

# Pennies for Your Thoughts: Costly Product Consideration and Purchase Quantity Thresholds\*

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## Abstract

Individual demand for consumer packaged goods shows discrete jumps between zero and large quantities, under a marginal change in price. Ruling out alternative explanations, we propose that these jumps are caused by costly consideration, independent of the purchase quantity. Such costs limit the amount of varieties chosen by each consumer, who uses prices to screen products in and out of the consideration set. In turn, the scarcity of attention at the shelf forces firms to compete more fiercely for customers. We structurally characterize rational decisions on consideration and purchase quantity, and estimate the resulting model on micro data from the yogurt category. We find that consideration costs \$1.52 for a brand not on feature, and \$1.21 for a brand on feature. In a world with more feature ads, firms enjoy higher equilibrium markups because competition is softened by the abundance of attention.

*Keywords:* Love for variety, promotion threshold, cost of thinking, limited consideration

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# 1 Introduction

A widely-held belief among practitioners is that small price discounts do not persuade consumers to buy, i.e., that consumers have a “promotion threshold”. For example, Della Bitta and Monroe (1981) document that many retailers believe that there is a minimum discount threshold of 15% before one can attract consumers to a sale. In the upper panel of Figure 1, we plot the demand for a brand of yogurt using consumer level purchase data. From this graph, consumers show little to no response to price changes when prices are high, but are very elastic to price changes when prices are low.<sup>1</sup> Further, the possibility that elasticity can be increasing in discount depth cannot be rationalized by a commonly used demand function such as logit. This paper documents that individuals are more elastic at intermediate prices than at high prices, proposes an explanation for such a pattern consistent with the theory of consideration sets, empirically tests the explanation against alternatives, and structurally quantifies the impact of costly consideration sets on consumer behavior and market prices.

Our explanation for the convex aggregate demand curve in the top graph of Figure 1 becomes understandable once we decompose it into individual demand curves. In the lower panel of Figure 1, we plot individual demand curves for the same product, separately for two groups of consumers having different “price thresholds”, i.e., observed maximum prices for buying, at the 25th and 75th percentiles of the overall price distribution. We find that individual consumer demand features discontinuities at the price thresholds, in that consumers either do not buy at all or buy large quantities, and the transition between these two decisions can be driven by marginal shocks to price. This pattern motivates the main feature of our theory, i.e., that even when prices are known, it is costly to collect the information relevant to make the purchase decision. Consider yogurt for concreteness. A consumer with some interest to shop for yogurt not only needs to know the price, but also needs to know and understand information about flavor, brand, nutritional content, available fridge space at home, and other information, before she is able to determine whether and which brand to purchase and how much quantity. If significant effort is required to understand and combine these non-price attributes of each brand, the consumer will likely restrict attention to a smaller consideration set, and – more importantly – use prices as cues to screen products in and

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<sup>1</sup>This pattern can also explain why price discounts are infrequent but large (Blattberg et al., 1995). An analogy on advertising response threshold is discussed in detail by Dubé et al. (2005).

out of the set. Therefore, marginal price changes are able to push a consumer in choosing between zero and large quantities, generating individual demand curves with jumps. Aggregate demand curves are “smoothed out” versions of these individual demand.

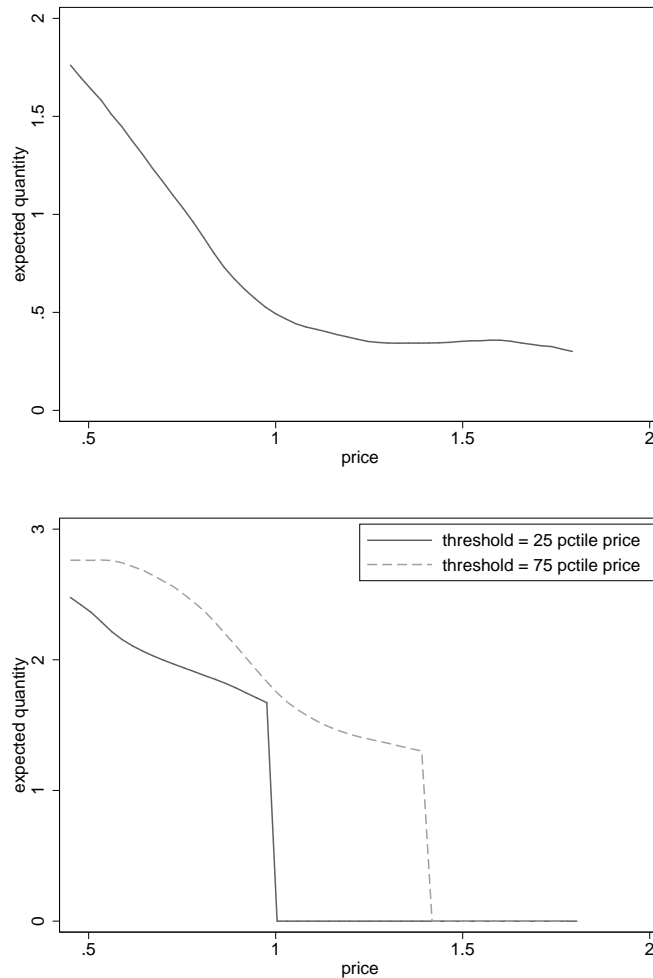


Figure 1: Overall- and by-cohort- demand for Dannon Light

**Notes:** The top panel pictures quantity demand for Dannon Light (including zeros) as a function of price, pooled over all individuals. The bottom panel portrays demand by “cohort” defined as consumers whose observed price thresholds (max accepted price) are similar. In particular, the bottom panel plots demand for two cohorts whose price thresholds are within \$0.1 from the 25th and 75th percentile of price distribution.

We start the paper by presenting a simple model with full information on price but costly information on unobserved match values. Consumers spend effort to discover match values before deciding whether and how much to buy. These “costs of consideration” are fixed to quantity and therefore incentivize consumers to consider fewer products and concentrate expenditure on a

subset – despite their preferences might feature love for variety. We numerically show that the price threshold depends on how much quantity a consumer *would* buy if consideration cost is expended.

Operationalizing the threshold as the maximum price where we observe a purchase, we test for the presence of a quantity discontinuity, without imposing a structural model. Using IRI data in yogurt category, we find very large quantity jumps when the price just becomes acceptable for an individual consumer in a given year. The magnitude of the quantity jump is not explained by a quantity discount or indivisibilities implied by the minimal quantity available. With a smooth consumption utility function, these discrete quantity jumps suggest existence of a fixed cost per variety, consistent with consumer consideration cost. We also test against alternative explanations that generate disproportional demand response at low prices, in particular (1) consumer and product heterogeneity and (2) forward buying and storing goods.

Next, we provide insights on identification before estimating the model. As a classical question in demand estimation, when we observe no purchase for a given product, it is difficult but important to distinguish between lack of consideration and low preference. The question is important because if it is the former case, a firm can provide information to foster consideration and purchase. Yet identification of such an effect is difficult in general without excluded variables that vary consideration costs independently from preference. However, specific to our setup, fixed consideration costs create scale economies in consideration and purchase, and encourages a consumer to either buy large quantities or not buy at all. With price variations, this mechanism will create large jumps in quantity that are not rationalized by a standard model. Therefore, consideration costs in our setup are identified from the observed discontinuities in quantity purchases, even without having to resort to exclusion restrictions. We provide evidence from Monte Carlo experiments that consideration costs are identified even when the functional form of utility is not parametrically known.

We structurally quantify the magnitude of consumer consideration cost, by estimating a model of product-quantity choice using household-level scanner data. To accommodate our identification strategy, our model characterizes demand for variety, as well as quantity choice for each product purchased, and is able to predict quantity discontinuities at price thresholds. Comparatively, standard models for multiple discrete choice (Hendel, 1999; Kim et al., 2002; Dubé, 2004) rely on the property that optimal quantity choice is everywhere continuous in price, and therefore can not

account for the quantity jumps at marginal price increases present in our empirical context.<sup>2</sup>

In our model, the consumer first forms a consideration set as a subset of all available products at a cost of consideration, and next chooses quantities within this consideration set. In the first stage, consumers choose bundles of products to consider, taking the second stage quantities into account. Our way of modeling sets of different products as independent bundles is related to Gentzkow (2007), who treats a reader's choice of combinations of newspapers in a similar way. In the second stage, the consumer –facing decreasing marginal utilities for each product– has a preference for variety within the chosen consideration set. Because the consideration sets are unobserved by the researcher, we then integrate quantity choices over all potential consideration sets. This approach is computationally intense (albeit manageable), but it allows for choices over multiple products, as well as discontinuous quantity demand at the price thresholds, both of which are key to our setting. In addition, we can also flexibly allow for nonlinear prices (quantity discounts) and discrete quantity sets (Allenby et al., 2004). Finally, using a full information approach, we ignore price search as it is non-central to our research question (and price search does not explain Figure 1). To accommodate this simplification, we condition consideration and quantity choice on category purchase decisions, both in the model and in the data.<sup>3</sup>

We estimate the model and find that consideration costs are non-negligible for all consumers. For consumers of yogurt who have purchased in the past week, we find that the cost of considering the product again is equivalent to \$1.52, or roughly half of the average total expenditure on a brand in a trip. The fixed cost increases with inter-purchase time. In the extreme, consumers with no recorded purchase at all have consideration costs more than 3 times as high. This suggests that a large proportion of the consideration cost comes from lack of familiarity and can be attributed to effort for information gathering. Also, feature advertising reduces consideration cost by \$0.3, consistent with the literature (see, e.g., Van Nierop et al., 2010).

We evaluate the role of price discounts in attracting consumer consideration. Because consideration is costly, discount strategies help overcome a consumer's consideration barrier. We therefore use our model to decompose price elasticities into an effect on inclusion of the consideration set,

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<sup>2</sup>Also, different from existing models of limited consideration – for example Goeree (2008), Van Nierop et al. (2010) and Dehmamy and Otter (2014) – the consideration decision in our case is endogenous to price.

<sup>3</sup>Consumers who buy likely have traveled to the focal product shelf. We use the argument in Seiler (2013) that such consumers can find price information easily, compared to the consumers who did not buy products in the refrigerated section. This condition also rules out travel costs within a store (Pinna and Seiler, 2014) and to a store.

and another effect on quantity choice given consideration-set membership. We find that elasticities given consideration-set membership are only about half of the overall price elasticities, which implies that a price discount is less effective on quantity choice once a consumer starts to think about the product. Consistent with this finding, putting a product on feature decreases the consideration costs and thus price elasticities from the consideration decision. This alleviates a firm's burden to compete fiercely for consumer attention and heuristics using prices. We use a static supply side model to find that a \$0.3 consideration cost decrease from feature advertising implies a 7-12% increase in equilibrium markup.

Our primary contribution is that we relate the descriptive literature on a promotion threshold effect, to the literature on limited attention. First, the previous literature has long noted that consumers show little response to small price discounts (Gupta and Cooper, 1992; Blattberg et al., 1995; Van Heerde et al., 2001; Briesch et al., 2002), but does not provide a deep explanation that relates to rational consumer decisions.<sup>4</sup> Our model of costly consideration contributes to the understanding of this empirical regularity, by providing a rational explanation to it. Second, we provide an alternative identification strategy that separates lack of consideration from lack of preference. In particular, our identification strategy relies on observations of “price thresholds”, i.e. the highest price at which the consumer would purchase positive quantities, and quantity discontinuities at these thresholds. Our usage of consumer level scanner data allows us to obtain a dense empirical support of price, which enables measurement of these “price thresholds.” We provide strong evidence of discontinuities in purchase quantity around these thresholds. With this identification strategy, we also propose direct tests for costly consideration using standard marketing data, as well as a structural model that can be used to quantify these costs. In addition, substantively, our empirical results give insights into the effects of price discounts, and marketing strategies that aim at overcoming consumers' consideration barriers.

The rest of this paper is organized as follows. Section 2 briefly surveys the related literature. Section 3 presents the data. Section 4 then discusses the model. First, we outline an illustrative model, which is simple enough to provide analytical as well as numerical solutions. This model generates key testable implications for the existence of costly consideration. Then, section

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<sup>4</sup>Della Bitta and Monroe (1981) and Gupta and Cooper (1992) relate this phenomenon to reference point theories in psychology.

5 parametrizes the model and discusses estimation details. Sections 6 and 7 discuss parameter estimates and counterfactual implications. Finally, Section 8 concludes.

## 2 Related literature

This paper draws primarily from three strands of literature. First, it relates to the literature on promotion effects. Van Heerde et al. (2001) estimate a semi-parametric model using sales and price data, conditional on feature and display, and find that sales is unresponsive to small price changes, and is most responsive to moderately large discounts. Briesch et al. (2002) estimate a discrete choice model where the effect of deals is non-parametric, and find that utility on deals can be convex for yogurt. We complement their work by providing individual level evidence and a structural model that explains these findings. To this end, we adjust for consumer heterogeneity, product heterogeneity and store heterogeneity, and the interaction across these. Using detailed individual-level scanner data, we find clear evidence that an individual is less responsive to price discounts less than 30% off the regular price. We contribute to this literature also in the sense that we provide an explanation that rationalizes this behavior. This explanation further complements the psychology literature that attributes the unresponsiveness to a consumer's innate threshold (Gupta and Cooper, 1992).

Second, our work is related to the literature on limited consideration. Among earlier works, Shugan (1980) provides psychological justifications for the existence of a consumer thinking cost and an analytical framework of its implications. The empirical literature teases apart lack of attention (from e.g., large thinking costs) from lack of preference, in several ways. One way is to obtain a direct measure of attention: for example, Roberts and Lattin (1991) and Draganska and Klapper (2011) utilize survey data and directly elicit consideration decisions. Another way is to provide exclusion restrictions that only enter consideration but not purchase: Goeree (2008) assumes that advertising is informative, and advertising expenditure acts as an exclusion restriction in the utility function (given consideration); Ranjan et al. (2016) leverage natural-experimental variations in shelf-space allocation, observed from a retailer's planogram data, to identify the impact of consideration set on consumer choice and store revenue. A third way to test for the lack of attention is to examine consumer behavior that is inconsistent with any full information model: Clerides and

Courty (2015) finds that consumers continue to purchase large packages in the event that per-unit price of large packages exceed that of smaller packages; Kawaguchi et al. (2016) focus on variations in product availability and show that responses in consumer choices are inconsistent with a full information model.<sup>5</sup>

The most closely related work to us is Dehmamy and Otter (2014). This paper utilizes the sunk cost property of consideration in a consumer's decision of purchase quantity. Fixed costs do not enter quantity choice because they are sunk. Therefore, they propose that one can test for whether variables (such as the number of facings) affect consumption utility directly, by testing whether they affect quantity choice conditional on purchase. In their experimental application, they provide evidence that the number of shelf facings and the location on the shelf only affect consideration, and therefore are good excluded variables from utility. However, their methodology requires data on shelf facings and planograms, which are not always available.<sup>6</sup> In our framework, we highlight the discontinuity in quantity choices due to fixed consideration cost, and endogenous consideration decisions. Our model implies that prices (and potentially other product characteristics) affect these decisions, and generates a quantity jump at the price acceptance threshold. We provide reduced-form tests that uses standard data-sets, and propose an alternative structural model that takes consideration as a first-stage decision.

Further, our work is related to the literature on variety seeking (Kahn et al., 1986; McAlister, 1982) and multiple discrete choice. Hendel (1999), Kim et al. (2002), and Dubé (2004) model a consumer's product and quantity choice, and make simplifying assumptions to isolate the choice from quantity decisions. While this approach eases computation burden, it abstracts from competition for consideration set membership. In our paper, we assume that the consumer takes into account the expected gain from purchase when she decides which product to include in her consideration set. Our model is in line with our proposed tests for limited consideration, but can also serve as an alternative model to characterize multiple discrete choice, when quantity decisions are isolated from choice. In addition, the model allows for the presence of nonlinear prices (quantity discounts) and discrete quantities (cf. Allenby et al. 2004).

Finally, Gilbride and Allenby (2004) discuss estimation issues related to two-stage decision

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<sup>5</sup>Relatedly, Caplin and Dean (2015) propose a theory where agents rationally trade-off information acquisition costs with probabilities of ex-post mistakes.

<sup>6</sup>Ranjan et al. (2016) use planogram data to identify consideration costs, but do not utilize variations in quantity.



models with decision heuristics. Our model falls into their characterization of a compensatory screening rule, where the utility of an alternative must exceed a given threshold. Their paper proposes a model and related estimation strategies, while our paper focuses on rationalizing the existence of such thresholds. Dzyabura and Hauser (2011) study consideration heuristics using machine learning methods.

## 3 Data and descriptive statistics

### 3.1 Construction

We use the 2001-2003 Behavioral Scan panel data from Information Resource Inc.’s (IRI) Academic Data Set (Bronnenberg et al., 2008).<sup>7</sup> We focus on the yogurt and yogurt drink categories. A “store visit” is recorded when a household purchases yogurt or yogurt drink in a trip. The data records, at the SKU level, the number of units the individual purchased in a given store-week, the total amount paid for the purchase, store level weekly data on the total units sold and revenue received on the given SKU, as well as product characteristics such as package size.

At the SKU level, prices are defined as store level revenue divided by units sold. Regular prices are defined as the 95th percentile of prices for a product in a given store-year. Discounts are defined as either absolute or percentage changes of prices from the regular price.<sup>8</sup> The data-set also records whether the product is on feature advertising, on in-store display, or on both.

Next, we aggregate the SKU level data. We define a “brand” as a product with a specific name recorded by the data, regardless of the flavor or package size. For example, “General Mills Columbo Light” is considered as a brand, where “General Mills Columbo Light, berry flavor, 8 oz” is a distinct SKU.<sup>9</sup> We consider the same brand with different package sizes as different quantity options of a homogeneous product. To this end, we find the minimum *available* package size of a brand in a given trip, and define “equivalent units” as total purchased volume divided by the

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<sup>7</sup>All our results, structural and reduced form, are robust when we add data in years 2004-2007.

<sup>8</sup>In an earlier version, we also defined regular prices as max price in the past 4 weeks. We also distinguished between “temporary” price discounts, where prices drop in one week but revert back to their previous regular prices in the following weeks, and “permanent” ones which are associated with a long-lasting price change. We do not find results to be different.

<sup>9</sup>In earlier versions of the paper, we defined a “brand” as a product name - flavor combination, and had similar descriptive results.

minimum package size. For example, for a brand with the minimum package size of 8 oz, an individual who purchased 1 unit of 8 oz, and 3 units of 16 oz ( $8 + 3 \times 16 = 56$  oz), is considered to have purchased 7 *equivalent units* ( $7 \times 8 = 56$  oz). Since few consumers bought non-integer equivalent units,<sup>10</sup> we characterize quantity choice as discrete and round the non-integer choices to the nearest integer.

We average feature advertising and in-store display incidence to the brand level, as sales-weighted averages in a given store and week from the SKU-level data. We use the same approach to aggregate discounts to the brand level, which we use in our descriptive analysis only.

We characterize price for a given quantity as follows. Starting with prices for each available SKU of a brand, we find for each possible purchase quantity, the least expensive combination of different package size that achieves it. For example, price of two equivalent units is the less expensive of buying two units of the smallest package, or one unit of the twice-as-large package, of the same brand. This captures discounts due to bulk purchase, frequently observed in this product category.

Finally, to manage the computational burden of the structural analysis, we restrict our attention to brands with a minimum package size smaller than 1 pint (16 oz). This precludes 24 out of 84 brands, but only removes 1/6 of the category sales volume. We also focus on the top 10 brands (among the remaining 60), ranked in terms of sales volume, in order to maintain consistency between the reduced form and structural analysis. Table 1 summarizes the set of brands in our analysis.

## 3.2 Summary statistics

### 3.2.1 Demographics

There are 8,397 households in the 2001-2003 sampling period. Taking a cross-section for the year 2003 (which consists of 6,558 unique households), we find that these households have an average size of 2.5 members, an average age of the household head of 53.7 years, and an annual income of \$44,114. Household characteristics in other years are very similar.

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<sup>10</sup>A total of 89% of non-zero quantity choices involve integer equivalent units.

Table 1: Set of brands in the analysis

	vol share	share sold on disc.	reg price	price on disc.
Dannon Light N Fit	0.13	0.09	1.53	1.04
Yoplait Original	0.13	0.06	0.89	0.72
Colombo Classic	0.07	0.05	1.09	0.83
Colombo Light	0.07	0.02	0.82	0.55
Yoplait Light	0.07	0.03	0.83	0.68
Dannon Regular	0.06	0.03	0.81	0.53
Yoplait Thick	0.05	0.02	0.72	0.48
Danon Stonyfield Farm	0.04	0.02	2.48	1.77
Wells Blue Bunny	0.03	0.01	0.65	0.56
Coolbrands International Breyers	0.03	0.02	0.76	0.54

**Note:** This table presents the set of brands, their in-sample sales volume share and share of volume sold on discount (defined as occasions when prices are 5% or more below the regular price). It also reports regular price and price given discount. These brands are used both in descriptive and structural estimates.

### 3.2.2 Trips

On average, a household is observed for 56.5 weeks between the first and the last recorded trip containing yogurt purchases at a given retailer. In this period, there are 9.5 weeks on average with yogurt purchases. Within those 9.5 weeks, 5.3 weeks are associated with purchase of the top 10 products, and 3.0 weeks are with the top 4 products.

As stated in the introduction, we condition on price awareness by dropping weeks without yogurt purchase. Essentially, we assume that the household has at least “glanced through” all the price tags on the shelf, and hence the price information is free. Thereby, we avoid having to model a costly search process on top of our love-of-variety model.

### 3.2.3 Products, prices and concentration

We compute in-sample market share, based on the shares of total consumer expenditure in yogurt, and find that concentration is moderate: overall, the top 10 products represent 61% of category sales. Among the top 10 products, average per-volume price is 0.14 dollar/oz, with a standard deviation of 0.07. The most popular sizes are 6 oz (51% of purchase occasions) and 8 oz (41%). The remaining 8% purchase occasions involve sizes of 1 or 2 pints.<sup>11</sup>

<sup>11</sup>Mostly from Dannon Light and Stonyfield. We adjust for availability of smaller sizes both in reduced form and structural analysis.

### 3.2.4 Discounts, feature and display

The use of feature and display is rare in the yogurt category. Only 7.1% of all product-store-week combinations have 50% or more of the SKUs on feature.<sup>12</sup> At 1.5% of all observations, displays are less common.

Discounts are frequently aligned with feature or display. That is, 80% of the products on feature or display are on a discount with no less than 5% price drop. On the contrary, when there is no feature or display, only 8% of the products are on a 5%-or-more discount. Further, conditional on being on feature or display, the discount distribution has a mode of around 30%. This suggests an unwillingness to set shallow discounts. This is in line with practitioner's belief that consumer response to discount is convex. The price discount distribution conditional on feature or display is shown in Appendix Figure 8.

### 3.2.5 Variety and quantity per trip

Within-trip expenditure is heavily concentrated. In 76% of all shopping trips, consumers buy more than one (equivalent) unit of purchase, and 23% more than 5 equivalent units. Note that equivalent units are defined such that unit 1 is always available. However, consumers are not willing to spread the expenditure across different varieties. Across all trips with purchase, a consumer buys *one or two* products in 97% of the time. This pattern agrees with the literature on soft drinks (Dubé, 2004; Chan, 2006).

In sharp contrast to the concentration of brands within a trip, we find that the total number of products purchased in the entire sample duration is much higher. Focusing on households who we observe between 20 to 40 trips that involve yogurt purchases,<sup>13</sup> we find that on average, a household purchases 1.2 distinct brands per trip, while purchasing no less than 7.9 distinct brands overall.<sup>14</sup> The large difference between these numbers suggests that a household does not focus on a narrow set of products in any given trip because of time-invariant preferences, which is in line with our theory where per-trip fixed costs will limit the amount of varieties in the short run. However, it could also be explained by variations of product characteristics such as price, feature

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<sup>12</sup>The percentage of feature is calculated as a sales volume weighted average.

<sup>13</sup>This selects a sub-sample of between median and 75th percentile in the trip distribution.

<sup>14</sup>For a full distribution of within and across trip variety, see Figure 9 in the appendix.

or availability.

### 3.3 Aggregate price response curves

In this section, we formalize the observations that demand is more responsive to large discounts – an example shown in Figure 1. With individual level data, we first calculate the average purchase quantity,  $\bar{q}_{ij\tau}$ , of an individual for a given product in a given year  $\tau$ , when prices are within 15% of the regular price. We then compute the percentage change of demand in each given trip,  $\frac{q_{ijt} - \bar{q}_{ij\tau}}{\bar{q}_{ij\tau}}$ , and likewise, percentage change in price from the regular price. We then deseason the two variables and plot them against each other.<sup>15</sup> Figure 2 presents local polynomial fit of such relations, pooled over all products and all occasions where the focal product is not on feature or display.

Because both axes represent percentage changes in quantity/price, the slope of the polynomial fit can be viewed as point elasticity for a given price drop from the regular price. Note that when price discounts are below 30%, demand is less elastic than -1 and almost constant elastic. However, with 50-60% discount, point elasticity goes up in magnitude to around -5. This shows that demand can be “log-convex” in a certain region, i.e. the elasticity can be increasing in price discounts.

It is useful to highlight that such increasing elasticity patterns are not shared with typical demand system such as log-log or logit. A log-log regression implies constant elasticity, or a linear relationship in Figure 2. A logit model with linear utility on price implies that elasticity is  $-\alpha \cdot price \cdot (1 - share)$  where  $-\alpha$  is the price coefficient. This means that logit elasticity is decreasing in market share, and the relationship in Figure 2 should be concave.

In the introduction, we informally documented that the increasingly-elastic price response on the aggregate level comes from individual level demand “jumps” (Figure 1). Section 4 proposes a model that formalizes such pattern. Section 4.5 rules out alternative explanations.

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<sup>15</sup>We regress each of the percentage changes of quantity and price against month dummies, take the residuals, and adjust each by a constant so that Figure 2 goes through the origin.

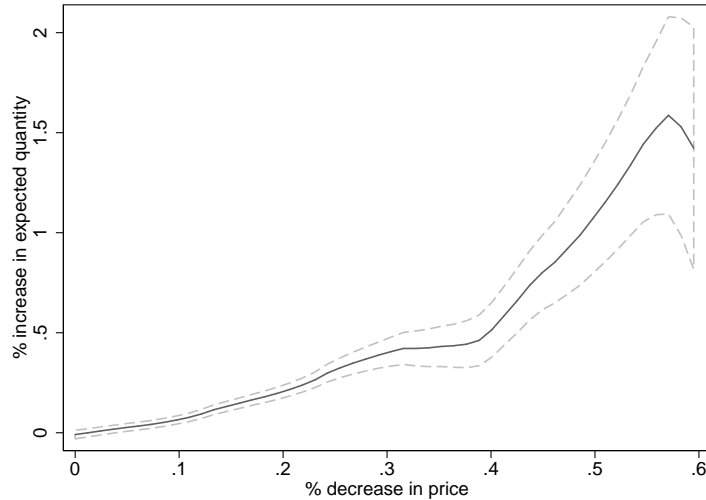


Figure 2: Convex response to discount

**Notes:** This figure shows the observed relationship between price and quantity in the yogurt category. The horizontal axis shows discounts from the regular price (in US dollars). The vertical axis shows the corresponding average increase in purchase quantity compared to the average purchase quantity under regular prices. The figure was constructed conditional on the (lack of) provision of additional price information (i.e. no feature or display) and controls for consumer-product-year fixed effects and month fixed effects.

## 4 Illustrative model and identification

### 4.1 Overview

Figure 2 shows that consumer demand is increasingly responsive to price discounts. In this section, we first construct an empirical model of endogenous consideration set formation that rationalizes this pattern. In our model, the consumer costlessly observes prices of a product, but needs to incur costs to “consider the purchase” – i.e., to acquire other information before the purchase decision. Because the consumer decides on quantity after consideration, such consideration costs are fixed to quantity. This makes consideration more likely at high discounts, because of the potential to purchase multiple units in such occasions. We numerically illustrate that such a model with endogenously-determined consideration sets after observing prices can accommodate the convex demand function, similar to Figure 2.

Next, we provide testable implications from the model and test it with consumer scanner data. A consumer would rather not consider at all, than considering the product and buying a very small

quantity. This is because small purchase quantity does not generate high enough utility level that justifies the consideration cost. We test this hypothesis by the purchase quantity distribution at each consumers' maximum accepted price, and find that the purchase quantity has a median of 4 units when the choice of 1 unit is feasible. In addition, in Appendix A, we numerically illustrate that with large fixed costs, the purchase probability (incidence) will drop to zero at high prices but the average quantity given purchase remains high. We also empirically find that, controlling for full consumer heterogeneity, individual consumer demand shows the same discrepancy between incidence and quantity.

Then, we show that the model can be identified when the only source of variation is price. The intuition is that incidence and quantity responds differently to price changes and the response pattern resembles a model with fixed costs. We run Monte Carlo simulations to show that parameters are very precisely estimated when we use the correct parametric model. When we do not know the correct consumption utility functional form (but instead approximate it by finite order polynomial), we show that key parameters including fixed costs can be estimated precisely. This suggests that consideration costs can be identified from price variation alone.

## 4.2 An illustrative model: setup

In this section, we present a simplified model that characterizes the purchase decisions of a given product for a representative consumer. We simplify the model in order to illustrate key testable implications of it, as well as to show how parameters of the model are identified. We extend the model to incorporate multiple varieties in Section 5.

An individual  $i$  wishes to purchase at least one unit of yogurt and travels to the refrigerated product shelf in trip  $t$ . To convey the essence of our argument, it suffices to focus on the purchase decisions of a single product. The consumer first observes the unit price of the product and decides whether it is optimal for her to “consider” the product – in which case she discovers her match value to the product but incurs effort costs. Upon consideration, she can then choose what quantity to purchase,  $q_{it}$ , with the possibility of  $q_{it} = 0$  symbolizing the choice of “other varieties” (the outside option).

The consumer solves the problem backwards. Given consideration, we specify her indirect

consumption utility as

$$c_{it}(p_t, q_{it}) = \beta \log(q_{it} + 1) - \alpha p_t q_{it} + \mu_{it}(q_{it}) \quad (1)$$

where  $\beta \log(q_{it} + 1)$  captures how consumption utility is increasing in quantity and how marginal utility is decreasing,  $-\alpha p_t q_{it}$  captures the dis-utility on expenditure, and  $\mu_{it}(q_{it})$  captures other product characteristics or match value that are unobserved to the researcher, and unobserved to the consumer prior to consideration. For example, consideration might involve picking up a product and evaluate its caloric or dietary content, which requires effort. Alternatively, consideration might involve planning ahead on which days in the coming week to consume yogurt, which also requires effort. For analytical simplicity, we model these unobserved characteristics or match values revealed through consideration, as quantity-specific utility shocks that are Type I Extreme Value with scale parameter  $\sigma_\mu$ .

Consideration reveals utility shocks  $\mu_{it}(\cdot)$  at the expense of (random) fixed costs  $f + \Delta\epsilon$ , and the decision is rational in the sense that the consumer weighs the expected net consumption utility against the consideration costs. Specifically, the consumer observes prices, and expects to receive total utility

$$u_{it} = \underbrace{\mathbb{E} \left[ \max_{q \in Q} (c_{it}(p_t, q)) \mid p_t \right]}_{\text{option value from consideration}} - \underbrace{(f + \Delta\epsilon_{it})}_{\text{fixed costs}} \quad (2)$$

if she considers the product, or zero if she does not consider. Note that the expectation term integrates over potential information on  $\mu$  –unobserved prior to consideration– therefore also the optimal consumption quantity.

The consumer chooses to consider the product if she gets positive expected total utility, i.e.  $u_{it} > 0$ . Given consideration, she chooses quantity that maximizes (1).

### 4.3 Testable implication: Quantity jump at the threshold price

We present and test the key implication for our model. For a consumer with a given draw of fixed cost shocks,  $\Delta\epsilon_{it}$ , consideration reduces to a threshold price rule in the sense that the consumer will consider with certainty when prices are below a threshold  $\bar{p}$ . This threshold price property eliminates (expected) small quantity demand, since expected consumption utility at high prices do



not justify spending the fixed cost. Therefore, take the maximum “accepted” price – highest price at which a given consumer decides to purchase – as proxy to the threshold price, and our model implies that her purchase quantity distribution at the threshold price will be bounded away from 1.

To numerically show this, we simulate optimal quantity choice from the model defined in (1) and (2) at parameters  $\beta = 3$ ,  $\alpha = 1$ ,  $f + \Delta\epsilon_{it} = 4$  and  $\sigma_\mu = 2$ , and allow quantity choices to take values in  $Q = \{0, 1, \dots, 12\}$ . We take 100,000 draws of  $\mu_{it}$  and prices, and plot the average purchase quantity conditional on price in Figure (3). The figure shows that there is a discrete jump in quantity at the threshold price because quantity demand at higher prices are “suppressed” – as they do not generate high enough expected consumption utility to justify the consideration fixed costs. Therefore, if the researcher knows the threshold price  $\bar{p}_t$  for each consumer-trip, she can then test for the presence of a consumer fixed cost  $f$ , by testing whether the quantity at a price *slightly* below  $\bar{p}_t$  – i.e. the threshold quantity  $\bar{q}_{it}$  – is significantly larger than zero.

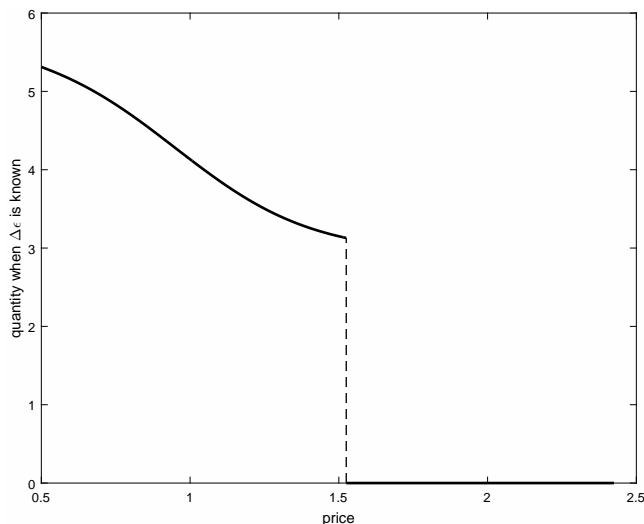


Figure 3: Quantity jump at the threshold price

**Notes:** The solid curve illustrates the average purchase quantity at different prices, from simulation exercises where demand is implied by (1) and (2). We take  $\beta = 3$ ,  $\alpha = 1$ ,  $f + \Delta\epsilon = 4$  and  $\sigma_\mu = 2$ . Choice set is discrete with  $Q = \{0, 1, \dots, 12\}$ .

Taking this intuition to our data, we construct the threshold price  $\bar{p}_{ij\tau}$  as the *maximum accepted price*, i.e. the highest price at which we observe individual  $i$  making a purchase of product  $j$  within the given year  $\tau$ . We do this by conditioning on observing at least 5 purchase occasions for a given

product within the year, and we take the highest purchase price among the 5 or more occasions. We compute threshold discount level by taking regular price minus the threshold price, in order to be able to compare across products having very different price levels. Thus, the threshold discount is the price discount that just makes a consumer buy. Next, we characterize the purchase quantity distributions for each individual and product, at different threshold values. given that the discount level is within 2.5 cents difference to her discount threshold, and that the individual purchases at the current discount level. Recall that quantity is measured in multiples of the minimum *available* package size. Therefore, a quantity of 1 is available by definition for each product in each trip.

We plot quantity distribution at the threshold discount across combinations of individuals and products with different discount thresholds, resulting in Figure 4. This figure shows that median purchase quantity at the discount threshold is 3-5 times the minimal available package size. The 25th percentile is 2 or 3, and 75th percentile is mostly 5, 6, or 7. This figure clearly documents the prevalence of quantity jumps at the discount thresholds. These jumps are consistent with a theory of (endogenous) costly consideration.

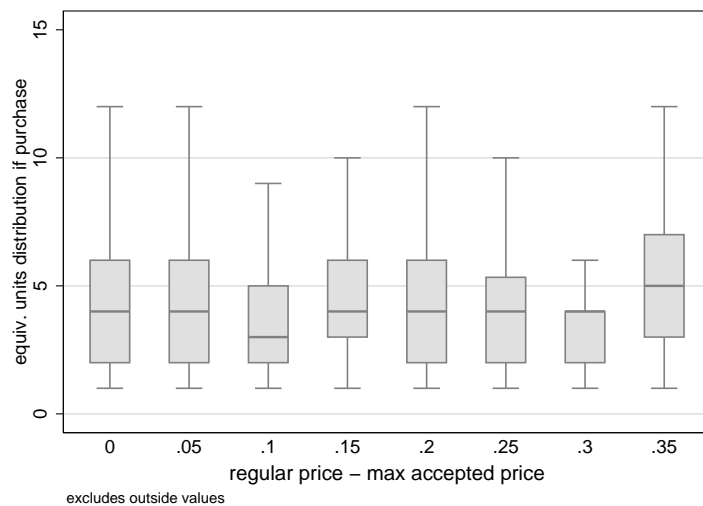


Figure 4: Quantity response to price for the marginal consumer

**Notes:** On the horizontal axis, we plot the difference between regular price and the maximum accepted price of a consumer, for a given product-retailer-year. On the vertical axis, we plot quantiles in the purchase quantity distribution, given that the consumer purchases at prices that are within \$0.025 of the max accepted price. The grey box represents 25% and 75% percentile, the center bar represents the median, and the outer range represent 5% and 95% percentiles.

## 4.4 Identification

### 4.4.1 Intuition

Figure 3 shows that, when the fixed cost is deterministic, the researcher observes under which threshold price the consumer considers the product with probability one. Therefore, below the threshold price, consumption utility is identified by the distribution of purchase quantities as a function of prices. Furthermore, at the threshold price, consideration cost equates the total expected value from consumption. Therefore, the location of threshold price identifies the size of consideration cost.

When there are random components in the consideration costs ( $\Delta\epsilon$ ), consideration costs generate a gap between quantity given purchase and purchase probability. Specifically, when prices are high, purchase incidence is low despite that quantity given purchase is high. In our simple model, the only element that explains this gap is a positive consideration cost  $f$ . A high  $f$  results in most consumers not thinking about the product when prices are high, therefore lowering the purchase probability considerably while not changing quantity at purchase.

### 4.4.2 Monte Carlo simulations

We run Monte Carlo simulations to confirm that we can uniquely pin down consumption utility parameters and fixed cost parameters separately (see Appendices A and B). We first simulate choices of quantity under different prices by a homogeneous set of individuals, under the same model and parameters that generates Figure 3. We find that all parameters can be estimated precisely and without bias, implying that consideration cost is identified by price variations alone within our framework, without having to resort to other covariates and exclusion restrictions. Appendix Table 1 presents the results.

We further confirm that our results are not driven by specific functional form assumptions, by estimating models with more flexible utility function than our data-generating process. Our results confirm that one can reliably estimate model parameters when consumption utility functional form is unknown but approximated by a polynomial. These results are presented in Appendix B.

## 4.5 Alternative explanations

### 4.5.1 Stockpiling

If the underlying product is storable, consumers with rational expectations will stockpile when prices are low and consume the inventory when prices are high, resulting in higher short-run price sensitivity (Erdem et al., 2003; Hendel and Nevo, 2006a). Stockpiling *per se* does not explain the log-convex demand (Figure 2) or the quantity jumps at individual price thresholds (Figure 3), because the underlying individual demand function in an inventory setting is still continuous and log-concave. However, in presence of stockpiling, short- and long- run price response differ and should be treated differently.

We test for stockpiling by estimating current purchase decision (incidence) and quantity given purchase, as functions of either time since last purchase or past 2 weeks of prices, controlling for current prices, individual fixed effects, and flexible specifications of time dummies. Consumers who takes advantage of a price discount to stock up will purchases less in the near future; therefore past prices should have positive effects on current sales if stockpiling is a concern. Similarly, consumers who stock up should purchase more in time elapsed since last purchase. We estimate linear specifications both at the category- and the brand level, shown in Table 2 and Appendix Table 4 respectively. Our results do not support stockpiling behavior.<sup>16</sup>

### 4.5.2 Unobserved individual and product characteristics

The increasing elastic demand that we find could be due to differences in characteristics or pricing patterns between products. For example, some products go on deep discounts more frequently and sell more, and those observations concentrate on the right end of Figure 2. Similarly, there might be heterogeneity in consumer price sensitivity correlated with their shopping patterns. For example, if price sensitive consumers travel to the category only when discounts are deep, they will be on the right end of the figure and thus explain the convexity.

To address these issues, we test whether demand is increasingly elastic among similar indi-

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<sup>16</sup>Columns 1 and 3 are similar to tests in Hendel and Nevo (2006b), who find weak evidence for stockpiling in the yogurt category compared to laundry detergent and soft drinks. Our evidence is opposite to what a stockpiling model would predict, but suggests that consumers with stronger category preference buy more frequently. In earlier versions, we instrument inter-purchase time by past preferences and do not find any effect on current purchase decisions, either. Brand-level evidence tells the same story.

Table 2: Test for consumer stockpiling: category level

	incidence	incidence	logvolume	logvolume
months since last purchase	-0.025***		-0.027***	
	0.001		0.002	
– squared	0.001***		0.001***	
	0.000		0.000	
log price	-0.213***	-0.165***	-0.408***	-0.340***
	0.008	0.019	0.015	0.039
– past week		-0.018		0.026
		0.019		0.038
– past 2 weeks		0.006		0.006
		0.019		0.038
years since 200101	0.053***	0.048***	0.017***	0.008
	0.001	0.003	0.002	0.007
Apr-Jun	-0.016***	-0.010*	-0.020***	0.018
	0.002	0.006	0.004	0.011
Jul-Sep	-0.030***	-0.024***	-0.014***	-0.009
	0.002	0.006	0.005	0.012
Oct-Dec	-0.030***	-0.015**	-0.039***	-0.043***
	0.003	0.006	0.005	0.012
individual FE	Yes	Yes	Yes	Yes
obs.	152631	26361	126312	22087

**Notes:** Category level evidence for stockpiling both in the extensive and intensive margin. Standard errors are reported beneath the parameter estimates. 1, 2 and 3 stars indicate significance levels at 10%, 5% and 1%, respectively.

viduals and products. To this end, we group data by product/retailer, by households of the same size, and condition on price discounts within a certain range. We estimate a linear-log specification controlling for a time trend:

$$q_{ijt} = \beta_g + \delta_t + \alpha_g \log(\text{price}_{jt}) + \varepsilon_{gt} \quad (3)$$

where  $g$  is a “group”, i.e. a unique combination of product, retailer and household size, given price discounts falling into given 15% grids.<sup>17</sup> Note that  $q_{ijt}$  can take value 0. After estimating  $\alpha_g$ , we then compute an estimate for elasticity  $\mathcal{E}_{gt} = \frac{\partial \bar{q}_{gt}}{\partial \text{price}_{jt}} \frac{\text{price}_{jt}}{\bar{q}_{gt}} = \alpha_g / \bar{q}_{gt}$  where  $\bar{q}_{gt}$  is the average quantity for the consumer-retailer-product group.

Within each group of product, retailer and household size, we take the ratio between elasticity at discount grids above 15%, and elasticity when discounts are between 0 and 15%. In a constant elasticity demand system, this ratio should be 1. In a logit demand system this ratio should be less than 1. Table 3 presents the median elasticity ratio because the mean is driven by extreme values. We find that elasticities at lower prices (larger discounts) are generally larger than elasticities around the regular price, in particular the median ratio between elasticities at 15-30% discounts compared to at 0-15% is significantly larger than 1 within a group of similar consumers.<sup>18</sup> Cases with larger discounts suffer from limited power issue because we cut the data into very thin subsamples, although the magnitude of elasticities at 30-45% does seem to be considerably larger.<sup>19</sup>

These results show that within a consumer segment elasticities increase with discount depth, and that our results are not simply due to aggregation over heterogeneous consumers.

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<sup>17</sup>We use 0-15%, 15-30%, 30-45% and 45-60%, each range including the lower bound.

<sup>18</sup>We compute the standard error of the sample median by

$$se(\hat{m}(x)) = \frac{1}{2\hat{f}(x) \cdot \sqrt{N}}$$

where  $x$  is the ratio of elasticity,  $\hat{f}(x)$  is the Kernel density of  $x$  evaluated at the median, and  $N$  is the sample size of  $x$ , i.e., the number of consumer groups. This formula follows the asymptotic distribution for sample quantiles (Walker, 1968, page 570).

<sup>19</sup>We alternatively estimate (3) within individual-product-store. We find qualitatively similar results but the sample is too thin to draw statistical inference.

Table 3: Ratio of price elasticity at different price range

	median	std err of median
15-30% discount	1.3	0.1
30-45% discount	1.9	0.2
45-60% discount	1.5	0.2

**Notes:** Estimates of price elasticity at different price range, for the same product and for the same “group” of consumers with similar observables. This is executed according to Equation (3).

### 4.5.3 Seasonality

Another alternative explanation to Figure 2 is that demand and prices are both seasonal. If prices are counter-cyclical – as documented by Nevo and Hatzitaskos (2006) and Haviv (2015) – low prices are correlated with high demand purely because of uncaptured seasonality. We allow for seasonality in our reduced form evidence and we find only limited evidence for it (for example, see Table 2).

## 5 Structural model and implementation

### 5.1 Overview

We generalize the model in Section 4.2 to be able to (1) accommodate more products in the choice set, (2) allow for choice of multiple products at the same time, and (3) account for observed characteristics and demographics as covariates. This section provides details on parametrization of each part of the model, the solution to the consumer problem, and implementation in estimation.

The consumer  $i$  maximizes her utility by choosing quantities, denoted  $\mathbf{q}_{it} = (q_{i1t}, q_{i2t}, \dots, q_{iJt})'$ . To choose any product the consumer has to first consider it, and we denote the (endogenous) set of products to consider as  $K_{it} \subset J$ . In our empirical implementation, we limit dimensionality by restricting the total number of products in the consideration set to be at most 2, i.e.  $\|K\| \leq 2$ . Recall from our data description that this still captures 97% of all trips with yogurt purchases. Limiting the consideration set size to 2 is therefore not far from reality in our context and greatly reduces computation burden.

## 5.2 Parametrization

### 5.2.1 Consumption utility

We specify the (indirect) consumption utility as

$$c_{it}(\mathbf{q}_{it}, \mathbf{p}_t) = \sum_{j \in K_{it}} \mathbf{x}'_{ijt} \beta_i \log(q_{ijt} + 1) + \gamma \prod_{j \in K_{it}} \log(q_{ijt} + 1) + \alpha \sum_{j \in K_{it}} p_{jt}(q_{ijt}) \cdot q_{ijt} + \mu_{it}(q_{ikt}, q_{ilt}) \quad (4)$$

where the consumption sub-utility is specified in log, and defined on *discrete* quantities  $q_{ijt} \in \{0, 1, \dots, \bar{q}\}$ . The consumption utility function takes the form similar to Kim et al. (2002) and Dehmamy and Otter (2014). The log specification in quantity implies decreasing marginal utility, and hence love-for-variety preference. To make the model less restrictive, we allow for additional love for variety captured by  $\gamma$  multiplying interactions between (log) utility of different products. A positive  $\gamma$  means that love for variety is stronger than implied by the “sum of log quantity” specification, while a negative  $\gamma$  implies weaker love for variety preference, i.e., a negative  $\gamma$  captures the degree of substitutability between products. Finally, as a matter of definition, when the choice set is singleton, one of the log-quantity terms becomes zero, effectively setting the interaction effect to zero.

$\mathbf{x}_{ijt}$  is a *vector* of indicators of brand characteristics, individual characteristics and time. Specifically, it contains a vector of brand dummies, indicator for characteristics “light”, household size, and a linear time trend. The product  $\mathbf{x}'_{ijt} \beta_i$  captures marginal utility to *percentage* increases in quantity. For example, Dannon Light has characteristics “Dannon” ( $x_{j2} = 1$ ) and “light” ( $x_{j5} = 1$ ), and therefore the marginal utility for log quantity is  $(0, 1, 0, 0, 1, hhsizet, t) \cdot (\beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}, \beta_6, \beta_7)' = \beta_{i2} + \beta_{i5} + \beta_6 \cdot hhsizet + \beta_7 \cdot t$ . Note that demographic and time coefficients are constant across households.

Prices affect decisions via the indirect utility function. We allow the per-product expenditure  $p_{jt}(q_{ijt}) \cdot q_{ijt}$  to be non-linear in quantity, to capture the potential quantity discounts that consumers could benefit from, by buying in large quantities. Recall,  $p_{jt}(q_{ijt})$  is the *lowest* across different quantity combinations, per-unit price one could get when choosing total quantity  $q_{ijt}$ .  $\alpha$  is the price coefficient, held fixed across households.

The consumer also receives random consumption utility shocks,  $\mu_{it}(q_{ikt}, q_{ilt})$ , unobserved by



the researcher, which capture taste shocks that favor, or oppose, purchasing a specific quantity combination. We assume, for a particular combination of quantity  $(q_1, q_2)$ , that  $\mu_{it}(q_1, q_2)/\kappa$  is i.i.d. type-1 extreme value distributed, where  $\kappa$  is a scale coefficient. We make the i.i.d. assumption for model tractability, because in this way we can explicitly solve for the inclusive value from quantity choice.<sup>20</sup> With this assumption, one should interpret the  $\mu$ 's as shocks to match value or decision error, rather than unobserved product characteristics.<sup>21</sup> We also assume that  $\mu_{it}$  is realized *after* the consumer forms consideration set  $K_{it}$ . One can interpret the fixed costs as costs of drawing utility shocks.

### 5.2.2 Consideration costs

The consumer also incurs a consideration cost,  $F_{it}(K_{it})$ , as a function of her consideration set. Denote  $W_{ijt}$  as the number of weeks since the consumer purchased  $j$  last time (measured in 100 weeks), and  $A_{ijt}$  whether a product is on feature advertising. In addition, we denote  $\mathbf{W}_{it}$  and  $\mathbf{A}_{it}$  as the vector of  $W_{ijt}$  and  $A_{ijt}$  over all products, and we adopt the convention that  $W_{ijt} = \infty$  if the consumer has not purchased  $j$  prior to  $t$ . Now, we parametrize the fixed cost as

$$F_i(K_{it}, \mathbf{A}_{it}, \mathbf{W}_{it}) = \sum_{j \in K_{it}} [f_{i0} + f_W \cdot W_{ijt} \mathbf{1}(W_{ijt} \neq \infty) + f_N \cdot \mathbf{1}(W_{ijt} = \infty) + f_A \cdot \mathbf{1}(A_{ijt} = 1)] + f_2 \cdot \mathbf{1}(|K_{it}| = 2) - \varepsilon_{iKt}, \quad (5)$$

where  $f_{i0}$  denotes the baseline per-product consideration cost for individual  $i$ , which is common across products.  $f_W$  is the change in fixed cost for every 100 weeks since the last purchase of the product,  $f_N$  is the additional fixed cost for consumers who never purchased the product before,  $f_A$  is the increase (negative means reduction) in fixed cost when the product is on feature, and  $f_2$  is the additional total consideration cost when considering two products.

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<sup>20</sup>An alternative approach to modeling quantity choices is Kim et al. (2002), who model marginal utility shocks as error terms to quantity choice. Although easier to interpret, estimation of their model relies on first order conditions on the optimal quantity, which cannot be used to estimate fixed costs. In addition, their model is less flexible in capturing non-smoothness in the quantity distributions in the data. In contrast to their approach, as in Gentzkow (2007), we model utility shocks as bundle specific to allow for a flexible specification of substitution or complementarity in consumption. Our approach allows one to characterize choice probabilities directly instead of first order conditions and therefore can be used to estimate fixed costs.

<sup>21</sup>In an earlier version, we control for product fixed effects both in  $c_{it}(\cdot)$  and consumer fixed costs and obtain very similar results.

The consumer also incurs an unobserved (by the researcher) cost shock  $\varepsilon_{iK_t}$ , specific to set  $K = K_{it}$ , which are independent type-1 extreme value random variables, across individual, trip and all potential sets  $K \subset J$ . In addition, for tractability,  $\varepsilon_{iK_t}$ 's are independent of  $\mu_{it}(q_{ikt}, q_{ilt})$ .

## 5.3 Solution of optimal choice rules

### 5.3.1 Quantity given consideration set

The consumer maximizes expected utility and solves the consumer problem backward. In the second stage, given that the consumer decides to consider products in set  $K_{it}$ , she reveals consumption utility shock  $\mu_{it}(\cdot)$  and chooses the quantity combination within  $K_{it}$  that maximizes utility in equation (4). In other words, she chooses  $(q_{ikt}, q_{ilt})$  given  $K_{it} = \{k, l\}$  ( $l = 0$  in case of a single-product consideration set). Note that fixed costs and the cost shocks are sunk and are irrelevant to the purchase decision once the consideration set  $K_{it}$  is fixed.

Given the Type I Extreme Value assumption on  $\mu$ , quantity choice is multinomial logit on combinations of quantity. Denote  $\bar{c}_{it}(\mathbf{q}_{it}, \mathbf{p}_t) = \sum_{j=k,l} (\mathbf{x}'_{ijt} \beta_i \cdot \log(q_{ijt} + 1) - \alpha \cdot p_{jt}(q_{ijt}) \cdot q_{ijt}) + \gamma \cdot \prod_{j=k,l} \log(q_{ijt} + 1)$ , choices over discrete quantity sets follow a multinomial logit probability

$$\Pr(q_{ijt}, q_{ikt} | K_{it}; \theta_i) = \frac{\exp(\bar{c}_{it}(q_{ikt}, q_{ilt}) / \kappa)}{\sum_{(q'_k, q'_l) \in Q^2} \exp(\bar{c}_{it}(q'_k, q'_l) / \kappa)}, \quad (6)$$

Where  $\theta_i$  denotes all relevant parameters. Because the quantity support  $Q$  includes zero, the set  $Q^2$  of possible quantity combinations includes buying *nothing*, or buying from only one product.<sup>22</sup>

### 5.3.2 Choice of the consideration set

Consideration is costly and the set  $K_{it}$  is a choice. On the one hand, the consumer spends effort considering products in a given set  $K_{it}$ , incurring cost  $F_i(K_{it}, \mathbf{A}_{it}, \mathbf{W}_{it})$  as defined in (5). On the other hand, before considering the product and revealing  $\mu_{it}$ , she does not perfectly predict her optimal choice, and evaluates the expected option value from a given consideration set in terms of the following “inclusive value” term, which is the expected maximum total utility from set  $K_{it}$ . Denote state  $\mathbf{S}_{it} = (\mathbf{p}_t, \mathbf{A}_{it}, \mathbf{W}_{it})$  for notational simplicity. Combining the expected gain from

<sup>22</sup>For singleton consideration sets, the quantity support reduces to  $Q$ .

consideration and the expected fixed cost, the net expected utility from considering a set  $K_{it}$  is:

$$\bar{v}_i(K_{it}, \mathbf{S}_{it}) + \varepsilon_{iK_{it}} = \mathbb{E} \left[ \max_{\mathbf{q} \in Q^2} (c_{it}(\mathbf{p}_t, \mathbf{q})) | K_{it}, \mathbf{p}_t \right] - F_i(K_{it}, \mathbf{A}_{it}, \mathbf{W}_{it}), \quad (7)$$

where  $\mathbf{q}$  can have at most two positive elements because we restrict the size of consideration set  $K_{it}$ . Note that from the GEV assumption on  $\mu$ , one can derive that

$$\bar{v}_i(K_{it}, \mathbf{S}_{it}) = 0.577 + \kappa \cdot \log \left( \sum_{(q'_k, q'_l) \in Q^2} \exp \left( \frac{c_{it}(q'_k, q'_l)}{\kappa} \right) \right) - F_i(K_{it}, \mathbf{A}_{it}, \mathbf{W}_{it}), \quad (8)$$

where 0.577 is the Euler constant. Then, given the type I extreme value cost shocks  $\varepsilon_{iK_{it}}$ , we can express the probability of choosing a consideration set  $K_{it}$  as:

$$\Pr(K_{it} | \mathbf{S}_{it}; \theta_i) = \frac{\exp(\bar{v}_{it}(K_{it}, \mathbf{S}_{it}))}{\sum_{K' \in \mathcal{K}} \exp(\bar{v}_{it}(K', \mathbf{S}_{it}))}, \quad (9)$$

where  $\mathcal{K}$  is the set of all possible consideration sets (up to the size limit of 2) – including  $\emptyset$ .

## 5.4 Construction of the likelihood function

### 5.4.1 Matching the observed choice probability

We have characterized the choice probability of consideration set  $K$ , and the probability distribution of purchase quantities given  $K$ . To match the data, note that what is observed are the choice probabilities of a specific quantity combination, or, the empirical counterparts of

$$\Pr(q_{ikt}, q_{ilt} | \mathbf{S}_{it}; \theta_i) = \sum_{K' \supset \{k, l\}} \Pr(q_{ikt}, q_{ilt} | K', \mathbf{S}_{it}; \theta_i) \cdot \Pr(K' | \mathbf{S}_{it}; \theta_i). \quad (10)$$

### 5.4.2 Likelihood with random coefficients

Given that each time series of choices by one individual is generated under each individual's independent realization of random coefficients, we can write the likelihood across the individual-trips, as

$$\mathcal{L}(\theta) = \prod_i \left( \int_{\theta_i} \left( \prod_t \Pr(q_{ikt}, q_{ilt} | \mathbf{S}_{it}; \theta_i) \right) dG(\theta_i; \theta) \right), \quad (11)$$

where  $(q_{ikt}, q_{ilt})$  are observed quantities. The solver then minimizes  $-\log(\mathcal{L}(\theta))$  with respect to parameter  $\theta$ .

### 5.4.3 Simulated maximum likelihood

The integral on  $\theta_i$  is computed by simulation. To implement the simulated maximum likelihood method, we first take  $M$  draws of random coefficients *shocks* on  $\beta_i$  and  $f_{i0}$ , denoted  $\hat{\beta}_m$  and  $\hat{f}_{m0}$  for draw  $m$ . Each dimension of the random coefficients is first independently drawn from standard normal distribution  $\mathcal{N}(0, 1)$ , and then adjusted in scale and location by model parameters. For example, the  $m^{\text{th}}$  draw of fixed cost parameter is  $f_{m0} = \bar{f}_0 + \sigma_f \cdot \hat{f}_{m0}$ , where  $\bar{f}_0$  and  $\sigma_f$  are mean and standard deviation of the coefficient. We restrict the interaction term coefficient  $\gamma$  and price coefficient  $\lambda$  to be homogeneous across individuals.

We then maximize the likelihood function with respect to the parameters, i.e., the mean and standard deviation of random coefficients, taking the draws as given. For a given parameter value, the empirical counterpart of the likelihood function is given by

$$\hat{\mathcal{L}}(\theta) = \prod_{i=1}^N \left( \frac{1}{M} \sum_{m=1}^M \left( \prod_t \Pr(q_{ikt}, q_{ilt} | \mathbf{S}_{it}; \theta_m) \right) \right). \quad (12)$$

## 5.5 Other details

### 5.5.1 Construction of the sub-sample

To restrict computation burden at a reasonable level, we implement the structural model on a random sub-sample of 5% of individuals in the data (422 households),<sup>23</sup> over all their in-sample trips. Because of dimensionality concerns, we focus on the 10 products that generate the highest overall sales (which consist of 56.2% of the total in-sample sales volume), and treat the rest as outside options. The set of products, with their respective share of sales volume, are listed in Table 1. Finally, as previously indicated, we only characterize consideration sets of sizes 0, 1 or 2.

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<sup>23</sup>In earlier versions, we compared model estimates on this sample and on a sample with 10% households, and find that they are essentially the same.

### 5.5.2 Construction of the quantity set

We measure purchase quantity by volume in pints, so that consumption utility can be compared across brands with different package sizes. Because the set of quantity available is not continuous, we define choice set to be multiples of the minimum package size,  $q_j^{min}$  – which is specific to brand but constant across trips. In the data, large quantity choices are scarce, but they should be allowed in the model. To balance computational burden and a realistic range of quantities, we discretize large quantity choices to coarse grids, so that the set of quantity one can choose from is  $Q_j = q_j^{min} \cdot \{0, 1, 2, 3, 5, 8, 12\}$ , where we bundle choices of 4-6 units into quantity 5, 7-9 into quantity 8, and 9-20 units into quantity 12.<sup>24</sup>

### 5.5.3 Product, household and time characteristics

Given the choice of product set, we choose to focus on four characteristics – 3 brand indicators (Dannon, Yoplait and Colombo), an “other brand” indicator, and the indicator for characteristics “light.” We conjecture that demand for quantity depends on how many members consume yogurt within a household. Therefore we include household size as a key predictor of the marginal consumption utility. We also include a (linear) time trend into the utility function. Given the mixed evidence for seasonality in demand, we do not add seasonality in the consumption utility.

### 5.5.4 Distribution of number of products and purchase quantity

We find that the distribution of the number of products in the sub-sample closely represents that in the full sample. In particular, as stated in Appendix Table 5 0.95% of our sub-sample purchased more than 2 different products. Allowing for 3 products in the consideration set will increase the number of alternatives (consideration set - quantity combinations) from 1,680 (10 single-product cases and 45 duo-product cases, each product allowing for 6 quantity levels) to 27,600 (adding 120 triple-product sets, each with 6<sup>3</sup> quantity combinations), and the 0.95% observations cannot justify the additional computation burden. As a side note, zero products indicates purchase of another yogurt not in the set of interest – so we condition on category purchase.

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<sup>24</sup>In the likelihood, we compensate for the width of quantity grids; for example, the observed probability of the (continuous) quantity falling into [4,6) is 3 times the model probability of choosing (discrete) quantity 5. In other words, our model treats the world as if there are only 6 possible quantity levels (plus zero quantity).

### 5.5.5 Choice-based sampling

From Table 5, we find that there are many observations with no purchase, and few observations with 2-product purchases. However, the model structure demands rich information in quantity choice given purchase, in particular multiple-product choice. Relatedly, the “no purchase” observations are not very informative of the consumption utility functional form. In light of this, we under-sample these observations to gain computation speed, and correct for the stratified sampling approach in the likelihood function, in the way proposed by Manski and Lerman (1977).

Specifically, within the 5% sub-sample, we draw 30% random sample among observations with no purchase (of inside goods), and 80% random sample among single-product purchase occasions; at the same time, we keep all observations with two-product choice sets. This reduces the sample size used in estimation from 6,816, to 4,472, saving 1/3 of the original computation time.

## 6 Estimation results

### 6.1 Consumption utility estimates

Table 4 reports all parameter estimates. The  $\bar{\beta}'s$  capture the marginal *consumption* utility for log-transformed quantity, which depends on brand, light versus regular, household size and linear time trend.  $\bar{f}_0$  captures the baseline consideration cost. Given the way we set up the cost structure in (5), the baseline consideration costs are for consumers who just purchased the same brand in the previous week.<sup>25</sup>

By defining random coefficients on product characteristics, we capture the within-consumer correlation in demand, so that, for example, consumers who like Yoplait products will have higher choice probabilities on both Yoplait Original and Yoplait Light. The mean brand coefficients suggest that on average consumers have a slightly higher marginal utility for Yoplait products or products from “other brands”, than for Dannon and Colombo. The “light” coefficient is insignificantly different from zero: this means that low-calories or organic products are approximately equally favored. Expansion of household size results in higher consumption utility. The effect is

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<sup>25</sup>Strictly speaking, the average baseline consideration cost is  $\bar{f}_0 + f_W \cdot 0.01$  for consumers who purchased in the past week (and week-since-last-purchase normalized to 100 weeks).

Table 4: Parameters estimates

	par. est.	std. err.
coef. for Dannon ( $\bar{\beta}_1$ )	5.22	0.48
coef. for Yoplait ( $\bar{\beta}_2$ )	5.44	0.51
coef. for Colombo ( $\bar{\beta}_3$ )	5.65	0.50
coef. for Other Brands ( $\bar{\beta}_4$ )	3.89	0.46
coef. for Light ( $\bar{\beta}_5$ )	-0.05	0.14
coef. for household size ( $\bar{\beta}_6$ )	0.14	0.09
coef. for (100x)weeks ( $\bar{\beta}_7$ )	-0.02	0.00
interaction of consumption utility ( $\gamma$ )	-3.80	0.77
price coef. ( $\lambda$ )	-2.17	0.15
baseline consideration cost ( $\bar{f}_0$ )	3.29	0.42
changes in consid. cost under feature ( $f_A$ )	-0.66	0.19
changes in consid. cost per 100 weeks-since-purchased ( $f_W$ )	0.53	0.16
changes in consid. cost if never purchased ( $f_N$ )	7.24	0.25
changes in consid. cost for two products ( $f_2$ )	0.78	0.36
scale of utility shock ( $\kappa$ )	2.94	0.27
std. dev. of brand coef. ( $\sigma_{\beta,1}$ )	1.40	0.11
std. dev. of characteristics coef. ( $\sigma_{\beta,5}$ )	0.74	0.19
std. dev. of mean consid. cost ( $\sigma_f$ )	1.05	0.14

**Note:** Estimates for the all parameters. Quantities are measured in pints. Standard errors are asymptotic (numerical).

not statistically significant, plausibly due to lack of variation of household size within a household. There is a small negative time trend to quantity demand.

Using the log-transforms of quantity restricts the curvature of consumption utility for a single product, which implies love-for-variety. In addition, parameter  $\gamma$  captures how purchase quantity of multiple products substitute one another, conditional on consideration. The magnitude of  $\gamma$  suggests that products are close substitutes.

## 6.2 Consideration costs

Our setup of consideration cost, in Equation (5), allows it to depend on purchase history, feature advertising and the size of consideration sets. Using the estimates for the baseline (money metric) consideration cost,  $\bar{f}_0/\lambda$ , we find that consideration costs \$1.52 for consumers who just bought the product in the past week. This is close to half of the average per-trip expenditure on a single yogurt product.<sup>26</sup>

However, for consumers who are less familiar with the product, consideration costs are estimated to be much higher. For new consumers who never purchase a given product, the cost of considering it is  $(\bar{f}_0 + f_N)/\lambda$ , or \$4.85. This is more than 3 times the consideration cost for a regular consumer. For those who purchased a while ago, their cost of consideration is in between the two extremes. For example, the consideration cost for consumers who have not purchased the focal product for 3 years is \$1.90 on average, 25% higher than when the consumer's memory for the product is fresh. These numbers suggest that the consideration cost barrier for customer acquisition is always there, but is considerably larger when the product has never been purchased by a customer.

In addition, the second product to be considered incurs fixed cost that is 24% higher than the first product, suggesting that attention for one product crowds out the other. Finally, putting a product on feature decreases consideration cost by \$0.30, or 20% of the baseline estimate.<sup>27</sup>

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<sup>26</sup>The mean (and median) expenditure given purchase is \$3.26 (and \$2.56), per brand.

<sup>27</sup>Our model excludes feature in the consumption utility. In an alternative version, we allow feature to enter consumption utility as well as fixed cost, and we find similar results.



### 6.3 Model fit

Figure 5 top panel presents the fit of our model with respect to the empirical distribution of quantity given purchase.<sup>28</sup> The model fits the empirical purchase probabilities to within 1% for most brands. Given purchase, the model-predicted quantity distributions resemble similar shapes to that of the data. However, there are spikes in the data distribution of purchase quantities that the model does not rationalize. A potential explanation is that our model contains a continuous consumption utility function, and any particular spikes in the data (that breaks smoothness) can only be rationalized by a particular low unit price at that quantity.

In the lower panel of the same figure, we predict price response separately for each product, by calculating the average purchase quantity given price. We find that the model predicts the convex price response reasonably well.

### 6.4 Price elasticities and decomposition into consideration and choice

We next present the price elasticities implied by the model computed as arc-elasticities. That is, we reduced, one at a time, prices for each of the 10 products by 15% and computed the changes in choice shares. To integrate out heterogeneity, we compute quantity choices based on each of 20 draws in the random coefficient, and then average them across draws.

We report the price elasticities in Appendix Table 6 and summarize them here. Own and cross elasticities are conventional, and the magnitude intuitive. For example, the own price elasticities across all products are in the range  $[-3.7, -2.3]$ . Under the assumption that retailers act as monopolists over shoppers in the store, these elasticities imply a sizable markup, of roughly 30%-50% for most products. These are consistent with the literature on yogurt. For example, Villas-Boas (2007) finds markups to be around 40% in most settings.<sup>29</sup>

Cross elasticities show higher substitution for products that are closer in characteristics. For example, a change in price of Yoplait Original has (relatively) large impact on the market shares

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<sup>28</sup>Note that in the top panel of Figure 5, the choice probabilities for large quantities – say quantity 5 – are computed as the average of choosing one quantity in its interval (say 4, or 5, or 6). Therefore, the model-predicted probability is computed as if the choice set were  $\{1, 2, 3, 5, 8, 12\}$ , but the data counterpart is the probability of choosing the interval (4, 5 or 6), divided by the width of the interval (in this example 3).

<sup>29</sup>Her own elasticity estimates are larger and cross-elasticities are smaller. The difference might come from that she models choices on the brand-flavor level while we focus on the brand level.

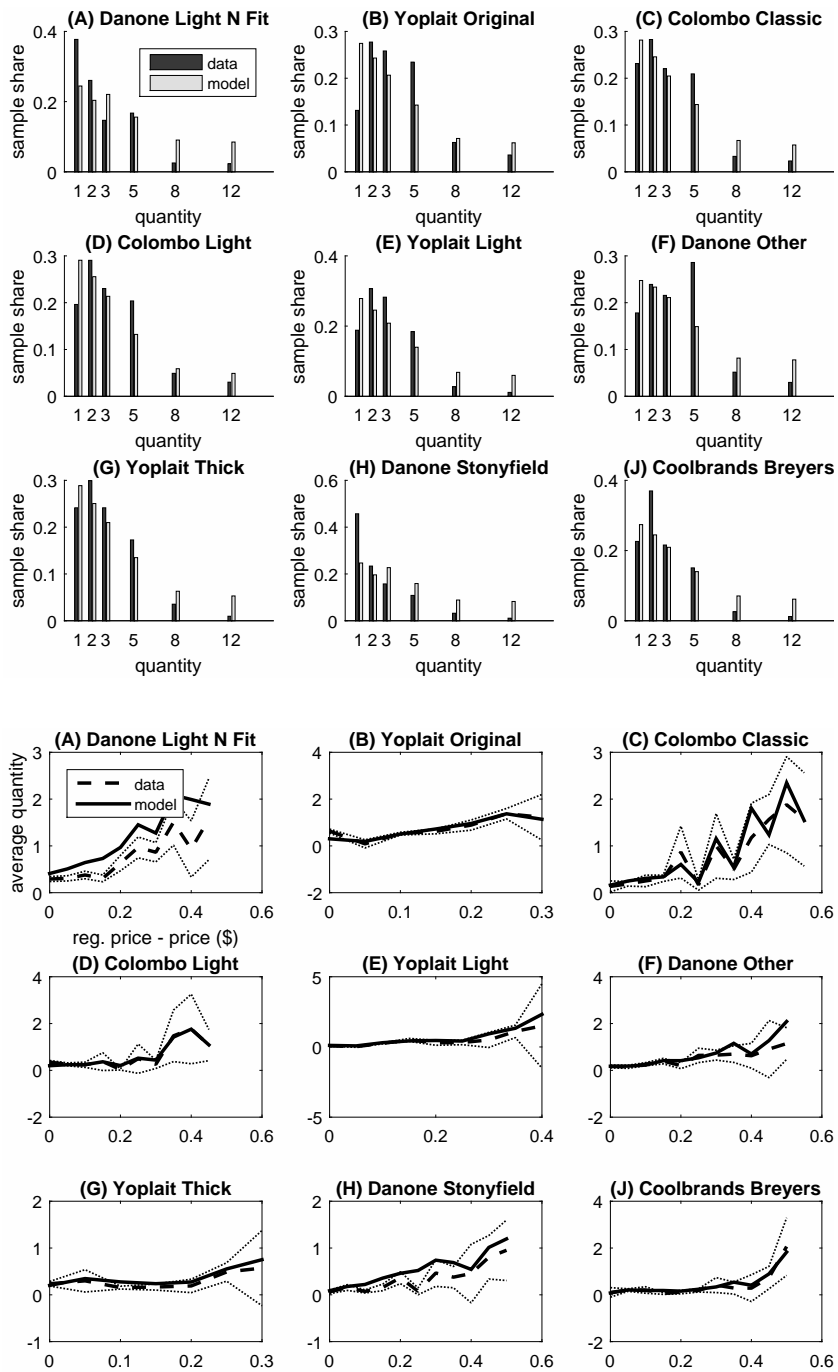


Figure 5: Model fit: purchase probability and quantity

**Notes:** The top graph compares the model-predicted quantities conditional on purchase with empirical distribution of purchase quantity, for 9 out of 10 products. Note that the quantity distribution is re-weighted by quantity grid width; for example, the sample frequency of choosing quantity 5 is 1/3 of the frequency of choosing 4, 5 or 6. The bottom graph plots model-predicted average purchase quantity against average quantity in the data, conditional on price.

Table 5: Elasticities of overall quantity, consideration incidence and quantity given consideration

	overall	consideration	quantity if consider
(A) Danone Light N Fit	-2.49	-1.23	-1.21
(B) Yoplait Original	-2.94	-1.36	-1.40
(C) Colombo Classic	-3.27	-1.47	-0.98
(D) Colombo Light	-3.69	-1.63	-1.09
(E) Yoplait Light	-3.41	-1.58	-1.47
(F) Danone Other	-2.87	-1.26	-1.44
(G) Yoplait Thick	-3.53	-1.60	-1.47
(H) Danone Stonyfield	-2.90	-1.26	-1.37
(I) Wells Blue Bunny	-2.33	-0.71	-1.14
(J) Coolbrands Breyers	-2.95	-1.18	-1.36

**Note:** The left column are own price elasticities of total demand. The middle column are consideration incidence elasticities measuring percentage changes in the probability that each brands falls into the consideration set, to a change in price. The right column are elasticities measuring percentage quantity change conditional on consideration set membership, which is operationalized as quantity given a product is in each of the 10 possible two-product consideration sets, weighted by the probability that each of the 10 sets occur.

of Yoplait Thick and Yoplait Light, and vice versa. This is driven by the random coefficients interacted with product characteristics.

In Table 5, we decompose price elasticities by measuring consideration incidence elasticity and quantity elasticity given consideration set. Specifically, for each product, we simulate the probability of which it falls into the consumer’s consideration set, and measure the elasticity of such incidence with respect to a 15% change of the own price. We also simulate purchase quantity conditional on each product falling into potential 2-product consideration sets (weighted by the corresponding consideration probabilities), and use it to measure the elasticity of purchase quantity given consideration. We find that half of the total demand response to a price change can be attributed to consideration incidence, and another half to quantity choice given consideration.

This result offers a different view of incomplete information. While costly information of price (e.g. Diamond, 1971) will attenuate price response and soften competition, costly information of other product characteristics after the consumer knows price can intensify price response. In our setting, prices are incentives for a consumer to incorporate a product into the consideration set, and we show that removing such incentive (through complete removal of the extensive margin) reduces price elasticities by half.

## 6.5 Semi-elasticity to feature

We compute the differences in consumer purchase quantities while placing, in turn, each of the 10 products *on and off* feature, for all trips in the sample. The results show that having a product on feature increases sales by 21-31%. Because the effect of feature goes through consideration costs, these results imply large consideration cost sensitivity.

# 7 The role of costly consideration on demand and prices

## 7.1 Counterfactual: all consideration costs changed by feature

From our estimates, we find that feature reduces consideration costs by 0.66 in utility terms, or \$0.3 in monetary-equivalence if weighted by the price coefficient. In this section, we set feature of *all* products to be on and off simultaneously to study the impact of feature-driven consideration costs on consumer demand, price elasticities and implied markup.

## 7.2 Impact of consideration costs on demand

Comparing two worlds where all products are on and off feature at the same time, we separately visualize the effect on the choices of purchase (extensive margin) and the distribution of quantities conditional on purchase (intensive margin). We find that the expected number of unique products a consumer purchases on a typical trip increases from 1.11 to 1.18 – that is, the number of varieties increases by approximately 6%. Compared to results in Section 6.5 where feature is changed for only one product at a time, the effect of simultaneously changing the feature status for all products is much smaller. This is because *relative* fixed costs for all products are unchanged.<sup>30</sup> In addition, because of the variety increase, quantity per variety decreases by a small amount as the consumer dilutes expenditure across more products.

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<sup>30</sup>The fact that consumer demand do not shift much from the outside option implies that our model mainly captures substitution among the 10 brands. Also, note that 1.18 varieties on average is still far away from the upper bound of the consideration set – assumed at 2, thus it is unlikely that this mechanical upper bound limits the choice of variety.

### 7.3 Impact of consideration costs on market prices

In the classical search literature (e.g. Diamond, 1971), limited information on price attenuates price response and increases equilibrium price. Differently, in our model, consideration sets are tighter when fixed costs increase. Since consumers use price information to make consideration decisions, firms will intensify price competition to fight for scarce consumer attention. Therefore, fixed costs lead to intense competition for memberships of consideration sets and puts downward pressure on equilibrium prices; and lowering such costs (for example, by feature) will increase market prices. In this section, we study the impact of setting all products to feature on static equilibrium prices. Although it is unlikely in reality that all brands feature at the same time, our counterfactual experiment can be considered as simulating an information shock that lowers consumer fixed cost by \$0.3.

We simulate equilibrium markup, *a la* Berry et al. (1995), under the assumption that retailer prices of all products as a monopolist. Specifically, we consider the static pricing decision of each retailer  $r$  trying to maximize flow profit  $\Pi_{rt}$  at week  $t$ , from all its products that it sells in set  $J_r$ :

$$\Pi_{rt} = \sum_{j \in J_r} (p_{jt} - mc_{jt}) \cdot sales_{jt}(\mathbf{S}_t) \quad (13)$$

where state  $\mathbf{S}_t$  includes all prices and other observables. Take first order conditions on (13) and we have

$$\frac{\partial \Pi_{rt}}{\partial p_{jt}} = sales_{jt}(\mathbf{S}_t) + \sum_{k \in J_r} (p_{kt} - mc_{kt}) \cdot \frac{\partial sales_{kt}(\mathbf{S}_t)}{\partial p_{jt}} = 0. \quad (14)$$

The above can be re-written in vector form over all products in a time time period:

$$\mathbf{p}_t = \mathbf{mc}_t + \Delta^{-1}(\mathbf{S}_t) \cdot \mathbf{sales}_t(\mathbf{S}_t) \quad (15)$$

where  $\Delta(\mathbf{S}_t)$  is the ownership matrix defined as

$$\Delta_{jk} = \begin{cases} -\frac{\partial sales_{kt}(\mathbf{S}_t)}{\partial p_{jt}} & \text{if } j \text{ and } k \text{ are sold by the same retailer} \\ 0 & \text{otherwise.} \end{cases} \quad (16)$$

It is clear (and standard) from (15) and (16) that we only need to track equilibrium markup

Table 6: Own-price elasticities and implied equilibrium markup

	no feature: elasticity	markup	all feature: elasticity	markup	percent diff
(A) Danone Light N Fit	-2.49	0.56	-2.33	0.63	0.11
(B) Yoplait Original	-2.97	0.53	-2.76	0.59	0.12
(C) Colombo Classic	-3.31	0.39	-3.15	0.42	0.09
(D) Colombo Light	-3.79	0.33	-3.61	0.36	0.09
(E) Yoplait Light	-3.45	0.34	-3.24	0.37	0.10
(F) Danone Other	-2.91	0.37	-2.80	0.40	0.07
(G) Yoplait Thick	-3.62	0.34	-3.37	0.38	0.11
(H) Danone Stonyfield	-2.91	0.37	-2.73	0.40	0.09
(I) Wells Blue Bunny	-2.34	0.27	-2.20	0.29	0.08
(J) Coolbrands Breyers	-3.06	0.31	-2.94	0.33	0.07

**Note:** The first two columns present own-price elasticity and implied markup  $-\Delta^{-1}(\mathbf{S}_t) \cdot \mathbf{sales}_t(\mathbf{S}_t)$  – setting all products *off* feature. The third and fourth columns present elasticity and markup setting everything *on* feature. The last column calculates percentage differences in markup, setting the on-feature markup as baseline.

$\Delta^{-1}(\mathbf{S}_t) \cdot \mathbf{sales}_t(\mathbf{S}_t)$  as a function of fixed costs (which is in turn a function of feature), prices and other observables.

To illustrate the intuition, we first simulate the impact of the counterfactual change in fixed costs on own-price elasticities for all brands. These are calculated in the same way as Table 6, and are presented in columns 1 and 3 in Table 6. We find that own-price elasticities decrease in magnitude, by about 5%, when feature advertising lowers the fixed costs by \$0.3.

We also simulate equilibrium markup, across the two scenarios with different consideration costs. In line with our intuition and the elasticity calculations, it is not surprising to see that implied markup increases in a market with lower fixed costs – that is, when every product is on feature. Specifically, a \$0.3 decrease in fixed costs increases markup by 7-12% depending on the brand.

## 8 Concluding remarks

In this paper, we quantify the consumer’s time or mental cost of considering a product. These costs generate scale economies in consumers’ quantity choices and encourage purchase of large quantities instead of many varieties. They also explain the existence of a quantity threshold and, relatedly, why consumers are unresponsive to small price discounts.

With many observations at the individual consumer level, we demonstrate how the existence

of quantity thresholds – under price discounts that are just enough to convert them to purchase – can be used to empirically disentangle consideration from preference. That is, without costly consideration, consumers would gradually re-allocate their expenditure under gradual price changes, rather than switching in larger quantities from one product to another. We demonstrate how one can test this using standard marketing scanner data, without imposing a structural model.

We then estimate a structural model of multiple product choice and subsequent quantity choices, with endogenous costly consideration decision in the first stage. Our results indicate that consumers have large consideration costs associated with purchasing a product. These costs are even larger if the consumer has not purchased the product for a long time, or ever. Our estimates imply inertia in brand choice stemming from informational frictions. Price discounts act as incentives to overcome these consideration barriers. We also quantify the role of feature advertising and past-purchase experience in this framework.

Our model is manageable with a small number of varieties, but is still computationally intensive. Future work may focus on developing computational methods to estimate larger versions of our model. A substantive limitation of our paper is that it models the supply side in a simple way. A richer supply side model can formally address whether consumer fixed costs (and their discrete price response) can explain the way firms switch between regular price and deep discounts.<sup>31</sup> We relegate this to future research.

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<sup>31</sup>This is related to Dubé et al. (2005) in their analysis on pulses of advertising.

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# Online Appendix Not for Publication

## A Additional testable implication: gap between quantity and incidence

In addition to Section 4.3, we present another way to test the implication of the model. When fixed cost shock  $\Delta\varepsilon_{it}$  is unobserved, consideration is a threshold-crossing decision with a random price threshold. At given parameters, we numerically show that the model implies high quantity demand given consideration, at both low and high prices. In particular, at high prices where consideration is unlikely, quantity given consideration remains to be large. This implies that purchase decision is price sensitive and quantity given purchase is less price sensitive, and can be tested in data.

We numerically simulate purchase and quantity decisions, and calculate the implied purchase probability as a function of price, as well as average quantity given purchase as a function of price. We maintain the parameters in the previous example,  $\beta = 3$ ,  $\alpha = 1$ ,  $f = 6$ ,  $\sigma_\mu = 2$  and choice set  $Q = \{0, 1, \dots, 12\}$ , but we now set  $\Delta\varepsilon$  to be logistic random variable. The average quantities and purchase probabilities are summarized in Figure 6. Compare the left panel with Figure 3 and one finds that the un-censored part of the average quantity is exactly the same – because only fixed cost shock  $\Delta\varepsilon$  is different between the two figures and it is sunk after consideration. However, while average quantity given purchase remains away from 1 at all prices, purchase probability is very low at high prices. This is because expected purchase of around 2 units will unlikely justify spending large fixed costs and the consumer will choose not to consider the product as a result.<sup>32</sup>

The gap between quantity and incidence can be tested with consumer purchase data. One potential test is to plot quantity given purchase and purchase probability *across* consumers, but it does not rule out the possibility that consumers who choose to purchase at high prices are selected with favorable preferences. When selection is involved, we will find sizable average purchase quantity at high prices without costly consideration. To control for selection, we estimate simple parametric models of quantity demand given purchase and purchase incidence, separately for each

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<sup>32</sup>If we set average fixed costs to zero in this model, the gap between quantity and incidence disappears. When  $\beta$  is large or the scale of consumption utility shock  $\sigma_\mu$  is large, both quantity and incidence remain large at high prices; when these parameters are small, both are low at high prices. This illustrates that sunk cost is the only factor that explains the difference between the two figures.

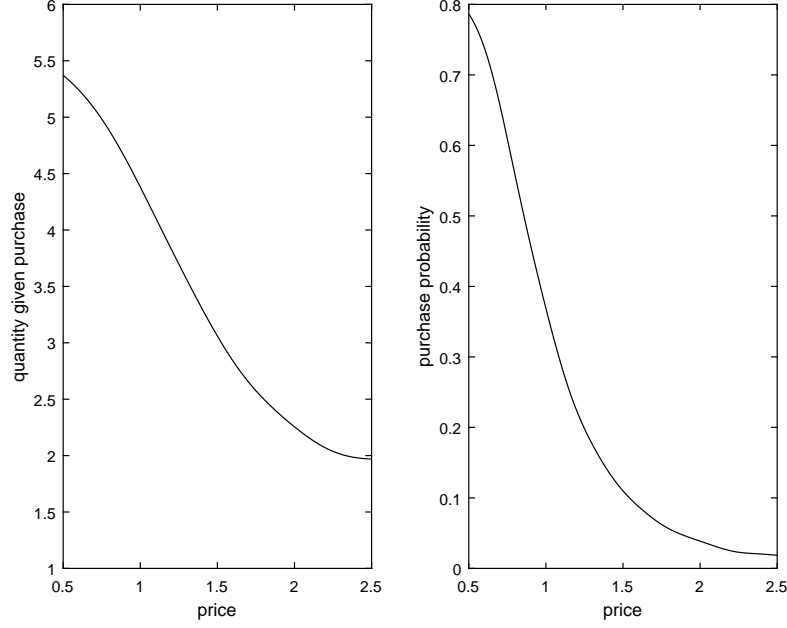


Figure 6: Average quantity given purchase and average purchase probability

**Notes:** Numerical illustration of model-predicted quantity given purchase (left panel) and purchase probability (right panel). These two figures are simulated from choices across 100,000 trips.

consumer and for each product. Specifically, we take a sub-sample of consumers who purchase a given brand for more than 10 times in the data, and estimate a constant-elastic demand function:

$$\log(q_{ijt}|q_{ijt} > 0) = \gamma_{0ij} + \gamma_{1ij} \log(p_{jt}) + \eta_{ijt} \quad (17)$$

in order to capture quantity given purchase. We also estimate a simple logit model for each consumer,

$$\mathbf{1}(q_{ijt} > 0) = \mathbf{1}(\delta_{0ij} + \delta_{1ij} p_{jt} + \Delta \varepsilon_{ijt} > 0) \quad (18)$$

in order to capture purchase incidence. We focus on trips where the focal product is not on feature or display, and we also control for year dummies because there is a clear time trend in price. Next, given estimates of  $\gamma$  and  $\delta$ , we predict expected quantity given purchase and purchase probability for each consumer at all prices. Finally, average across predicted quantity and incidence at given prices between \$0.4 and \$1.2. This procedure ensures that we do not summarize quantity across different *sets* of consumers at different prices.

The average quantity and incidence is plotted separately for the top 4 products in Figure 7. Within reasonable prices, we see choice probability drops close to zero at high prices while quantity given purchase stays bounded away from 1 – which is by construction feasible. This is in line with a theory of costly consideration set, and cannot easily be explained by rational choice theory without some form of fixed acquisition costs.

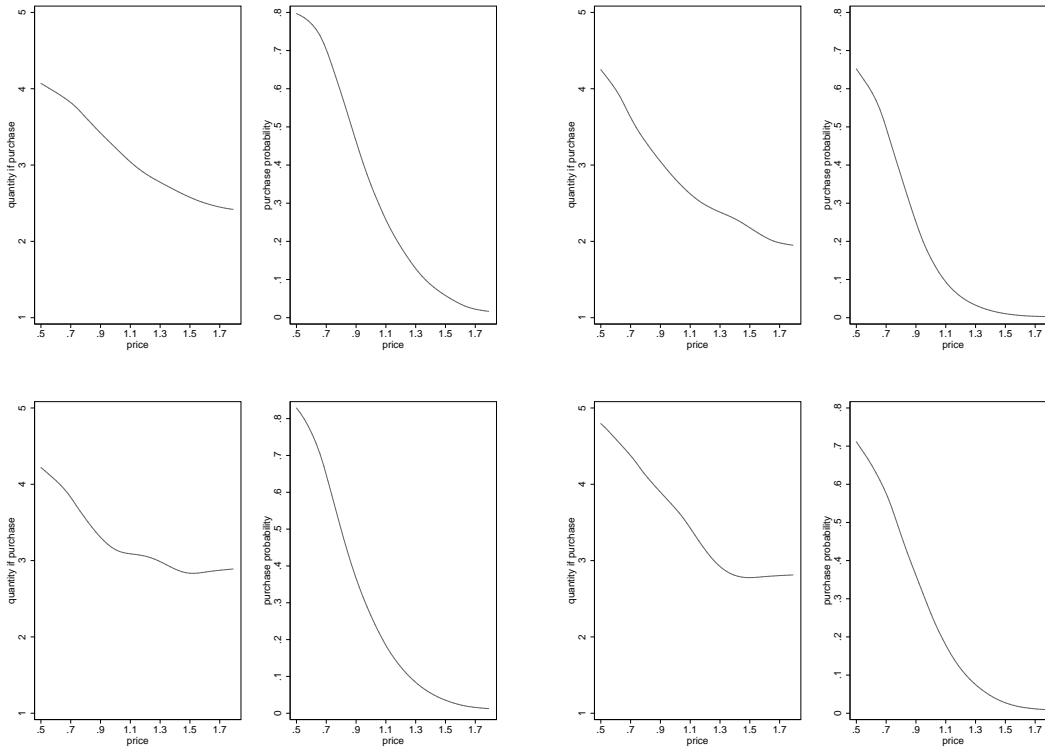


Figure 7: Within-individual predictions on quantity and incidence: top 4 brands

**Notes:** By-individual-product predictions of quantity given purchase (left panel in each block) and purchase probability (right panel), then averaged across individuals over a fixed set of prices. The top blocks are (left to right) Dannon Light and Yoplait Original, and the bottom two are Colombo Classic and Columbo Light.

## B Monte Carlo results

We specify a simple model as in Section 4.2, and try to estimate model parameters without additional exclusion restrictions. First, we assume that the analyst has correctly specified utility functional form as in the data-generating process. We simulate data and estimate parameters in 100 experiments and find that one can reliably estimate model parameters – these results are shown in

Appendix Table 1: Monte Carlo results with parametric utility

	mean	median	stdev
$\alpha$ - true $\alpha$	0.00	-0.00	0.04
$f$ - true $f$	-0.00	-0.00	0.01
scale of $\mu$ - true scale of $\mu$	0.00	-0.00	0.05
$\beta$ - true $\beta$	-0.00	0.00	0.04

**Note:** Distribution of the gaps between true parameter and estimated parameters from 100 Monte Carlo experiments. We use the same parametric model – in equation (1) and (2) – in both the data-generating process and the estimation routine.

Table 1.

To further confirm that our results are not driven by specific functional form assumptions, we simulate choices using the same model but now estimate an auxiliary model where the consumption utility function is approximated by a polynomial. Specifically, in estimation, we specify the utility function as

$$c_{it}(p_t, q_{it}) = \sum_{\tau=1, \dots, 5} b_{\tau} q_{it}^{\tau} - \alpha p_t q_{it} + \mu_{it}(q_{it}) \quad (19)$$

where  $b_{\tau}$  are coefficients of the polynomial specification and  $\tau$  is up to the 5th order. Price disutility and consumption utility shock  $\mu$  are specified in the same way as (1). Note that equation (19) is a mis-specified utility function for finite order  $\tau$ .

The monte carlo results are summarized by Table 2. We find that with low-order polynomial, the disutility for expenditure  $\alpha$  and fixed cost  $f$  are estimated precisely but with bias. However, when the consumption utility is better approximated by a higher order polynomial (in our case to the 5th order), such biases go away and both  $\alpha$  and  $f$  can be consistently estimated. That is to say, we can reliably estimate the fixed cost parameter relative to the value of outside option. On the other hand, there still exists some biases in the consumption utility components due to mis-specification error. Further increasing the order of the polynomial will reduce such biases at the cost of power.

Appendix Table 2: Monte Carlo results with polynomial utility

	mean	median	stdev
$\alpha$ - true $\alpha$	-0.02	-0.03	0.02
f - true f	-0.10	-0.08	0.18
scale of $\mu$ - true scale of $\mu$	-0.13	-0.12	0.05
b(1) - true b(1)	0.35	0.33	0.10
b(2) - true b(2)	0.00	0.00	0.01
b(3) - true b(3)	0.01	0.01	0.01
b(4) - true b(4)	-0.00	-0.00	0.00
b(5) - true b(5)	-0.00	-0.00	0.00

**Note:** Monte carlo results similar to Table 2, except that consumption utility is modelled in a flexible polynomial form as in Equation (19), with  $\tau$  set at the 5th order.

## C Additional tables and figures

Appendix Table 3: Variety and quantity per trip

	nr. brand						Total
	1	2	3	4	5	6	
1 unit	17.03	0.00	0.00	0.00	0.00	0.00	17.03
2 units	14.87	1.40	0.00	0.00	0.00	0.00	16.27
3 units	9.85	1.72	0.11	0.00	0.00	0.00	11.68
4 units	11.82	2.22	0.19	0.01	0.00	0.00	14.24
5 units	7.59	1.96	0.27	0.02	0.00	0.00	9.85
6 units	8.68	2.15	0.29	0.03	0.00	0.00	11.15
7 units	1.85	1.14	0.23	0.04	0.00	0.00	3.26
8 units	2.23	1.02	0.21	0.03	0.01	0.00	3.50
9 units	0.86	0.62	0.17	0.03	0.00	0.00	1.68
10+ units	7.04	3.14	0.89	0.23	0.04	0.01	11.34
Total	81.81	15.37	2.36	0.39	0.05	0.01	100.00

**Notes:** this table reports percentage share of observations for a given variety-quantity combination.

Appendix Table 4: Test for consumer stockpiling: brand level

	Danone light	Danone light	Yoplait original	Yoplait original	Colombo classic	Colombo classic	Colombo light	Colombo light
months since last purchase	-0.01***	-0.01***	-0.01***	-0.01***	-0.00*	-0.00**	-0.01***	-0.01***
- squared	0.00	0.00	0.00	0.00	0.00	0.00***	0.00	0.00
log price	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
log price	-0.10***	-0.11***	-0.11***	-0.11***	-0.11***	-0.10***	-0.10***	-0.10***
0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
- past week	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**
0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
- past 2 weeks	0.00	0.00	0.00	0.00	0.01*	0.01*	0.01	0.01
0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
years since 200101	0.02***	0.02***	0.02***	0.02***	-0.01**	-0.01**	-0.01**	0.02***
-0.02***	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Apr-Jun	0.02***	-0.00	-0.02***	-0.01**	-0.03***	-0.01	-0.02***	0.01
0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Jul-Sep	-0.00	-0.02**	-0.02***	-0.02***	-0.02***	-0.01	-0.01	0.01**
0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01
Oct-Dec	-0.01**	-0.02***	-0.00	-0.01***	-0.01***	-0.00	-0.02***	-0.01
0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
obs.	56449	17398	62591	17296	37296	13145	34667	14028

Notes: Brand level evidence for extensive margin only. Intensive margin suffers power issues due to limited sample size.



Appendix Table 5: Distribution of number of products in the sub-sample

	nr. prod.					Total
	0	1	2	3	4	
0 unit	31.31	0.00	0.00	0.00	0.00	31.31
1 unit	0.00	8.48	0.00	0.00	0.00	8.48
2 units	0.00	9.91	0.44	0.00	0.00	10.35
3 units	0.00	7.43	0.68	0.03	0.00	8.14
4 units	0.00	9.72	0.91	0.06	0.00	10.69
5 units	0.00	5.67	0.88	0.06	0.00	6.60
6 units	0.00	7.67	1.15	0.06	0.01	8.89
7 units	0.00	1.53	0.66	0.11	0.01	2.31
8 units	0.00	2.26	0.61	0.06	0.01	2.95
9 units	0.00	0.73	0.41	0.04	0.03	1.21
10+ units	0.00	6.67	1.93	0.43	0.06	9.08
Total	31.31	60.08	7.66	0.84	0.11	100.00

**Note:** The table presents the joint distribution of number of different purchased products, and the total number of units, in the sub-sample used for structural estimation.

Appendix Table 6: Implied elasticities

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
(A) Danone Light N Fit	-2.49	0.15	0.16	0.28	0.28	0.24	0.17	0.17	0.32	0.18
(B) Yoplait Original	0.17	-2.94	0.26	0.24	0.46	0.25	0.60	0.14	0.22	0.19
(C) Colombo Classic	0.08	0.11	-3.27	0.41	0.04	0.12	0.10	0.22	0.00	0.24
(D) Colombo Light	0.13	0.10	0.40	-3.69	0.11	0.07	0.10	0.14	0.03	0.16
(E) Yoplait Light	0.17	0.24	0.06	0.15	-3.41	0.05	0.27	0.05	0.21	0.06
(F) Danone Other	0.13	0.10	0.12	0.08	0.04	-2.87	0.13	0.15	0.03	0.12
(G) Yoplait Thick	0.11	0.31	0.12	0.14	0.29	0.15	-3.53	0.07	0.07	0.13
(H) Danone Stonyfield	0.04	0.04	0.14	0.08	0.02	0.08	0.04	-2.90	0.00	0.20
(I) Wells Blue Bunny	0.06	0.04	0.00	0.01	0.07	0.01	0.02	0.00	-2.33	0.00
(J) Coolbrands Breyers	0.05	0.05	0.13	0.09	0.03	0.06	0.06	0.18	0.01	-2.95

**Note:** The  $i, j$  element is the elasticity of total purchase quantity of product  $j$ , on price change of product  $i$ , or  $\frac{\partial Q_j}{\partial p_i} \cdot \frac{p_i}{Q_j}$ .

Appendix Table 7: Implied semi-elasticities to feature

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
(A) Danone Light N Fit	0.21	-0.03	-0.03	-0.05	-0.05	-0.04	-0.03	-0.03	-0.06	-0.03
(B) Yoplait Original	-0.03	0.24	-0.04	-0.04	-0.07	-0.04	-0.09	-0.02	-0.04	-0.03
(C) Colombo Classic	-0.01	-0.02	0.26	-0.06	-0.01	-0.02	-0.02	-0.03	-0.00	-0.04
(D) Colombo Light	-0.02	-0.02	-0.06	0.30	-0.02	-0.01	-0.02	-0.02	-0.01	-0.03
(E) Yoplait Light	-0.03	-0.04	-0.01	-0.03	0.29	-0.01	-0.04	-0.01	-0.04	-0.01
(F) Danone Other	-0.02	-0.02	-0.02	-0.01	-0.01	0.21	-0.02	-0.02	-0.01	-0.02
(G) Yoplait Thick	-0.02	-0.05	-0.02	-0.02	-0.04	-0.02	0.32	-0.01	-0.01	-0.02
(H) Danone Stonyfield	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	0.24	-0.00	-0.03
(I) Wells Blue Bunny	-0.01	-0.01	-0.00	-0.00	-0.02	-0.00	-0.01	-0.00	0.22	-0.00
(J) Coolbrands Breyers	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	-0.03	-0.00	0.27

**Note:** The  $i, j$  element is the percentage change in quantity  $\Delta Q_j/Q_j$  of the column product  $j$ , when the row product  $i$  is *on* or *off* feature. We hold prices and feature of other products as given by the data.

Appendix Table 8: Expected number of variety with lower consideration costs

	exp. nr. brands
baseline	1.10
counterfactual	1.18

**Notes:** Baseline expected number of brands a consumer purchases per trip, in contrast to the counterfactual number of brands when consideration costs are lowered by \$0.30 – the monetary equivalent of a feature.

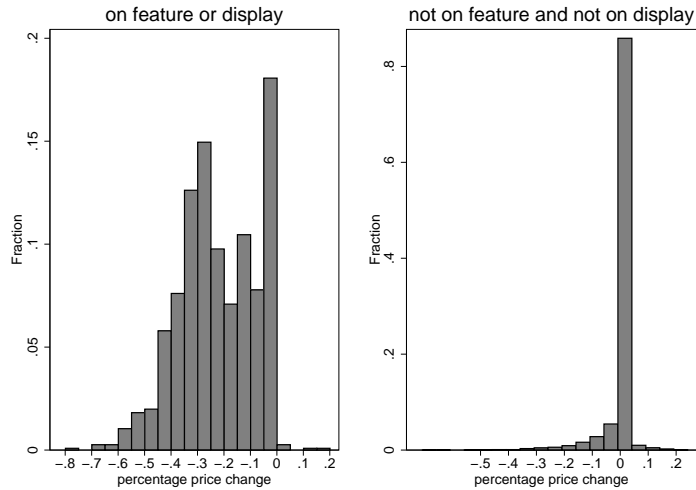


Figure 8: Distribution of price changes

**Notes:** This figure plots the distribution of percentage price changes. Base price is defined as the maximum price in the past 4 weeks. Feature and display are defined as at least *half* the SKUs for a given product are on feature or display, respectively.

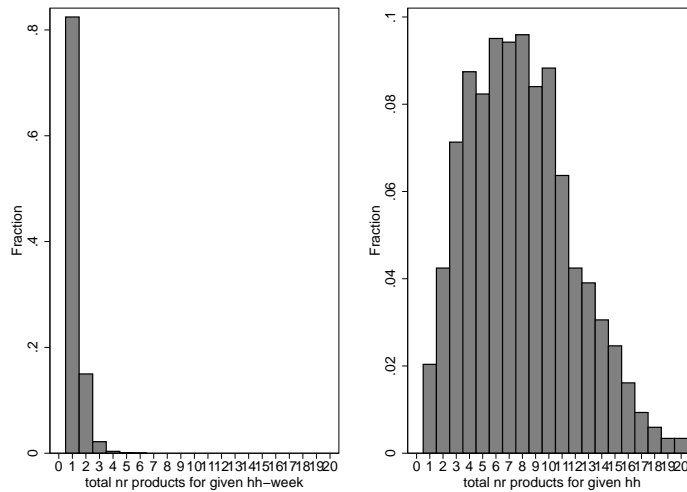


Figure 9: Per-trip and total variety for a given household

**Notes:** Left: distribution of total number of products purchased in a given trip, for households who had between 20 and 40 trips involving yogurt purchase in the sample. Right: distribution of total number of products purchased in the entire sample duration for the same set of households.

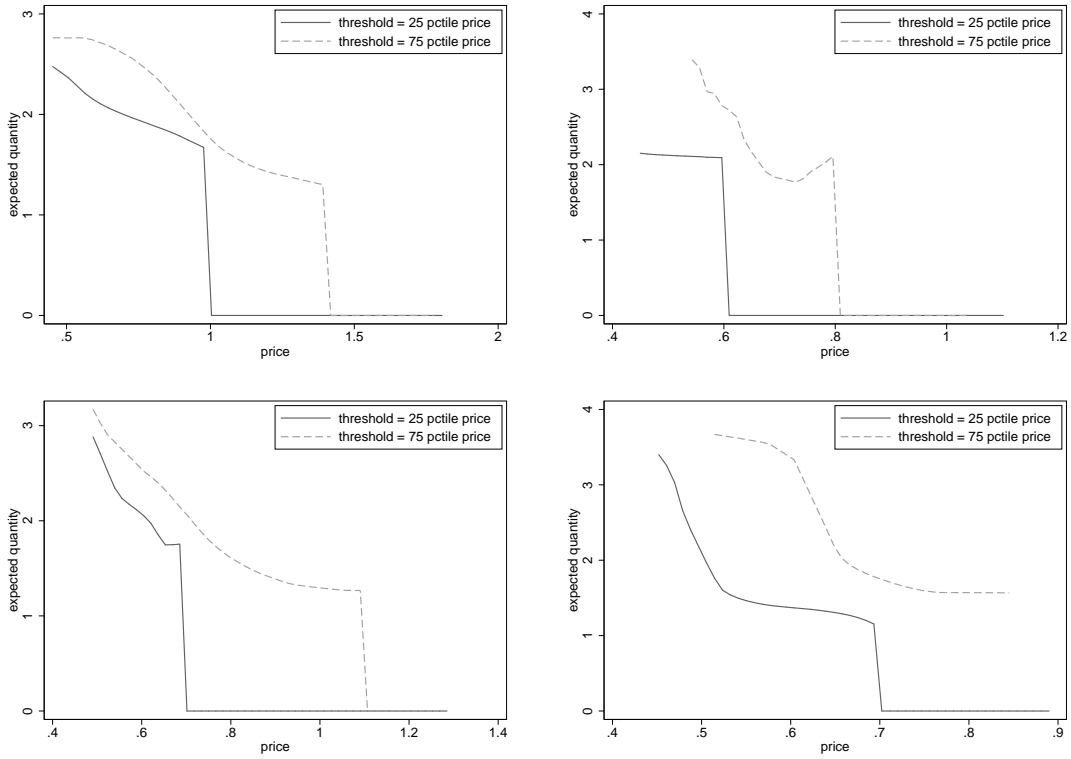


Figure 10: Individual demand by cohort: top 4 brands

**Notes:** Demand by “cohort” defined as consumers whose observed price thresholds (max accepted price) are similar. See description for Figure 1. The top blocks are (left to right) Dannon Light and Yoplait Original, and the bottom two are Colombo Classic and Columbo Light.