problems with this procedure is that it ignores stock-outs. Nevertheless, I believe that the measurement error created by computing the consumption rate is small since I observe several purchases for each household and the consumption rate is consumer-specific.

For the estimation I assume $\delta_{ijxt} = \alpha_i p_{jxt} + \xi_{jx}$. Thus, the parameters to be estimated are the price coefficient α_i, the brand-size dummies ξ_{jx}, the parameterized functions for storage costs, consumption behavior and search costs.

I assume storage costs are quadratic: $T(I_t) = \theta_0 I_t + \theta_1 I_t^2$; and the utility of consumption is $u(C_t) = 0.1C_t$. The taste for a product is characterized by brand-size dummies. As for the search costs, I assume that the fixed cost of searching $\bar{S}$ is a function of non-detergent expenditure and the specific cost sc of searching a product is a function of product display and feature ads[18]. For the empirical application, specific functional forms for $\bar{S}$ and sc need to be specified. In my model it is not possible to identify the baseline search cost separately from the intrinsic quality of the products for an additive specification. I take that into account in the choice of the functional forms. For the fixed cost I assume that

$$\bar{S} = \tilde{S}.\exp\left(z^{s\prime}\beta^s\right)$$

where z^s are the covariates that affect the fixed search cost and $\tilde{S}$ and β^s are parameters to be estimated. For sc I assume that

$$sc = \tilde{s}.\exp\left(z^{g\prime}\beta^g\right)$$

where z^g are the covariates that affect variable search costs and $\tilde{s}$ and β^g are parameters to be estimated. The functional forms make sure that fixed and variable search costs have the same sign for all values of the respective covariates. The direction in which search costs shift with z^s and z^g is not constrained a priory. The fixed and variable search costs can be positive or negative depending on the direction of $\tilde{S}$ and $\tilde{s}$, respectively. A simple t-test on those coefficients enables to test for the relevance of fixed and variable search costs.

The estimation procedure is performed using visits 9-36 of each household. I use purchases without store information to update inventories but I do not use those purchases in the estimation of the likelihood.

Given the heterogeneity in the price coefficients and consumption rate, without further aggregation, I would have to solve a dynamic programming problem for each household. To avoid that, I aggregate households into different types that vary by income, family size, consumption rate, and by the brands that can be included in the

[18] In my model product display and feature ads only have effects on the search costs. Therefore, the role of those variables is to create salience and to inform consumers about the characteristics and prices of a product. It is usually assumed that displays and feature ads reduce price search costs to zero because they give price information. Nevertheless, as pointed out by Mehta et al. (2003), some consumers do not observe displays and feature ads, so one must model each consumer as being exposed to the stimuli created by displays and feature ads. Therefore, at the aggregate level, one would only expect the search costs for a product's posted price to reduce by a certain fraction (and not to zero) in the presence of displays or feature ads.

consideration set.

For the estimation I normalize one unit of inventory holdings and size to be 10 pounds and one unit of non-detergent expenditure to be \$10. The discount factor associated with the dynamic problem was set equal to 0.99.

6 Identification

The identification of the price coefficient α_i and the brand-size dummies ξ_{jx} is standard. Variation over time in prices and choices identifies the sensitivity to price. Household heterogeneity in price sensitivity is captured by making the sensitivity to price a function of household income and size. Therefore, differences across households enable us to recover the heterogeneity in price sensitivity. The brand-size dummies are identified from the variation in market shares across products.

A common issue in the estimation of discrete choice models is the potential endogeneity problem that arises if prices are correlated with the unobserved variable ξ. I deal with potential endogeneity by (i) assuming that $\xi_{jxt} = \xi_{jx}$ and controlling it with fixed effects, (ii) controlling for displays and feature ads through their effects on search costs, and (iii) using weekly price data for each store.

According to my modelling assumptions, if all products have the same level of display and feature ads, the cost of searching increases linearly with the number of products searched. In contrast, the benefit of searching tends to have a concave shape on the number of searched products because it is the expected inclusive value of each consideration set. As illustrated by table 4, an increase in inventory decreases the number of searched products. In my model, inventory changes the benefit of searching but not the cost of searching. Therefore, I can use the shifts on the benefit of searching created by changes in inventory to identify the marginal cost of searching. That is, when the level of display and feature ads is equal for all products, we can use the variation in inventory to identify $\tilde{s}$.

The effects of product display and feature ads on variable search costs can be inferred from the patterns of purchases, from the variation over time and across products in displays and feature ads, and from the assumption about consideration-set formation. I assume that product display and feature ads only have effects on search costs. This exclusion restriction implies that once the decision to search is made, displays and feature ads do not influence the choice. Nevertheless, those variables will have an effect on whether the household searches a product. The variation over time and across products in displays and feature ads will affect the likelihood of including a product in the consideration set and thus will influence the likelihood of purchasing a specific product during a particular shopping trip. Therefore, I can use the variation in choices and the variation in displays and feature ads to identify the effects of product display and feature ads on the marginal cost of searching. Likewise, I can identify $\tilde{s}$ because this parameter determines how much product display and feature ads matter relative to the other components of the utility.

Similarly, one of the key elements for the identification of the fixed search costs is the exclusion restriction I impose on the variables that determine these costs. It is not expected that non-detergent expenditures have an effect on the preferences for buying or consuming detergent. I therefore assume that non-detergent expenditures affect only the fixed cost of searching. Hence, non-detergent expenditures do not influence the choice after searching but they affect the likelihood of going to the detergent aisle and search. I can identify the fixed search costs through the variation created by non-detergent expenditures in the likelihood of buying detergent.

The identification of consumption behavior is critical for the identification of the utility and storage costs. If inventory and consumption were observed, the identification of the functions of these variables would follow standard arguments. However, I do not observe inventory and consumption and thus I need to be able to identify consumption behavior.

An important point is the distinction between storage and search costs since both can reduce the possibility of exploiting price reductions. There do exist some specificities in the model that allow me to distinguish between the two. First, the exclusion restrictions ensure that the variation in the variables that determine the search costs only influences the search costs. In particular, if the proportion of missed promotions is lower when products are displayed or featured, or when non-detergent expenditures are larger, one expects search costs to play an important role.

Second, the possibility of purchasing different sizes creates other source of variation to distinguish storage costs from search costs. On one hand, large pack-sizes increase inventory, which creates higher disutility from storage costs. On the other hand, large pack-sizes reduce the likelihood of searching during future shopping trips, which decreases search costs. Therefore, if consumers miss promotions and purchase large pack-sizes, search costs should be high. Conversely, if consumers miss promotions and purchase small pack-sizes, storage costs should be high.

7 Results

7.1 Parameter Estimates

The parameter estimates are reported in table 5. The price coefficient and the storage cost are significant and have the expected sign. According to my estimates, if the beginning of period inventory is 3lb, buying a 6.25lb container of liquid detergent increases the storage cost for the median household by nearly $0.51.

As for the variable search costs, I find that the display and feature ads of a product reduce the additional cost of searching that product. The effect is significant and large. I find feature ads to be more effective than displays in influencing search behavior. The positive effects of displays and feature ads on reducing a product search cost are in line with some of the findings in the economics and marketing literatures (see, for example, Gentry, 2011). Product display and feature ads provide price information, which explains the positive effects they have on reducing the price search cost. One expects that search costs decrease with advertising for reasons related to memory, accessibility and expertise (see Hauser and Wernerfelt, 1990). Moreover, a product on display is easier to find, which also reduces the search cost of that product.

My estimates reveal a fixed cost of searching that is decreasing in the non-detergent expenditure. In particular, if the non-detergent expenditure during the typical (median) shopping trip increases by 10 percent, the fixed cost of searching decreases by nearly 11 percent. This result is in line with the findings in Seiler (2011). For the typical household during a typical shopping trip, the fixed search cost is equal to 38 percent of the cost of searching a product that is neither displayed nor featured.

Overall, my estimates reveal that: (i) conditional on visiting a store, the cost of going to the detergent aisle is small but the cost of searching a specific product is large, (ii) the cost of searching a product that is not displayed or featured is nearly twice the cost of searching a product displayed and featured, and (iii) non-detergent expenditures can significantly reduce the fixed search costs.

In order to evaluate the importance of search costs, I computed the display-demand elasticities using the estimates of the model. These elasticities also illustrate some of the effects of displays.[19] Table 6 reports the estimated display-demand elasticities. According to that table, product display has a positive effect on the purchase of the displayed product and seems to be more beneficial for products less often present in consideration sets[20]. In my model, the display of one product can have positive or negative effects on the other products. Nevertheless, due to the small size of the consideration sets in my empirical application, normally the only effect of displays is switching the products in the consideration set, and thus the display of one product is usually negative for the other products.

Figure 4 shows that the probability of searching is very sensitive to inventory holdings. For a typical household during a typical shopping trip, the probability of searching drops from 0.65 to 0.27 when inventory holdings grow from 0 to 20 pounds[21]. Conditional on searching, consumers usually only search one or two products. The probability of searching more than one product decreases with inventory levels.

[19] See section 8 for a detailed discussion of the effects of marketing devices.

[20] This result is partially explained by the assumptions regarding the functional forms. In my model, the effect of displaying a product on the probability of choosing that product is decreasing in the probability of searching that product and in the probability of buying it conditional on searching. Therefore, one only would expect a lower effect of display for products that are less often in the consideration set if the probability of searching was negatively correlated with the probability of buying a product conditional on searching.

[21] For these estimates I consider a household whose consideration sets can include all brands and I assume all products are neither displayed nor featured.

7.2 Model Fit and Comparison with Alternative Models

In this subsection I compare the proposed model with alternative models. The objective of this comparison is twofold. The first goal is to evaluate the biases created by assuming full information, no search costs or no demand accumulation. The second is to evaluate the fit of the proposed model. Table 7 reports the estimates for alternative choice models. Column 1 shows the results for a model without consideration sets and demand accumulation. Column 2 shows the results for a model with demand accumulation but without consideration sets. Column 3 shows the results for a dynamic model without consideration sets where product display and feature ads change preferences. Finally, column 4 shows the results for a model with consideration sets but without demand accumulation.

According to my results, ignoring search costs and consideration sets overestimates storage costs, except in the case of large inventory holdings. Seiler (2011) found a similar result. Both search costs and storage costs lead consumers to miss price promotions. Therefore, if the estimation ignores search costs, the estimated storage costs need to be higher in order to fit the observed missed promotions.

Table 7 shows that ignoring demand accumulation has the following effects on the estimates of fixed and variable search costs: (a) overestimates the effects of non-detergent expenditures on reducing the fixed cost of searching; (b) overestimates the effects of product display and feature ads on reducing the variable search costs; (c) for the median household, overestimates the additional cost of searching an additional product without display or feature ads and slightly affects the variable search cost with product display and feature ads; and (d) for the median household, underestimates the fixed search cost when the non-detergent expenditure is large and overestimates it when the non-detergent expenditure is small.

Traditional discrete choice models assume that displays and feature ads only influence consumers' choices by changing preferences. To evaluate whether displays and feature ads change preferences or affect the consumers' search behavior, I compare my model with a dynamic model without search costs where product display and feature ads change preferences. Column 3 in table 7 reports the estimates from that model. These estimates reveal that displays and feature ads have a positive and significant effect on the utility of purchasing. Hence, both my model and a model where product display and feature ads change preferences predict a positive effect of these marketing devices on consumers' utility. In the counterfactual simulations, I show, however, that the effects of displays and feature ads can be very different in the two models because in my model displays and feature ads influence consideration sets. The comparison of the log-likelihood of the two models shows that my model outperforms the model where product display and feature ads change preferences.

I evaluate the fit of my model by comparing it with the actual data as well as with the predictions of alternative models. I test the competing models in terms of the market shares of each product. These market shares are obtained from a simulation of consumers' choices[22] using the estimates in tables 5 and 7. I assume that random shocks in the search and purchase stages are independent and identically distributed extreme value type I. In the simulations, I consider a random subsample of the data and hold constant all the characteristics of a shopping trip (including prices, displays, feature ads, and expenditure during the shopping trip).

Table 8 reports the market shares (including the outside option) for the actual data (subsample used in the simulation) and for the simulated choices from the different alternative models. My model provides the best fit for the actual data in terms of market shares and predicts well the choice patterns observed in the data, particularly for the products with the largest market shares. For almost all products the predicted market shares preserve the ranking observed in the data. The market share of the outside option is also accurately predicted. The two models that ignore consideration sets have the worst performance. The results in table 5 and table 7 show that my model outperforms the alternative models in terms of the log-likelihood.

7.3 Implications for Price Elasticities

Tables 9 and 10 show, respectively, the own- and cross-price elasticities computed from the estimates in table 5. Table 9 reveals a large heterogeneity for the own-price elasticities of the different products. Top products (i.e., products with higher market shares) have low own-price elasticities, suggesting some market power for these products due in part to limited consumer information and to the existence of consideration sets. For the other products, the own-price elasticities are higher and, in some cases, large. The cross-price elasticities reveal that substitution across products is small.

The elasticities from the dynamic model with consideration sets and demand accumulation will differ for two reasons from the elasticities of models that ignore consideration sets, demand accumulation, or both. First, the coefficients obtained from models that ignore consideration sets or demand accumulation are biased and inconsistent. Second, the models are structurally different. For example, forward-looking behavior and long run responses are ignored in a model without demand accumulation. Likewise, ignoring consideration sets creates a competitive and a non-reaction distortion in the estimation of price elasticities. On one hand, a model without consideration sets ignores that price changes have no effects on products outside the consideration set and interprets this absence of effects as price insensitivity, thus creating a non-reaction distortion. This distortion underestimates the own-price elasticities. On the other hand, a model without consideration sets ignores that a consumer may never choose some of the products, and thus products in the consideration set will face fewer competitors. This competitive distortion overestimates the own-price elasticities. Since the two distortions created by ignoring consideration sets lead to a bias in different directions, the sign of the total bias is ambiguous. Nevertheless, it is expected that the competitive

[22] I obtain simulated households' choices by simulating shopping trips rather than households. The same procedure is used to simulate households' choices for the counterfactuals.

distortion is the strongest for products that are more often present in considerations sets while the non-reaction distortion is the strongest for products less often present in consideration sets.

Tables 9 and 11 suggest that ignoring consideration sets and demand accumulation overestimates own-price elasticities for products that are more often present in consideration sets and underestimates the own-price elasticities for products that are less often present in consideration sets. For products more often present in consideration sets, the non-reaction distortion occurs less frequently and the dominant distortions (the competitive distortion and the distortion created by ignoring demand accumulation) push up the own-price elasticities in a static model without consideration sets. In contrast, for products less often present in consideration sets, the non-reaction distortion occurs frequently and my results show that it is stronger than the other distortions that increase own-price elasticities in a static model without consideration sets. According to my results, most of the cross-price elasticities are underestimated if one ignores demand accumulation and consideration sets.

Estimates of the price elasticities are often used to compute price-cost margins. If the price elasticities are biased, the price-cost margins computed in this way will also be biased. For single-product firms, the magnitude of the bias of price-cost margins computed from a static model without consideration sets is equal to the ratio of the own-price elasticities. Therefore, the results in table 9 suggest that for single-product firms and products more often present in consideration sets, the price-cost margins computed from my model are higher than those obtained from a static model without consideration sets. A single product firm that needs to choose the price for a product that is more often present in consideration sets will set a price below the optimal price if it ignores consideration sets and demand accumulation. This happens because the firm believes consumers are more price sensitive than they really are. For products less often present in consideration sets, the opposite biases occur.

The price-cost margins for multi-product firms depend on the cross-price elasticities. Since those are usually underestimated in a static model without consideration sets, the price-cost margin bias of products more often present in consideration sets is even larger for multi-product firms than for single-product firms. In contrast, the price-cost margin bias of products less often present in consideration sets is lower or reverses with multi-product firms.

Demand estimates are important elements in antitrust analysis and in the evaluation of mergers. Hence, the previous results show the relevance of allowing for consideration sets and demand accumulation when addressing policy issues.

8 Counterfactuals

In this section I propose some counterfactual exercises to study the strategic effects that arise from the existence of consideration sets. My demand estimates show that firms can use marketing devices (e.g., product display, feature ads) to push a product into the consideration set. These devices normally also inform consumers about a product's posted price. The use of these devices can therefore have different effects. To evaluate these effects, I start by investigating a situation where these devices are not available. Next, I study the interaction between pricing and search costs. In particular, I explore the effects of lowering a product search cost during a price promotion. Finally, I investigate the strategic effects associated with constraints on the number of products than can employ marketing devices to influence consideration sets.

8.1 Effects of influencing consideration sets

In this subsection, I evaluate the importance of the instruments that firms can employ to influence consideration sets. To perform the analysis, I study households behavior and consequent effects on revenues if displays and feature ads were not available. This exercise shows that the direction of the effects of employing instruments to influence consideration sets depends on the specific values of the model parameters.

The absence of displays and feature ads keeps the cost of searching an additional product always high. On one hand, this creates a negative effect because it reduces the likelihood of including a product in the consideration set. On the other hand, the high search costs created by the absence of displays and feature ads can have positive effects. For products that are included in the consideration set when there are no marketing devices, keeping high search costs can decrease the competition within the consideration set due to the smaller size of the consideration set. Furthermore, the absence of marketing devices removes the differences in the marginal cost of searching. Thus, if displays and feature ads were not available, products for which less is invested in those activities would be in a more advantageous situation when competing against other products to influence consumers to search.

Table 12 shows that the purchases and total revenues of liquid detergent are lower when displays and feature ads are not available. Nevertheless, the effects are heterogeneous. Although for most of the products the market shares and the revenues are lower without displays and feature ads, some products have higher market shares and revenues in that situation.

According to my results, the number of products in the consideration set is always small. Therefore, the potential negative effect of marketing devices on the competition within the consideration set is small, and thus this effect cannot explain the gains of some products. The gains of some products in a situation without displays and feature ads is explained by the end of the competitive disadvantage during consideration-set formation against products for which more would be invested in displays and feature ads. The end of this competitive disadvantage increases the probability of searching products for which less is invested in marketing devices, thus leading to more purchases of those products.

This counterfactual illustrates some of the specific effects of marketing devices in my model and their importance on revenues. In my model, there is an unambiguously positive effect of product display and feature ads on the probability of choosing the displayed and featured products but these instruments can have negative effects on the other products. Displays and feature ads can create product switching and purchase acceleration, which reduces their overall positive effect. In fact, with consideration sets, displays and feature ads can decrease the overall purchases in a product category if they induce the consumer to search products that are not bought rather than searching products that would have been bought conditional on searching. The aforementioned effects explain the higher revenues of some products in the absence of marketing devices.

I evaluate the interaction between the fixed search costs and the effects of product display and feature ads by repeating the counterfactual for levels of non-detergent expenditure 10%, 50% and 75% higher than in the actual data. My results suggest that the fall in the total revenues of detergent created by the absence of marketing devices is lower when the non-detergent expenditure is higher. Furthermore, the gains of some products in the absence of marketing devices are larger with higher non-detergent expenditures.

Overall, my results reveal that product display and feature ads are important instruments because they encourage consumers to search, which increases the purchases and revenues for most of the products. Nevertheless, due to the competition to be part of the consideration set, a situation where marketing devices cannot be used is desirable for some products because it improves their revenues by equalizing the search costs of all products.

8.2 Price promotions and search costs

In this subsection, I explore the interaction between price promotions and search costs. In particular, I evaluate the implications of employing product display and feature ads to reduce a product search cost during a price promotion. I assume a product is only displayed and featured if there is a price promotion. The display and feature ads of a product will reduce the additional cost of searching that product and hence will make more consumers aware of the price promotion. Although the exercise implies that a product is displayed and featured if and only if there is a price promotion, I assume that households do not change their price expectations when they observe a product displayed or featured (i.e., households do not infer that there is a price promotion when they observe a product's display or feature ad). A promotional price is defined as a price below the tenth percentile of the price distribution of a product in my sample. This implies that the number of occasions in which a product is displayed or featured in the counterfactual is usually higher than in the actual data. Therefore, the exercise not only reduces the likelihood of consumers missing a promotion but also decreases the overall search costs across shopping trips.

Although my results suggest heterogeneity across products on the effects of the policy, I find that the total number of purchases and the overall liquid-detergent revenues increase when promotions are accompanied by lower search costs. The effects on revenues, however, are modest: total revenues only increase by 2.6% and some products have lower revenues (see table 13).

In order to decompose the effects of reducing the likelihood of missing a promotion from the effects of decreasing search costs, I compare the results from accompanying price promotions with product display and feature ads with the results from randomly displaying and advertising each brand in 10% of the weeks. This comparison reveals that total purchases of liquid detergent increase by 6.8%, but some products are purchased less frequently with a policy of lowering a product search cost during a price promotion. The overall category revenues are nearly equal in the two situations (they are 0.5% higher with the policy of lowering a product search cost during a price promotion). In fact, only Arm&Hammer, Era, and Wisk have significant increases of revenues with the policy, and the revenues of Xtra, Purex, and the Private label fall (see tables 14 and 15).

The previous results suggest that a policy of employing product display and feature ads to lower a product search cost during a price promotion has some positive effects on market shares, but the effects on revenues are modest and even negative for some products. One explanation for those results is a substitution of consumers' choices towards products at a lower price. The policy increases the incentives of including in consideration sets products that are on promotion and decreases the likelihood of including products that are not on promotion. Thus, several purchases will be made at the lowest price of a product, which reduces the revenues from each pound sold. Since some of these purchases steal consumers away from other products (or the same product during future shopping trips) that are not on promotion, there is an attenuation of the possible gains from the policy. The overlap of price promotions in the same week also reduces the potential positive effects of lowering search costs.

In order to understand the specificities of my model, I compare the effects of the suggested policy in my model with the effects of the same policy in alternative models. For instance, in a model where consumers can only search all products or none (e.g., Seiler, 2011), lowering a product search cost during a price promotion[23] can only lead to a substitution towards products at a lower price over different shopping trips because, by a revealed preference argument, a product bought in the absence of the policy is also bought when the policy is in effect. Therefore, when search is a binary choice, lowering a product search cost during a price promotion leads exclusively to "category expansion" during the shopping trip and the only "business stealing" that occurs is across shopping trips through purchase acceleration. In contrast, in my model, lowering a product search cost during a price promotion can influence the consumer to switch from one product to a product on promotion during the same shopping trip. This is one of the reasons for the more modest results in my model.

In a model with consideration sets but without demand accumulation, the only "stealing effect" that occurs is within a shopping trip. In this case the "stealing effect" of lowering a product search cost during a price promotion is also underestimated because the model ignores the purchase acceleration across shopping trips.

This counterfactual highlights some of the specificities of my model and their importance in the interaction between price promotions and marketing devices that influence consideration sets. In particular, employing product

[23]Seiler (2011) does not have information for display or feature ads, so the specific counterfactual exercise is to accompany a promotion with a reduction in search costs. Without loss of generality in this section I assume the reduction in search costs is due to a decrease in display and feature ads.

display and feature ads to reduce a product search cost during a price promotion can create product switching and purchase acceleration. In those cases, the strategy typically implies a substitution towards products at lower prices. These specificities reduce the incentives of a strategy that lowers a product search cost during a price promotion.

8.3 Strategic effects with constraints on the number of displayed products

The space and opportunities to employ marketing devices are often limited. In my model, restrictions on the number of products that can be displayed or featured create strategic effects associated with those devices. For instance, when the number of displayed products is restricted due to physical constraints, the incentives of displaying a product include the direct effects of product display and also the possibility of foreclosing the display of other products. The foreclosure of other products' display creates a competitive advantage during consideration-set formation and tends to reduce the competition within the consideration set by decreasing the number of searched products. Foreclosing the display of other products also avoids potential negative effects that the display of those might have. The existence of these strategic effects increases the willingness to pay for display space.

To analyze the implications and effects associated with limitations to the number of products that can be displayed, I assume the following: (a) only one product can be displayed, (b) product display only takes place in 15% of the weeks, and (c) the medium package of Purex and the medium package of All are the only products that can be displayed. To restrict my attention to the effects of product display, I set prices equal to the average prices observed in the data and I assume that no products are featured.

The previous assumptions imply that it is possible to have three different situations: (i) no products are displayed, (ii) the medium package of Purex is displayed in 15% of the weeks, and (iii) the medium package of All is displayed in 15% of the weeks. The simulated revenues of the medium package of Purex, of the medium package of All, and of the sum of all products for each situation are reported in table 16.

My results show that the medium package of Purex and the medium package of All have important gains in revenues associated with product display. The results also suggest that the direct effects of product display are much larger than the strategic effects because the revenues of a product are only slightly lower when the other product is displayed. Nevertheless, since only one product can be displayed, both products have a large incentive to be the displayed product.

If display space were allocated through an auction, that auction, according to my results, would be won by the medium package of Purex because it has a higher willingness to pay. The medium package of Purex is willing to pay 15% of the revenues obtained without display of all products. The willingness to pay of the medium package of All is 14% lower. If the strategic effects were ignored, the willingness to pay of both products would be lower.

According to my results, the total revenues are higher when the medium package of Purex is displayed. Thus, the outcome of an auction that allocates display space will satisfy retailers' incentives. If the outcome of that auction implied lower total revenues, retailers would prefer to allocate display space through a mechanism other than an auction. For instance, they could allocate the display space by direct bargaining with the manufacturers.

Each of the analyzed products obtains the highest revenue when it is the only displayed product and the lowest revenue when only the other competitor is displayed. Total revenues are higher when the medium package of Purex and All are both displayed. Although my example is extreme and very simplified, in many markets there are physical and economic constraints that create limits to the number of products that can employ marketing devices. I hope my example provides useful insights for the problem faced by firms in those situations.

9 Conclusion and Future Research

I investigate the effects of consideration sets in storable goods markets and evaluate the biases created by ignoring consideration sets in these markets. The study of consideration sets with a storable good introduces a new source of identification and allows testing the existence of consideration sets using purchase data alone. Consideration sets are usually not observed, and thus the study of consideration sets in storable goods markets can be extremely useful.

To perform the analysis, I propose a structural model and apply it to liquid laundry detergent. I find important effects of ignoring consideration sets in the estimation of dynamic choice models. In particular, the own-price elasticity of the products that are more often present in consideration sets is overestimated and the own-price elasticity of products that are less often present in consideration sets is underestimated in a static model without consideration sets. The results reveal that assuming full information and a static model leads to incorrect conclusions regarding the intensity of competition.

My results suggest that consumers have significant search costs. Search is sensitive to inventory and the cost of searching a specific product decreases with display and feature ads of that product. Displays and feature ads therefore have a strategic effect because firms can use them to influence consideration sets.

My paper does not propose a specific model for the supply side. There are several interesting questions associated with the effects of the model on the supply side that I hope to explore in more detail in the future. In particular, I would like to evaluate the effects of consideration sets on firms' decisions about product lines.

I would also like to evaluate optimal pricing and discrimination in a model with consideration sets. Price promotions and marketing devices have effects on consideration-set formation, which creates different levels of consideration. Consideration sets are endogenous and are one source of consumer heterogeneity. Consumer heterogeneity therefore can be seen as endogenous in a model with consideration sets. Furthermore, consideration sets can create specific incentives for implementing (or not) price promotions in storable goods markets. In fact, it is expected that two main characteristics of the model are important in the choice of the optimal pricing strategy.

First, due to the limited information, price promotions can only affect households' choices when the households search. Second, due to stockpiling, price promotions can affect search behavior during future shopping trips.

In future research, I expect to extend the model to analyze the choice of product categories to search during each shopping trip. Demand accumulation creates the opportunity of searching different product categories during different shopping trips, thus avoiding large search costs during each trip. This creates important questions about the choice of the product categories to search during each shopping trip and the variables that determine that choice.

The relation between my model and the literature on bounded rationality and choice overload is another possible topic for future research.

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Appendix A: Tables and Figures

Table 1: Summary Statistics

	mean	sd	skewness	min	max	p25	p50	p75
Shopping trip characteristics								
Time elapsed since last shopping trip (weeks)	0.679	0.651	2.018	0	25	0	1	1
Time elapsed since last purchase (weeks)	5.786	5.333	1.585	0	32	2	4	8
Quantity bought in the last purchase (lb.)	10.068	6.959	5.084	0.75	160	6.25	8	12.5
Total Expenditure ($)	62.99	61.52	1.922	0	1,264.63	17.99	43.38	89.09
Non-detergent expenditure($)	62.31	60.93	1.928	0	1,264.63	17.82	42.88	88.03
Store Knowledge	0.947	0.224	-3.994	0	1	1	1	1
Mean Price ($/lb.)	1.019	0.071	-0.055	0.815	1.259	0.967	1.021	1.073
Demographics								
Income (0000$)	4.801	2.560	0.384	< 0.5	> 10	3	5	7
Household's size	2.757	1.272	0.503	1	6	2	2	4
Purchase of liquid laundry detergent								
Price ($/lb.)	0.745	0.253	0.446	0.282	1.611	0.546	0.724	0.915
Size (lb.)	7.085	1.382	0.878	3.125	13.67	6.32	6.923	7.731
Number of brands purchased	5.636	3.253	0.384	1	17	3	5	8
Number of units purchased	45.49	28.85	1.934	1	236	25	38	59
Household Brand HHI	0.500	0.300	0.529	0.102	1	0.233	0.405	0.784
Household Manufacturer HHI	0.579	0.281	0.349	0.158	1	0.333	0.501	0.889
Shopping Behavior								
Total Expenditure ($)	72.80	37.28	1.134	12.53	274.89	46.00	65.78	92.85
Non-detergent expenditure ($)	71.95	36.89	1.134	12.42	271.70	45.48	64.88	91.76
Number of trips	337.16	207.18	1.375	36	1574	181	300.5	443
Nbr trips with purchases of liq.laundry det.	38.36	20.86	2.066	17	173	24	32	47
Time elapsed btw purchases (weeks)	6.900	2.764	0.547	0	17.56	4.815	6.595	8.595
Time elapsed between trips (weeks)	0.869	0.353	0.381	0	2.25	0.614	0.875	1.071
Store visits								
Total number of stores visited	6.896	3.334	0.371	1	14	4	7	9
Store HHI (liq.laundry detergent)	0.632	0.263	0.051	0	1	0.390	0.598	0.902
Brand Attributes								
Brand Price ($/lb.)	0.826	0.464	1.557	0.231	2.558	0.473	0.731	1.046
Brand Size (lb.)	5.930	1.910	-0.372	2	10.25	5	6.25	7.254
Number of UPC's	9.865	13.58	1.933	1	58	2	3	10
Market Share	0.027	0.048	2.085	0.00003	0.206	0.0005	0.003	0.016
Brand HHI	0.110	0	.	0.110	0.110	0.110	0.110	0.110

Note: For Shopping Trip Characteristics an observation is a purchase instance. For Brand Attributes an observation is a brand. For the remaining statistics an observation is a household. Store knowledge is the proportion of shopping trips that took place in a store visited by the household in the previous 12 weeks. Mean Price is the average price per pound of the brands available in the purchase occasion. Household Brand HHI is the sum of the square of the volume share of the brands bought by each household. Similarly, Household Manufacturer HHI is the sum of the square of the manufacturers' volume share by each household and Store HHI is the sum of the square of the expenditure share spent in each store by each household. Brand HHI is the sum of the square of the market share of each brand.

Table 2: Brand Market Shares and Promotional Activities

Brand	Manufacturer	Share(Qty Sold)	Share(Revenues)	Display	Feature	Price($/lb.)
Tide	P&G	0.206	0.321	0.061	0.094	1.252
Dynamo	PHOENIX	0.128	0.110	0.055	0.054	0.898
Xtra	C&D	0.122	0.072	0.062	0.077	0.370
Purex	DIAL	0.113	0.091	0.056	0.087	0.614
All	LEVER	0.082	0.083	0.055	0.081	0.893
Arm&Hammer	C&D	0.079	0.064	0.053	0.063	0.728
Era	P&G	0.070	0.070	0.061	0.077	0.856
Wisk	LEVER	0.061	0.071	0.051	0.086	1.133
Private Label	-	0.040	0.025	0.036	0.049	0.547
Others	-	0.100	0.093			

Note: Column labeled Share(Qty Sold) are shares of volume sold in my sample, and column labeled Share (Revenues) are shares of revenues in my sample. The columns labeled Display and Feature present, respectively, the proportion of occasions a brand is displayed and featured. P&G = Procter and Gamble; C&D = Church and Dwight.

Table 3: Likelihood of Purchasing Liquid Laundry Detergent

	(1)	(2)	(3)	(4)
	Purchase Dummy	Purchase Dummy	Purchase Dummy	Purchase Dummy
Price of the most purchased brand	-0.147^{***}	-0.150^{***}	-0.146^{***}	-0.134^{**}
	(0.00465)	(0.00472)	(0.00463)	(0.0433)
Average price of brands available	0.0573^{**}	0.0511^{*}	0.0358	0.0307
	(0.0214)	(0.0217)	(0.0213)	(0.0416)
Non-detergent expenditure	0.00124^{***}		0.00124^{***}	0.00124^{***}
	(0.0000131)		(0.0000131)	(0.0000132)
Store knowledge	0.0168^{***}		0.0178^{***}	0.0183^{***}
	(0.00292)		(0.00291)	(0.00293)
Time elapsed since the last purchase		0.00531^{***}	0.00514^{***}	0.00517^{***}
		(0.000128)	(0.000125)	(0.000126)
Quantity previously purchased		-0.00279^{***}	-0.00282^{***}	-0.00285^{***}
		(0.000119)	(0.000117)	(0.000118)
Store FE	YES	YES	YES	YES
Households FE	YES	YES	YES	YES
N	225,597	225,597	225,597	222,280
R^2	0.106	0.078	0.114	

Note: The dependent variable in all regressions is a dummy variable equal to 1 if there was a purchase of detergent and 0 otherwise. Each observation is a shopping trip. The most purchased brand is household specific, and thus the price of the most purchased brand is also household specific. Time elapsed since the last purchase is the number of weeks since the last purchase of liquid detergent. Quantity previously purchased is the quantity of detergent purchased when the last purchase of detergent occurred and is measured in pounds. The first 3 columns report estimates of a ordinary least squares procedure and column 4 reports estimates of a 2-stage least squares procedure. In regression 4 the instruments are the average prices in South Carolina. All specifications include a constant, store fixed effects, and household fixed effects. Standard errors in parentheses. Stars denote the significance level of coefficients $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4: Likelihood of choosing the most purchased brand conditional on buying detergent

	(1)	(2)	(3)	(4)
	Purchase Favorite	Purchase Favorite	Purchase Favorite	Purchase Favorite
Price of the most purchased brand	-0.615^{***}	-0.615^{***}	-0.615^{***}	-0.392^{**}
	(0.0215)	(0.0215)	(0.0215)	(0.150)
Average price of the other brands	0.286^{**}	0.290^{***}	0.290^{***}	0.288^{**}
	(0.0879)	(0.0880)	(0.0880)	(0.0927)
Display most purchased brand	0.137^{***}	0.137^{***}	0.136^{***}	0.140^{***}
	(0.0104)	(0.0104)	(0.0104)	(0.0114)
Feature most purchased brand	0.178^{***}	0.178^{***}	0.178^{***}	0.209^{***}
	(0.00941)	(0.00941)	(0.00941)	(0.0242)
Non-detergent expenditure	0.0000404		0.0000394	0.0000424
	(0.0000481)		(0.0000481)	(0.0000487)
Store Knowledge	0.0455^{**}		0.0448^{**}	0.0416^{*}
	(0.0164)		(0.0164)	(0.0166)
Time elapsed since the last purchase		-0.00110^{*}	-0.00107^{*}	-0.00121^{*}
		(0.000537)	(0.000537)	(0.000545)
Quantity previously purchased		0.000534	0.000533	0.000519
		(0.000574)	(0.000574)	(0.000584)
Store FE	YES	YES	YES	YES
Households FE	YES	YES	YES	YES
N	24,796	24,796	24,796	24,445
R^2	0.381	0.381,	0.381	

Note: The dependent variable in all regressions is a dummy variable equal to 1 if the household's most purchased brand was bought and 0 if other brand was bought. The most purchased brand is household specific. Each observation is a shopping trip with a purchase of liquid detergent. The first 3 columns report estimates of a ordinary least squares procedure and column 4 reports estimates of 2-stage least squares procedure. In regression 4 the instruments are the average prices in South Carolina. All specifications include a constant, store fixed effects, and household fixed effects. Standard errors in parentheses. Stars denote the significance level of coefficients $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 5: Estimates for dynamic model with consideration sets

Dynamic model with consideration sets		
	Coeff.	SE
Price Coefficient		
Constant	-9. 2747	0.4048
Income	0.0989	0.0432
Family Size	0.0432	0.0528
Income * Family Size	-0.0197	0.0092
Storage Cost		
Linear	5.0109	0.8221
Quadratic	-0.8825	0.0427
Search Cost		
Fixed Search Cost		
Constant	4.1943	0.1540
Non-detergent Expenditure	-0.1744	0.0098
Variable Search Cost		
Constant	3.5702	0.1113
Display	-0.2427	0.0291
Feature	-0.3765	0.0270
Product (Brand/Pack-size) dummy variable	YES	
Number of brands/Sizes	10/3	
Maximum Number of brands in CS	10	
Log-likelihood	-11,250.15	
N	19,257	

Note: The rate of consumption of each household is the ratio of the total amount purchased to the overall time in the sample. To estimate inventory, I start with an initial guess and then update inventory in each week using the observed purchases and the estimated consumption. Estimation is performed using a nested fixed point algorithm where the solution of the dynamic problem is nested within the parameter search. The price coefficient includes size fixed-effects and an interaction between income and size fixed-effects. Also included brand-size fixed effects. Assymptotic standard errors are reported.

Table 6: Display-demand Elasticity

	Disp.TIDE Small	TIDE Med.	XTRA Med.	PUREX Med.	ARM Med.	ALL Med.
Sh.TIDE Small	1.1671	-0.0459	-0.0276	-0.0368	-0.0184	-0.0092
TIDE Med.	-0.0420	0.8409	-0.0210	-0.0168	0.0021	0.0021
XTRA Med.	-0.0095	-0.0114	0.9072	-0.0229	-0.0305	-0.0038
PUREX Med.	-0.0124	-0.0227	-0.0268	0.8919	0.0206	-0.0124
ARM&HAMMER Med.	-0.0142	0.0356	-0.0214	-0.0285	0.9752	0.0071
ERA Med.	-0.0220	-0.0044	-0.0264	-0.0176	-0.0044	-0.0044
TIDE Large	-0.0665	-0.1065	-0.0266	-0.0266	-0.0266	-0.0133

Note: Cell entries i and j, where i indexes row and j indexes column, report the percent change in market share of product i with a change from 10 to 11 percent in the percentage of weeks with display of product j. The results are based on table 5.

Table 7: Estimates for alternative models

	Alternatives Model							
	No CS & No Inv.		Inv. & No CS		Ads in Utility		CS & No Inv.	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Price Coefficient								
Constant	-4.2558	0.1839	-4.5716	0.1837	-3.1861	0.1971	-5.7514	0.4270
Income	0.1504	0.0365	0.1752	0.0365	0.1787	0.0366	0.1006	0.0417
Family Size	0.2386	0.0384	0.2508	0.0389	0.2325	0.0383	0.0805	0.0429
Income * Family Size	-0.0169	0.0073	-0.0177	0.0074	-0.0160	0.0073	-0.0166	0.0079
Display					0.5154	0.0630		
Feature					1.0468	0.0573		
Storage Cost								
Linear			3.5274	0.4226	3.8035	0.4217		
Quadratic			-0.5910	0.0401	-0.6017	0.0406		
Search Cost								
Fixed Search Cost								
Constant							4.1813	0.1351
Non-detergent expenditure							-0.2097	0.0101
Variable Search Cost								
Constant							3.1164	0.0818
Display							-0.3093	0.0309
Feature							-0.4585	0.0167
Brand-size dummy	YES		YES		YES		YES	
Nbr. of brands/Sizes	10/3		10/3		10/3		10/3	
Nbr. brands in CS	NA		NA		NA		10	
Log-likelihood	-14,672.48		-14,494.55		-14,217.76		-11.620,17	
N	19,257		19,257		19,257		19,257	

Note: For the specifications with storage costs and demand accumulation the rate of consumption of each household is the ratio of the total amount purchased to the overall time in the sample. To estimate inventory, I start with an initial guess and then update inventory in each week using the observed purchases and the estimated consumption. Estimation is performed using a nested fixed point algorithm where the solution of the dynamic problem is nested within the parameter search. The price coefficient includes size fixed-effects and an interaction between income and size dummies. For all specifications also included brand-size fixed effects. Assymptotic standard errors are reported.

Table 8: Predicted Market-shares in the different models

	Market-Shares		
	Small	Medium	Large
	Data		
TIDE	0.5037	2.0668	0.6387
XTRA	0	1.6150	0.1661
DYNAMO	0.0623	0.9087	0.0104
PUREX	0.0364	1.6981	0.0883
ARM & HAMMER	0.0259	0.6283	0.1090
ALL	0.1662	1.1476	0.04154
ERA	0.0311	1.1476	0.1038
WISK	0.0727	0.5089	0.0156
Private Label	0.1558	0.4881	0.0364
Other	0.3115	1.2203	0.0208
	Static model without consideration sets		
TIDE	0.2248	0.8561	0.2419
XTRA	0	0.6814	0.0586
DYNAMO	0.0276	0.3503	0.0023
PUREX	0.0167	0.6592	0.0274
ARM & HAMMER	0.0117	0.2372	0.0288
ALL	0.0764	0.4768	0.0105
Private Label	0.0684	0.1906	0.0173
	Dynamic model without consideration sets		
TIDE	0.2022	0.7293	0.2031
XTRA	0	0.5770	0.0502
DYNAMO	0.0259	0.3153	0.0036
PUREX	0.0123	0.6092	0.0249
ARM & HAMMER	0.0103	0.2245	0.0346
ALL	0.0636	0.4107	0.0124
Private Label	0.0592	0.1721	0.0124
	Static model with consideration sets		
TIDE	0.2070	1.7065	0.5037
XTRA	0	1.4735	0.0982
DYNAMO	0.0244	0.7844	0.0075
PUREX	0.0105	1.5862	0.0550
ARM & HAMMER	0.0060	0.4585	0.0888
ALL	0.0533	0.9698	0.0217
Private Label	0.1201	0.4384	0.0203
	Dynamic model with consideration sets		
TIDE	0.2222	1.7985	0.4604
XTRA	0	1.5288	0.1107
DYNAMO	0.0277	0.8772	0.0100
PUREX	0.0105	1.6693	0.0580
ARM & HAMMER	0.0090	0.5294	0.1014
ALL	0.0643	1.0834	0.0256
ERA	0.0076	1.0070	0.0885
WISK	0.0193	0.5222	0.0163
Private Label	0.1167	0.5045	0.0274
Other	0.1286	1.1095	0.0336

Note: Cell entries i and j, where i indexes row and j indexes column, report the simulated market share of brand i of size j for the specified model. The market shares include the outside option of not purchasing any detergent. Simulations for each model are based on tables 5 and 7.

Table 9: Own-Price Elasticities and ratios of elasticities computed from alternative models to elasticities computed from dynamic model with consideration sets

Own price-elasticity and ratios of own-price elasticities	Small	Medium	Large
Dynamic model with consideration sets			
TIDE	-4.3122	-2.4891	-6.5414
XTRA	N/A	-0.6585	-3.8483
DYNAMO	-3.8298	-2.4964	-2.5974
PUREX	-3.1746	-1.1716	-8.4813
ARM & HAMMER	-6.4000	-2.4034	-4.1875
ALL	-4.9231	-1.9015	-9.3366
ERA	-5.7971	-1.7459	-4.4862
WISK	-5.9233	-3.0369	-9.3385
Private Label	-0.9550	-1.5827	-5.8968
Other	-3.8901	-2.6084	-1.4440
Static model without consideration sets			
TIDE	0.7189	1.6509	1.1462
DYNAMO	0.4518	1.1081	0.8021
PUREX	0.8100	1.7554	0.5967
ALL	0.6344	1.4689	0.8724
ERA	0.3582	1.6468	1.5841
Private Label	1.8282	1.2342	0.7027
Other	0.7081	1.0682	1.5829
Dynamic model without consideration sets			
TIDE	0.7576	1.5171	1.1163
DYNAMO	0.6217	1.0526	0.6016
PUREX	0.4315	1.6550	0.4780
ALL	0.3397	1.5554	0.7270
ERA	0.4228	1.8132	1.5985
Private Label	1.4846	1.2739	0.5347
Other	0.7105	1.0660	1.5055
Static model with consideration sets			
TIDE	1.1450	1.0974	1.0895
DYNAMO	1.1182	0.6478	1.2727
PUREX	1.8421	1.5275	0.4489
ALL	0.6810	1.3057	0.6675
ERA	0.5799	0.9970	1.0659
Private Label	1.0203	1.1181	0.7194
Other	1.0876	1.0075	0.3440
Dynamic model where display and feature change pref.			
TIDE	0.6740	0.8593	0.8530
DYNAMO	0.5021	0.4511	1.1000
PUREX	0.4688	0.7355	0.4387
ALL	0.4476	0.7263	0.6191
ERA	0.5409	0.6772	0.8840
Private Label	1.5551	0.5625	0.8633
Other	0.4210	0.6881	1.4230

Note: For the first 10 rows cell entries i and j, where i indexes row and j indexes column, report the percent change in market share of brand i of size j with a 1 percent change of its price. For the remaining rows cell entries i and j report for brand i of size j the ratio of the own-price elasticity in the model specified to the own-price elasticity in my model. The results are based on tables 5 and 7.

Table 10: Cross-Price Elasticities and average ratios of cross-price elasticities computed from alternative models to elasticities computed from dynamic model with consideration sets

	Cross Price-Elasticity and ratios of cross-price elasticities			
	Price TIDE Med.	DYNAMO Med.	ALL Med.	ERA Med.
Dynamic model with consideration sets				
Share TIDE Med.	-2.4891	0.0135	0.0373	0.0406
Share XTRA Med.	0.0389	0.0130	0.0259	0.0519
Share DYNAMO Med.	0.0476	-2.4964	0.0476	0.0408
Share ALL Med.	0.0412	0.0258	-1.9015	0.0309
Share ERA Med.	0.0759	0.0526	0.0234	-1.7459
Static model without consideration sets				
Share TIDE Med.	1.6509	1.2348	0.1497	0.2744
Share XTRA Med.	0.5399	2.1596	0.2699	0.1350
Share DYNAMO Med.	1.1448	1.1081	0.2862	0.6678
Share ALL Med.	1.6999	0.3885	1.4689	0.3238
Share ERA Med.	0.7369	0.2129	0.4790	1.6468
Dynamic model without consideration sets				
Share TIDE Med.	1.5171	0.5666	0.6181	0.7555
Share XTRA Med.	1.2462	0.7477	0.3739	0.3739
Share DYNAMO Med.	1.1187	1.0526	0.0001	1.3051
Share ALL Med.	0.6612	0.5290	1.5554	0.0001
Share ERA Med.	0.1862	0.5378	0.0001	1.8132
Static model with consideration sets				
Share TIDE Med.	1.0974	0.7991	0.3875	0.7991
Share XTRA Med.	1.1810	1.6104	0.9663	0.8857
Share DYNAMO Med.	0.8244	0.6478	1.3190	0.5771
Share ALL Med.	1.2322	0.7393	1.3057	1.2322
Share ERA Med.	1.4823	0.6297	1.1335	0.9970
Dynamic model where display and feature change pref.				
Share TIDE Med.	0.8593	0.0001	0.1599	0.2932
Share DYNAMO Med.	0.2956	0.4511	0.2956	0.3449
Share ALL Med.	0.2577	0.4123	0.7263	1.0308

Note: For the first 5 rows, cell entries i and j, where i indexes row and j indexes column, report the percent change in market share of product i with a 1 percent change of product j. For the remaining rows cell entries i and j report the ratio of the cross-price elasticity of products i and j in the model specified to the cross-price elasticity in my model. The results are based on tables 5 and 7.

Table 11: Probability of searching a brand-size

	Pr($j \in CS$)			
	Small	Medium	Large	Total
TIDE	0.0083	0.0263	0.0079	0.0425
XTRA	0	0.0235	0.0045	0.0280
DYNAMO	0.0027	0.0146	0.0025	0.0198
PUREX	0.0034	0.0263	0.0039	0.0335
ARM & HAMMER	0.0029	0.0113	0.0037	0.0179
ALL	0.0039	0.0171	0.0030	0.0240
ERA	0.0027	0.0168	0.0036	0.0231
WISK	0.0022	0.0092	0.0023	0.0137
Private Label	0.0033	0.0093	0.0019	0.0144
Other	0.0068	0.0216	0.0035	0.0319

Note: Cell entries i and j, where i indexes row and j indexes column, report the average probability of searching brand i of size j in a shopping trip. Average over all shopping trips of the sample used for estimation. The results are based on table 5.

Table 12: Ratio of the revenues without display and feature ads to the revenues of the simulated choices from the actual data

Ratio Revenues w/o Display&Feature Ads/ Revenues from data				
	Small	Medium	Large	Total
TIDE	1.0298	0.8775	0.8271	0.8786
XTRA	N/A	0.9206	0.9425	0.9233
DYNAMO	1.0564	0.8292	0.9000	0.8434
PUREX	1.0645	0.8542	1.0091	0.8642
ARM & HAMMER	0.9460	0.8564	0.8425	0.8548
ALL	1.0590	0.8238	1.0484	0.8403
ERA	1.0635	0.7296	0.7748	0.7358
WISK	1.0393	0.7337	0.9014	0.7472
Private Label	1.0203	0.8793	1.0073	0.9060
Other	0.9634	0.7508	1.0813	0.7787
Total	1.0187	0.8295	0.8575	0.8426

Note: Cell entries i and j, where i indexes row and j indexes column, report for brand i of size j the ratio of its revenues when display and feature ads are eliminated to its revenues when display and feature ads are equal to my sample. Simulated choices in each scenario are based on table 5.

Table 13: Ratio of the revenues with display and feature ads if and only price is below the 10th percentile to the revenues of the simulated choices from the actual data

Ratio of revenues display and feature ads iff price below 10th percentile to revenues from simulated choices from actual data				
	Small	Medium	Large	Total
TIDE	1.2106	1.0411	1.0272	1.0516
XTRA	N/A	1.0637	1.0141	1.0578
DYNAMO	1.0519	1.0346	1.6482	1.0406
PUREX	1.1047	0.9075	1.4193	0.9381
ARM & HAMMER	1.0062	1.0794	1.2813	1.1133
ALL	1.6002	1.0106	1.1782	1.0437
ERA	2.3157	0.9471	1.3733	0.9961
WISK	1.0456	0.9998	1.4285	1.0119
Private Label	1.2079	0.9716	1.1533	1.0146
Other	1.4396	0.9013	3.9063	0.9960
Total	1.2896	0.9938	1.1471	1.0259

Note: Cell entries i and j, where i indexes row and j indexes column, report for brand i of size j the ratio of its revenues when a product is displayed and featured if and only if there is a price promotion to its revenues when display and feature ads are equal to my sample. Simulated choices in each scenario are based on table 5.

Table 14: Ratio of the market-shares with display and feature ads if and only if price is below the 10th percentile to the market-shares with random display and feature ads in 10% of the weeks

Ratio of market shares of display&feature iff price below 10th percentile to market shares with 10% of random display&feature ads				
	Small	Medium	Large	Total
TIDE	1.0060	1.0382	1.1144	1.0415
XTRA	N/A	1.0072	0.9458	1.0035
DYNAMO	0.8102	1.2303	1.6937	1.1596
PUREX	0.9103	0.9298	1.2436	0.9394
ARM & HAMMER	0.8080	1.1709	1.4498	1.1957
ALL	1.2822	1.0898	0.9695	1.1073
ERA	1.8014	1.1456	1.6573	1.1830
WISK	0.8137	1.1990	1.5091	1.1786
Private Label	1.0147	0.9922	0.9811	0.9970
Other	1.3665	1.0660	3.5618	1.1652
Total	1.0823	1.0545	1.2583	1.0677

Note: Cell entries i and j, where i indexes row and j indexes column, report for brand i of size j the ratio of its market-shares when a product is displayed and featured if and only if there is a price promotion to its market-shares when products are randomly displayed and featured in 10 percent of the weeks. Simulated choices in each scenario are based on table 5.

Table 15: Ratio of the revenues with display and feature ads if and only if price is below the 10th percentile to the revenues with random display and feature ads in 10% of the weeks

Ratio of revenues display&feature iff price below 10th percentile to revenues with 10% of random display&feature ads				
	Small	Medium	Large	Total
TIDE	0.9781	0.9926	1.0575	1.0045
XTRA	N/A	0.9680	0.9162	0.9618
DYNAMO	0.8042	1.0230	1.45375	1.0101
PUREX	0.8302	0.8834	1.1586	0.9019
ARM & HAMMER	0.7634	1.0303	1.2427	1.0631
ALL	1.2243	1.0078	0.8797	1.0182
ERA	1.7005	1.0566	1.4920	1.1053
WISK	0.7927	1.0936	1.3257	1.0872
Private Label	0.9456	0.9131	0.9266	0.9192
Other	1.1957	0.9694	2.9509	1.0319
Total	1.0308	0.9881	1.1265	1.0055

Note: Cell entries i and j, where i indexes row and j indexes column, report for brand i of size j the ratio of its revenues when a product is displayed and featured if and only if there is a price promotion to its revenues when products are randomly displayed and featured in 10 percent of the weeks. Simulated choices in each scenario are based on table 5.

Table 16: Incentives to do display

	Revenues Purex Med.	Revenues All Med.	Total Revenues
No Display	11.69	9.13	100.00
Only Purex Med. Displayed	13.43	9.08	101.35
Only All Med. Displayed	11.67	10.59	101.26
Purex and All Med. Displayed	13.37	10.50	102.55

Note: The table reports the revenues of the medium package of Purex, of the medium package of All, and the overall detergent category when varying the product displayed. All the remaining products are not displayed. The prices of all products are equal to the respective average price in my sample. No products are featured. Revenues are normalized by total revenues in the situation with no display (i.e., the value in each cell is the percentage of the revenues on that specific situation to the total revenues with no display). Results based on table 5.

Figures

Figure 1: Distribution of purchases as function of time elapsed since the last purchase

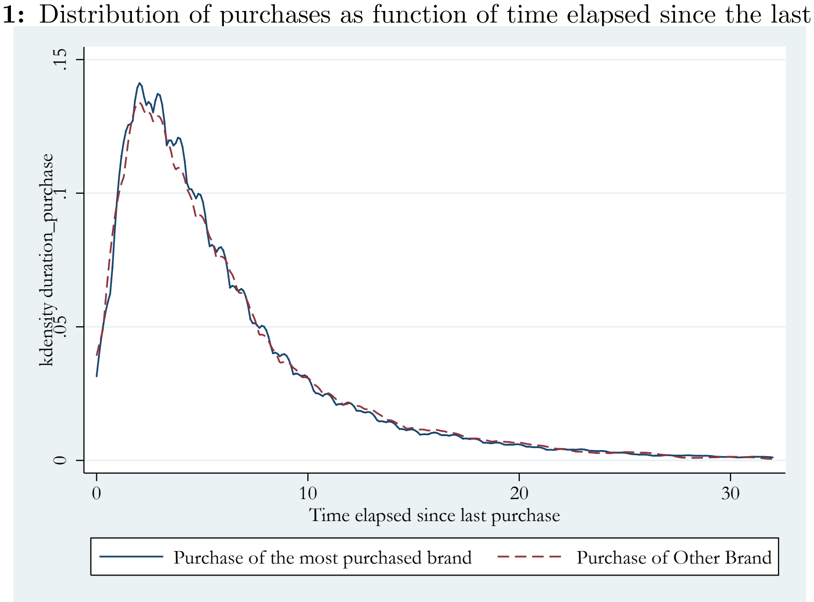


Figure 2: Distribution of purchases as function of time elapsed since the last purchase for consumers that only have purchased two different brands over the 6-year period

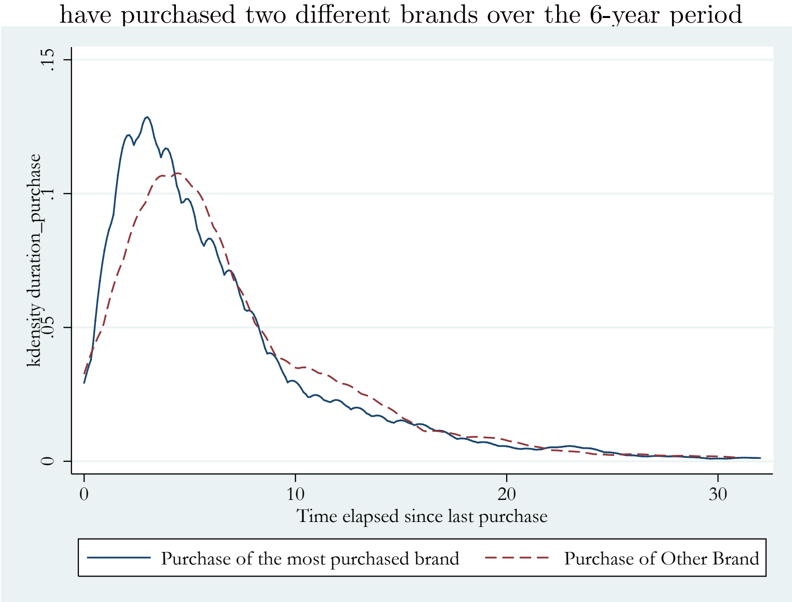


Figure 3: Pattern of prices over time for Tide 6.25lb, Xtra 8lb, All 6.25lb and Era 6.25lb at a particular store

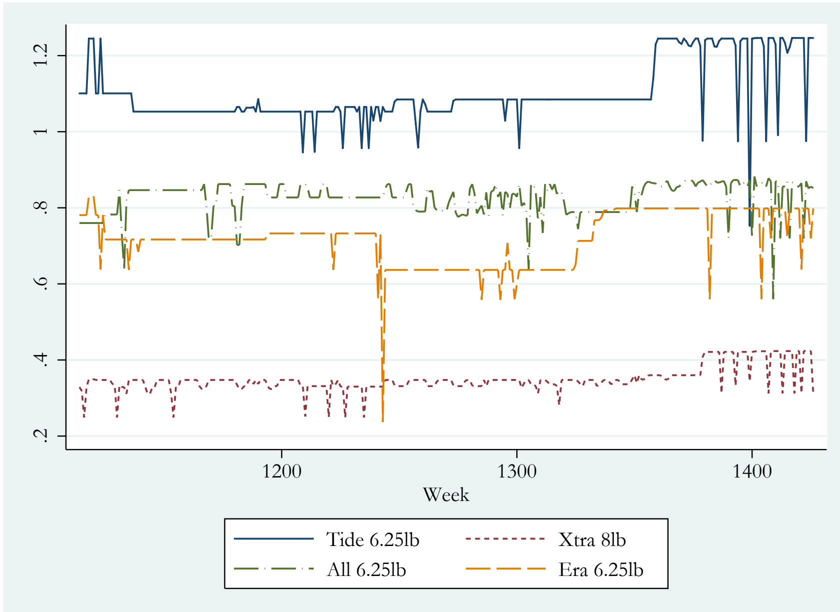
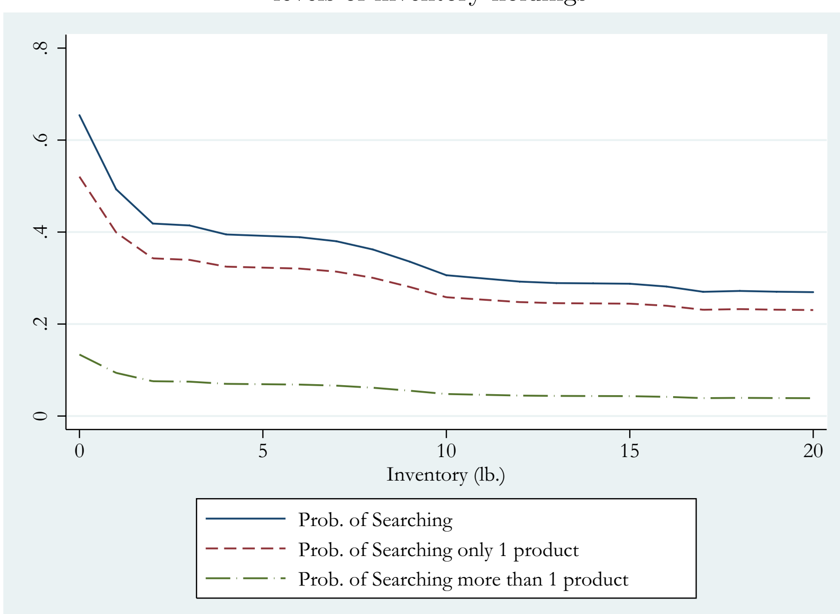


Figure 4: Probability of searching and distribution of consideration sets' size in the actual data and for different levels of inventory holdings



Note: The graph reports the probability of searching (solid line), probability of searching only one product (dashed line), and probability of searching more than one product (dash-dotted line) for a tipical (median) household in a tipical shopping trip (all brand-sizes are neither displayed nor featured) for the level of inventory specified. All brand-sizes can be part of the household consideration set (i.e., all brands were bought by the household at least one time in my sample). The results are based on table 5.

Appendix B: Procedures to clean the raw data

For the liquid laundry detergent category, the store-level movement data contain 24,189,141 observations (an observation is defined as the triplet (week, store, upc)), which include 2,697 stores, 87 brands, and 990 upc's.

The panel data can be split into two types of files. One contains information for all shopping trips made by each household in the panel, regardless of the product bought in the trip and the store visited. In this file an observation is the purchases of a particular household in a particular store on a particular moment. For each trip I observe the total expenditure, the visited store, and the exact moment when the trip took place. This file contains 4,039,349 observations including 11,184 households and 81 stores. The other type of file contains the complete purchase history for each product category with detailed information about the characteristics of each purchase occasion. In those files an observation is defined as the purchase of a specific upc by a particular household at a particular store during a particular shopping trip. For the liquid detergent category there are 139,506 observations for a sample with 7,579 households, 67 stores, 48 brands, and 551 upc's.

To obtain a sample suitable for estimation, I undertook several procedures to clean the raw data. First, I excluded from the panel data all the households that purchased more than one brand of liquid detergent at least in one trip (48,732 observations dropped). Second, I collapsed the panel data such as one observation is characterized by the purchases of a particular household at a particular store in a particular week (6,688 observations collapsed). Third, I dropped observations from households for whom I could not match at least one observation in the purchase file with the trip file (23,432 observations dropped). Fourth, for each household I dropped all observations before the first purchase and after the last purchase of liquid laundry detergent (1,557,598 observations dropped) and I excluded the first 12 weeks in the data (19,810 observations dropped). Fifth, I only kept the observations from households with at least 16 purchases of liquid laundry detergent, that have never bought a non-liquid laundry detergent[24] and for whom the time between purchases is never larger than 32 weeks (966,179 observations dropped). Sixth, I dropped households whose number of shopping trips is lower or equal than 36 (58 observations deleted). Finally, I lost 11,767 observations in the panel data that cannot be matched with store level movement data[25].

For some products I observe zero purchases in a store in a given week. This can happen for two reasons: the product either was available but no one bought it or was not available at that store in that week. For products without purchases at a store in a given week I input a price equal to the maximum observed price for that product at that store and I set that the product was neither displayed nor featured. Thus, I assume the product was available but no one purchased it.

[24] At this stage I excluded the observations from households that bought at least once a laundry detergent that was not in the liquid form.

[25] I lost these observations because the panel data includes all purchases made by the households, including the purchases in stores that are not in the IRI system. For these purchases I cannot recover the store information. These observations are never used in estimation, however for the structural model I will use these observations to construct the inventories of each household in each week.

For the preliminary analysis and descriptive statistics products are aggregated by brand (different size boxes and packages of the same brand are aggregated) and for the estimation of the structural model products are aggregated by brand-size (different boxes, packages and scents of the same brand and size are aggregated in the same product).

Appendix C: Test for consideration sets in storable goods markets

In this section I propose a simple setup to derive a formal test for consideration sets in storable goods markets. This basic setup keeps the model as simple as possible. I go back to a more comprehensive structure in section 4.

The timing of the model is the following. When the consumer enters a store, she knows the available brands but she does not know the price or the realization of the shocks of each brand. To collect information about a subset K of brands, the consumer needs to pay a search cost $SC_{Kt}(z)$ where z includes the variables with effects on search costs. Thus, within the store the consumer chooses whether to search or not. Searching implies the choice of the set of brands to search. If the consumer does not search, she does not have to make another decision in the current time period. If the consumer searches, she chooses whether to purchase one of the searched brands or nothing at all.

Let d_t^{ps} and d_t^{ss} describe, respectively, consumer's choice in the purchase stage and in the search stage. Define $d_t^{ss} = \phi$ if the consumer chooses not to search and $d_t^{ss} = K$ if the consumer chooses the consideration set K in the search stage. Let $d_{ijt}^{ps} = 1$ if consumer chooses brand j in the purchase stage and $d_{ijt}^{ps} = 0$ otherwise. Define $d_{it}^{ps} = \sum_{j=0}^{J} j d_{ijt}^{ps}$. Since alternatives are mutually exclusive, then d_{it}^{ps} is equal to the brand chosen. Let Ω_t be the set of available brands and let Λ_t be the powerset of Ω_t excluding the empty set.

The value obtained by household i at period t from purchasing brand j is

$$U_{ijt}^{PS} = f_i(C_{it}, I_{it}) + u_i(p_{jt}, a_{jt}, \varepsilon_{jt}) + \epsilon_{ijt}$$

where I_{it} is the inventory at time t, C_{it} is the consumption of liquid laundry detergent at period t, p_{jt} is the price of alternative j at time t, a_{jt} are nonprice observed attributes of alternative j at time t, ε_{jt} is an idiosyncratic taste for brand j and ϵ_{ijt} is a random shock to consumer choice. In this specification $f_i(.)$ captures the utility obtained from consumption at time t and the storage costs to keep inventory I_{it}.

The value of not purchasing is

$$U_{i0t}^{PS} = f_i(C_{it}, I_{it}) + \epsilon_{i0t}$$

In my setup, conditional on purchasing, the consumption at time t is independent of the brand purchased and hence inventory is also independent of the brand purchased. The evolution of inventory if the household chooses alternative j is characterized by

$$I_{it} = I_{it-1} + \delta 1 \left[j \neq 0 \right] - C_{it}$$

Consumers are forward looking and their problem can be described by an infinite sequence of decision rules that maximizes the present expected value of future utility flows. Let v_k^{ss} and v_j^{ps} denote, respectively, the choice-specific value function in the search and in the purchase stage net of the error terms. Let s_t^{ss} and s_t^{ps} denote, respectively, the state variables in the search and in the purchase stage.

The choice-specific value function in the purchase stage net of the error terms can be written as

$$\begin{aligned} v_{ij}^{ps}\left(s_t^{ps}\right) &= U_{ijt}^{PS} + \beta E\left[\max_{k\in\Lambda\cup\{\phi\}}\left\{v_{ik}^{ss}\left(s_{t+1}^{ss}|s_t, d_{it}^{ps}=j\right)+\tilde{\epsilon}_{ikt+1}\right\}\right] \\ &= u_i\left(p_{jt}, a_{jt}, \varepsilon_{jt}\right) + M_i\left(s_t, j\right) \end{aligned}$$

where

$$M_i\left(s_t, j\right) = f_i\left(C_{it}, I_{it}\right) + \beta E\left[\max_{k\in\Lambda\cup\{\phi\}}\left\{v_{ik}^{ss}\left(s_{t+1}^{ss}|s_t, d_{it}^{ps}=j\right)+\tilde{\epsilon}_{ikt+1}\right\}\right]$$

The choice-specific value function in the search stage if the consumer chooses not to search can be written as

$$\begin{aligned} v_{iNS}^{ss}\left(s_t^{ss}\right) &= f_i\left(C_{it}, I_{it}\right) + \beta E\left[\max_{k\in\Lambda\cup\{\phi\}}\left\{v_{ik}^{ss}\left(s_{t+1}^{ss}|s_t, d_{it}^{ss}=NS\right)+\tilde{\epsilon}_{ikt+1}\right\}\right] \\ &= M_i\left(s_t, 0\right) \end{aligned}$$

and the choice-specific value function in the search stage when consumer chooses the consideration set K can be written as

$$v_{iK}^{ss}\left(s_t^{ss}\right) = E\left[\max_{j\in K}\left\{v_{ij}^{ps}\left(s_t^{ps}\right)+\epsilon_{ijt}\right\}\right] - SC_{Kt}$$

I assume that conditional on purchasing, the transition of the state variables is independent of the purchased brand. This assumption and the assumption that consumption is independent of the purchased brand imply that, conditional on a purchase, $M_i\left(s_t, j\right)$ is equal for all brands. As an additive constant, I can normalize the choice-specific value function in the purchase stage such that $M_i\left(s_t, j\right) = M_i\left(s_t\right)$ simply drops out. Using that normalization, I can rewrite the choice-specific value functions in the purchase stage as

$$\tilde{v}_{ij}^{ps}\left(s_t^{ps}\right) = u_i\left(p_{jt}, a_{jt}, \varepsilon_{jt}\right)$$

$$\tilde{v}_{i0}^{ps}\left(s_t^{ps}\right) = h_i\left(I_{it-1}, \nu_t\right)$$

where $h_i\left(I_{it-1}, \nu_t\right) = M_i\left(s_t, 0\right) - M_i\left(s_t\right)$ and ν_t are the state variables excluding the beginning-of-period inventory.

I assume that

$$\frac{\partial h_i\left(I_{it-1},.\right)}{\partial I_{it-1}} > 0 \text{ for all } I_{it-1}$$

This assumption implies that the normalized value of the outside option is increasing with the beginning-of-period inventory.

In the following lines I informally discuss the main assumptions of the basic setup.

The basic setup described implies that, conditional on purchasing, consumption is equal across brands. This assumption ensures a separability between the consumption decision and the choice of the brand to purchase. The assumption is consistent with consumers that differentiate among the brands at the moment of the purchase but after the purchase they see all brands as equal. One of the advantages of this assumption is that allows to specify inventory as a one-dimensional object, since we do not need to specify a different inventory for each brand.[26]

The assumption $\frac{\partial h_i(I_{it-1},.)}{\partial I_{it-1}} > 0$ for all I_{it-1} is extremely important when I introduce consideration sets in the setup. With consideration sets that maximize the difference between the benefits of including an additional product and the cost of searching it, the previous assumption ensures that, ceteris paribus, the size of the consideration set decreases with the beginning-of-period inventory. This implies that one cannot test if consideration sets are decreasing in current inventory. In fact, the model takes that as an assumption. I rely on conventional wisdom and economic intuition to justify this assumption.[27]

Finally, this basic setup does not take into account that brands can be sold at different sizes, and thus within and across alternatives one may have differences on sizes. I make this assumption by two main reasons. First, in this basic setup I want to keep the model as simple as possible. I will relax this assumption in section 4. Second, the size of the chosen alternative is between 6.25 and 8 pounds for nearly eighty percent of the purchases in the data and for nearly sixty percent of the purchases the size is 6.25 pounds. Therefore, there is small variation on the purchased sizes and thus I believe that the assumption is not too restrictive.

This basic setup nests the following models

1. Static model without consideration sets

2. Dynamic model without consideration sets

3. Static model with consideration sets

4. Dynamic model with consideration sets

In the following lines I describe the household behavior for each alternative. For all alternatives the household chooses the brand that gives the highest utility. However, due to the different characteristics, in each alternative

[26] See Hendel and Nevo (2006) for a discussion of those assumptions.

[27] For example, this assumption is verified with a fixed consumption rate, quadratic storage costs and utility of consumption equal to consumption.

the household solves a different problem. Alternative (1) is the standard static discrete choice problem and so consumer's problem is characterized by

$$\begin{aligned}
&\max_{\{d_{ijt}\}_{j\in\Omega}} \left\{ d_{i0t}^{ps} \times \epsilon_{i0t} + \sum_{j\in\Omega} d_{ijt}^{ps} \left[u_i \left(p_{jt}, a_{jt}, \varepsilon_{jt} \right) + \epsilon_{ijt} \right] \right\} \\
s.t \quad &: \quad \sum_{j\in\Omega} d_{ijt}^{ps} = 1
\end{aligned}$$

For alternative (2) the consumer's problem is characterized by

$$\begin{aligned}
&\max_{\{d_{ijt}\}_{t=0,j\in\Omega}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left\{ d_{i0t}^{ps} \times \left[h_i \left(I_{it-1}, \nu_t \right) + \epsilon_{i0t} \right] + \sum_{j\in\Omega} d_{ijt}^{ps} \left[u_i \left(p_{jt}, a_{jt}, \varepsilon_{jt} \right) + \epsilon_{ijt} \right] \right\} \\
s.t \quad &: \quad \sum_{j\in\Omega} d_{ijt}^{ps} = 1 \\
&: \quad I_{it} = I_{it-1} + \delta 1 \left[d_{it} \neq 0 \right] - C_{it}
\end{aligned}$$

For alternative (3) the consumer's problem is characterized by

$$\begin{aligned}
&\max_{\{d_{ijt}\}_{j\in\Omega}} \left\{ d_{i0t}^{ps} \times \epsilon_{i0t} + \sum_{j\in\Omega} d_{ijt}^{ps} \left[u_i \left(p_{jt}, a_{jt}, \varepsilon_{jt} \right) + \epsilon_{ijt} \right] \right\} \\
s.t \quad &: \quad \sum_{j\in\Omega} d_{ijt}^{ps} = 1 \\
&: \quad d_{ijt}^{ps} = 0 \text{ if } j \in K \\
&: \quad K = \arg \max_{K\in\Lambda\cup\{\phi\}} \left\{ \mathbf{1} \left[k = \phi \right] \times \left(\bar{\epsilon}_{iNSt} \right) + \sum_{L\in\Lambda} \mathbf{1} \left[k = L \right] \times \left(E_{p,\epsilon} \left[\max_{j\in L\cup\{0\}} \left\{ \tilde{U}_{ijt}^{PS} \right\} \right] - SC_{Lt} \left(z \right) + \bar{\epsilon}_{iLt} \right) \right\}
\end{aligned}$$

For alternative (4) the consumer's problem is characterized by

$$\begin{aligned}
&\max_{\{d_{ijt}\}_{t=0,j\in\Omega}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left\{ d_{i0t} \times \left[h_i \left(I_{it-1}, \nu_t \right) + \epsilon_{i0t} \right] + \sum_{j\in\Omega} d_{ijt} \left[u_i \left(p_{jt}, a_{jt}, \varepsilon_{jt} \right) + \epsilon_{ijt} \right] \right\} \\
s.t \quad &: \quad \sum_{j\in\Omega} d_{ijt} = 1 \\
&: \quad d_{ijt} = 0 \text{ if } j \in K_t \\
&: \quad K_t = \arg \max_{K\in\Lambda\cup\{\phi\}} \left\{ \mathbf{1} \left[d_t^{ss} = \phi \right] \times \left[v_{NS}^{ss} \left(s_t^{ss} \right) + \bar{\epsilon}_{NSt} \right] + \sum_{L\in\Lambda} \mathbf{1} \left[d_t^{ss} = L \right] \times \left\{ v_L^{ss} \left(s_t^{ss} \right) + \bar{\epsilon}_{iLt} \right\} \right\} \\
&: \quad I_{it} = I_{it-1} + \delta 1 \left[d_{it} \neq 0 \right] - C_{it}
\end{aligned}$$

In this basic setup, one can test the existence of consideration sets in storable goods markets using scanner panel data alone. The next implication explains the intuition for the test.

Implication 1: *If the random shocks to consumer choices are independent and the true model is alternative (1), (2) or (3), the likelihood of choosing a brand conditional on purchasing does not depend on inventory holdings. If the true model is alternative (4), the likelihood of choosing a brand conditional on purchasing may depend on inventory holdings.*

Proof. In alternatives (1) and (3) households' behavior never depends on inventory holdings and thus the likelihood of choosing a brand conditional on purchasing cannot depend on inventory. In alternative (2) the likelihood of choosing a brand conditional on purchasing is characterized by

$$P\left(d_{it}^{ps}=j|q_t=1\right)=P\left(v_{ij}^{ps}\left(s_t^{ps}\right)+\epsilon_{ijt}\geq\max_{l\in\Omega\cup\{0\}}\left\{v_{il}^{ps}\left(s_t^{ps}\right)+\epsilon_{ilt}\right\}\middle|\, q_t=1\right)$$

$$=P\left(\epsilon_{i0t}\leq u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-h_i\left(I_{it-1},\nu_t\right)+\epsilon_{ijt},...,\epsilon_{iJt}\leq u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-u_i\left(p_{Jt},x_{Jt},\varepsilon_{Jt}\right)+\epsilon_{ijt}\right|q_t=1\Big)$$

where q is a dummy variable equal to 1 if the household makes a purchase and 0 otherwise.

If the random shocks to consumer choices are independent

$$P\left(d_{it}^{ps}=j|q_t=1\right)=\int F_{\epsilon_0}\left(u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-h_i\left(.\right)+\epsilon_{ijt}|q_t=1\right)\times$$

$$\times F_{\epsilon_1,..,\epsilon_J}\left(u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-u_i\left(p_{1t},x_{1t},\varepsilon_{Jt}\right)+\epsilon_{ijt},...,u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-u_i\left(p_{Jt},x_{Jt},\varepsilon_{Jt}\right)+\epsilon_{ijt}|q_t=1\right)dF_{\varepsilon_j}$$

$$=\int F_{\epsilon_1,..,\epsilon_J}\left(u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-u_i\left(p_{1t},x_{1t},\varepsilon_{Jt}\right)+\epsilon_{ijt},...,u_i\left(p_{jt},x_{jt},\varepsilon_{jt}\right)-u_i\left(p_{Jt},x_{Jt},\varepsilon_{Jt}\right)+\epsilon_{ijt}|q_t=1\right)dF_{\varepsilon_j}$$

Since $F_{\epsilon_1,..,\epsilon_J}\left(.|q_t=1\right)$ does not depend on inventory holdings, then $P\left(d_{it}^{ps}=j|q_t=1\right)$ does not depend on inventory holdings if the random shocks to consumer choices are independent and the true model is alternative (2). On the other hand, for alternative (4) the likelihood of choosing a brand conditional on purchasing is characterized by

$$P\left(d_{it}^{ps}=j|q_t=1\right)=\sum_{K\in2^{\Omega}}P\left(d_{it}^{ps}=j|q_t=1,d_{it}^{ss}=K\right)P\left(d_{it}^{ss}=K|q_t=1\right)$$

As previously shown, if the random shocks to consumer choices are independent, $P\left(d_{it}^{ps}=j|q_t=1,d_{it}^{ss}=K\right)$ does not depend on inventory holdings for all $K\in2^{\Omega}$. However, $P\left(d_{it}^{ss}=K|q_t=1\right)$ may depend on inventory holdings. In implication 1a I explore a situation where $P\left(d_{it}^{ss}=K|q_t=1\right)$ varies with inventory. ∎

Implication 1a: *If the random shocks to consumer choices are independent and the true model is alternative (4), conditional on purchasing, conditional on the intrinsic quality of each brand and on the search costs, the likelihood of choosing brands that are more often present in consideration sets should be increasing in inventory holdings.*

Proof. For alternative (4) the likelihood of choosing a brand conditional on purchasing is characterized by

$$P\left(d_{it}^{ps}=j|q_t=1\right)=\sum_{K\in 2^{\Omega}} P\left(d_{it}^{ps}=j|q_t=1,d_{it}^{ss}=K\right)P\left(d_{it}^{ss}=K|q_t=1\right)$$

As previously shown, if the random shocks to consumer choices are independent, $P\left(d_{it}^{ps}=j|q_t=1,d_{it}^{ss}=K\right)$ does not depend on inventory for all $K\in 2^{\Omega}$. In contrast, one expects that $P\left(d_{it}^{ss}=K|q_t=1\right)$ depends on inventory holdings. In particular, if I assume search costs are equal for all brands and brands' intrinsic quality is constant over time, the size of the consideration set decreases with inventory and brands will be added to the consideration set according to their intrinsic value. That is, the brand with the highest valuation will be in all consideration sets with at least one brand while the brands with the lowest valuation only are in the consideration set when its size is large. The assumption of equal search costs and constant intrinsic value is very strong, but I believe it is reasonable to assume that intrinsic qualities will not have a large variation over time and search costs will not be very different across brands. Hence, I expect that the brand with the highest average intrinsic quality is more often in the consideration set, and thus when inventory holdings are larger, the likelihood of choosing a set that includes other alternatives apart from the brand with the highest valuation is low. In other words, let $P\left(d_{it}^{ps}=j|q_t=1\right)$ be a weighted average of $P\left(d_{it}^{ps}=j|q_t=1,d_{it}^{ss}=K\right)$ where the weights are given by $P\left(d_{it}^{ss}=K|q_t=1\right)$. When the inventory is larger, one gives higher weights to the larger probabilities of choosing the brand with the highest valuation and thus the likelihood of choosing the brand with the highest valuation should be increasing in inventory.

■

Formally, it is possible to test the previous implications by evaluating the effect of the time elapsed since the last purchase and the quantity bought during the last purchase on the likelihood of choosing the most purchased brand conditional on buying. This test assumes that the time elapsed since the last purchase and the quantity bought during the last purchase are good proxies for inventory.