Why Do Consumers Pay More for Less?

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Abstract

This paper studies quantity surcharges and heterogeneity in consumer attention, and demonstrates the importance of considering consumer inattention in demand estimation. Quantity surcharges exist for packaged goods when a smaller package size is cheaper than its larger size counterpart per unit. Quantity surcharges are frequent in the data, and households have heterogeneous purchasing behavior during quantity surcharge periods: some households purchase multiple small size jars, but others pay extra for large jars ("miss" purchases). Existing models cannot accommodate those miss purchases. Hence I develop a demand model for packaged goods that explains those miss purchases as a result of consumer inattention. I use Bayesian methods to estimate the model on a rich panel of household peanut butter purchases. Then I compare the estimation results to the ones from two alternative models: a model that does not consider quantity surcharges and a model that explains preference on package sizes as a reason for those miss purchases. Among the three models I consider, the consumer inattention model has the smallest prediction error for expected demand.

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1 Introduction

Quantity surcharges exist when a small package size item is cheaper than its larger size counterpart per unit (e.g., roll, ounce). The opposite of quantity surcharges, quantity discounts, may be the more intuitive pricing strategy. Quantity surcharges, however, are frequently observed at grocery stores (Widrick (1979)). Data plans for smart phones that allow customers to use a certain amount of data at a fixed fee and then charge a lot more per byte once they pass the limit are also an example of quantity surcharges.

In this paper, I study quantity surcharges on the consumer side, focusing on heterogeneity in attention. I use rich scanner data in the peanut butter category for the study. Consumers show heterogeneous purchasing patterns when quantity surcharges exist. The two most distinct patterns are purchasing multiple small size jars versus one large size jar. I develop a structural demand model that allows heterogeneity in consumer attention, and then estimate the model using Bayesian methods.

I found two interesting purchasing patterns from the household panel data. First, multiple small size jar purchases are four times more frequent in quantity surcharge weeks than in quantity discount weeks. This is not a surprise once we understand the substitution opportunity in quantity surcharge periods: consumers who demand a large quantity can save money by purchasing multiple small size items instead of one large size item. However, 19.43% of households purchased large size jars in quantity surcharge weeks. Clerides and Courty (2017) argue that those households who miss substitution opportunities are "inattentive".

To understand these empirical findings, I study a series of demand models. The first model assumes standard preferences and rationality. Then I explore two extensions of this basic model. First extension explains preference on package sizes as the motivation for "miss" purchases (large package size purchases in quantity surcharge weeks). Second extension considers consumer inattention as the main motivation. It restricts the choice set where consumers choose the optimal quantities from in case of miss purchases. All three models yield a complex optimization problem as they feature multiple discrete choices. I solve this problem using Allenby, Shively, Yang, and Garratt (2004)'s two stage optimization approach.

I estimate the models using the Markov Chain Monte Carlo (MCMC) methods. The likelihood function to maximize is complicated as the models include two stage optimizations and the number of elements in the choice set is big. The Bayesian methods have been shown to be more robust in this setting.

The estimation results support the model with consumer inattention. The extended model with consumer inattention predicts demand that are closest to the actual demand observed, compared to the two other model specifications. These results emphasize the importance of considering consumer inattention in demand estimation.

The peanut butter category is ideal for studying quantity surcharges for the following reasons. The dominance of three national brands shortens the list of brands to consider. Also, peanut butter products are relatively homogeneous, which makes it easier to compare apple to apple. Both quantity discounts and quantity surcharges are widely observed at grocery stores, with quantity surcharges being slightly more frequent (52% to 63%) than quantity discounts.

Even though consumers face quantity surcharges in their daily lives, minimal research has been done on this topic. Also, most of this research is limited to use store level data and fails to catch heterogeneity in consumer behavior (Agrawal, Grimm, and Srinivasan (1993), Sprott, Manning, and Miyazaki (2003), and Clerides and Courty (2017)). Analyzing heterogeneity in attention is important, especially for packaged goods in the presence of nonlinear pricing. Not considering consumer inattention will overemphasize preference on package size and bias predictions.

1.1 Literature Review

Few papers in the marketing literature study quantity surcharges. Widrick (1979) is the first paper to measure the frequency of quantity surcharges. The author focused on 10 product categories at 37 grocery stores in upper New York State using cross-sectional data. He found a high percentage of quantity surcharges across the categories (e.g., 84.4% for canned tuna fish and 33.3% for laundry detergent).

Agrawal, Grimm, and Srinivasan (1993) and Sprott, Manning, and Miyazaki (2003) study quantity surcharges on the seller side. Agrawal, Grimm, and Srinivasan (1993) interpret quantity surcharges as a practice of price discrimination against consumers with high demand. On the other hand, Sprott, Manning, and Miyazaki (2003) argue that stores practice quantity surcharges in order to build a low store-price image. Stores have incentive to lower the price of small size items when those are the items with a high sale volume. However, neither analyzes household purchasing behavior with the existence of quantity surcharges.

Clerides and Courty (2017) is the first attempt to analyze quantity surcharges on the consumer side, to the best of my knowledge. Using store level data in the laundry detergent category in the Netherlands, the authors found that roughly 45%–75% of households are inattentive in the sense that they miss the substitution opportunity to switch from the large package size to the small size in quantity surcharge weeks. The authors suggest search costs as a rationale for consumer inattention: consumers vary in search costs for finding the best deal, and for those consumers with high search costs, it is rational for them not to spend time on keeping track of quantity surcharges. The authors call it "rational" inattention. However, due to the limitation of store level data, the authors cannot analyze the behavior of "attentive" households.

One of the key purchasing patterns in the peanut butter category is frequent multiple jar purchases. Hence allowing the multiple discrete choice is crucial for the analysis. Several papers have tried to handle the multiple discrete choice problem. Hendel (1999) suggests a multiple discrete choice model for personal computers allowing both multiple units and multiple brands, when personal computers are differentiated. Kim, Allenby, and Rossi (2002) and Dubé (2005) also take similar approaches to handle the multiple discrete choice. All the three papers mentioned consider that consumers buy complementary products to cater for their various needs.[1] Hence the authors cannot handle a household's decision to whether or not purchase multiple small size jars for a large quantity.

Allenby, Shively, Yang, and Garratt (2004) introduce a multiple discrete choice model specifically designed for packaged goods. In this model, consumers purchase multiple items for a larger quantity. However, the authors assume quantity discounts only, and fail to analyze consumer inattention when quantity surcharges exist.

To summarize, my paper is the first analysis of heterogeneous household behavior when quantity surcharges exist. I propose a novel approach to structurally analyze households' purchasing decisions for packaged goods. The model assumes general nonlinear pricing and allows consumer inattention.

The paper proceeds as follows. Section 2 describes the data sets used for the analyses and provides summary statistics. Section 3 shows the results of several reduced form analyses, including households'

[1] Especially Dubé (2005) considers items with the same characteristics but different package sizes as complements, whereas I consider them as perfect substitutes.

heterogeneous purchasing patterns with the existence of quantity surcharges. Section 4 introduces a structural demand model based on the purchasing patterns identified in section 3. Section 5 describes the estimation procedure, and section 6 shows the estimation results. Section 7 concludes the paper.

2 Data

2.1 Description of Data

I use weekly panel scanner data collected by Information Resources Inc. (IRI) for the analysis. The data set covers a period from January 2001 to December 2011, and 31 categories of products, including beer, carbonated beverages, and laundry detergent. IRI collected data from supermarkets in 50 regional markets defined by IRI, and also from household panels from two of the regional markets. For the analysis, I focus on the peanut butter category in the Eau Claire, Wisconsin, market, from January 2008 to December 2010. Eau Claire is one of the two markets that have both store level and household level data.[2] The store level data consist of weekly peanut butter product sales observations at store-UPC (Universal Product Code) level in Eau Claire, including the number of jars sold, total sales in terms of dollar amount, and information on promotional activities. The household level data consist of peanut butter purchases, trips to grocery stores, and household demographic characteristics. There is also an additional data set available on the attributes of peanut butter products.

I merged the three household level data sets and product attributes data in order to extract the maximum information on households' product purchases. Then I merged the store level data set to get additional information on price levels and promotional activities. I dropped the observations that were not matched during the merging processes. I also dropped the households who showed extreme purchase history: more than six jars on a single trip or more than 100 jars combined during the time period. Section A.2 describes how I merged each data set in detail. The final data set contains 2,368 households with 244,154 purchase observations in total. Those households purchased 123 UPCs of peanut butter items of 26 brands from six grocery stores. From now on, I use "grocery stores" and "stores" interchangeably.

[2] The other household panel market is Pittsfield, Massachusetts.

2.2 Peanut Butter Market in Eau Claire

The big three national brands in the market are Jif, Skippy, and Peter Pan. Jif and Skippy have significantly high market shares in Eau Claire, at 31% and 28%, respectively. The market shares of the top 10 selling brands are listed in Table 1. J.M. Smucker Company, Jif's current parent company, acquired Jif from P&G in 2001. In addition to other Jif brands, such as Simply Jif, Jif to Go, and Jif Natural, J.M. Smucker Company also owns Santa Cruz Organic and its own peanut butter brand, Smucker's. Skippy belongs to Unilever, which also owns Skippy Natural and Skippy Super Chunk. The third top selling brand, Private Label, is actually not a brand. It is also known as a store brand or generic brand, and its market share increased over the period I analyzed (2008–2010).

Table 1: Top 10 Selling Brands

Rank	Brand	Parent Company	Market Share (%)	Cum. Market Share (%)
1	Jif	J.M. Smucker Co.	31.02	31.02
2	Skippy	Unilever	28.25	59.27
3	Private Label	Private Label	16.39	75.66
4	Peter Pan	Conagra Foods, Inc.	7.87	83.53
5	Smucker's	J.M. Smucker Co.	5.17	88.71
6	Skippy Natural	Unilever	3.50	92.21
7	Skippy Super Chunk	Unilever	2.43	94.64
8	Smart Balance	Smart Balance, Inc.	1.13	95.77
9	Simply Jif	J.M. Smucker Co.	1.12	96.88
10	Holsum	Holsum Foods	0.51	97.39

Note: The data used are store level peanut butter product sales data from six grocery stores in the Eau Claire market, 2008–2010. The market share is based on the total number of peanut butter jars sold in the market.

The panel data include 2,368 households who purchased at least one jar of peanut butter. Fifty percent them purchased more than 11 jars, and 25% of them purchased more than 20 jars. One interesting purchasing pattern is that households frequently purchased multiple jars of peanut butter products on a single trip: 45.5% of the times when they purchased peanut butter products, they purchased more than one jar.

Looking into the multiple jar purchases in detail, most of them are of the exactly same item, rather than two different peanut butter items. Table 2 shows the relationship between multiple jar purchases and multiple UPC purchases. The data show that 8,814 times, the households purchased two jars of peanut butter products on a single trip, and 8,336 times out of that, the two jars have the same UPCs. UPC is the finest way to define a product, and that means two jars with the same UPC are identical. Similarly, 1,166 out of 1,955 times that the households purchased three or more jars, the jars have the same UPC. This suggests that most of the households purchased multiple jars at a time for a large quantity, not for variety.

Table 2: Household PB Multi-UPC and Multi-Jar Purchases on a Trip

	Number of UPCs			
Number of Jars	1	2	3	Total
1	12,521	0	0	12,521
2	8,336	478	0	8,814
3+	1,166	456	16	1,955
Total	22,023	934	16	22,973

Note: The data used are household level panel data from the Eau Claire market between 2008 and 2010.

3 Reduced Form Analyses

In this section, I share the results of the reduced form analyses. First I show the existence and magnitude of quantity surcharges at stores. Then I provide evidence of heterogeneity in household purchasing behavior when quantity surcharges exist.

3.1 Evidence of Quantity Surcharge

In this section, I study quantity surcharges at stores. I first define a product and quantity surcharges. I identify products from the data using the definition, and then quantity surcharges within products. Quantity surcharges are more frequently observed than quantity discounts. Also, the price gap between sizes are bigger in quantity surcharge weeks than in quantity discount weeks.

Define a product as a group of items that are identical except for the package size. Suppose a product with two different package sizes, small (S) and large (L). The product is quantity surcharged if

$$p_S < p_L, \tag{3.1}$$

where p_S and p_L are prices of the small and large size packages, respectively, normalized to their package sizes. Quantity discount exists if the opposite holds: $p_S > p_L$. It is important to control the product characteristics between the two items that we compare, except for the package size. Otherwise, we cannot separate quantity surcharges from price differences due to product differentiation.

I identify products in the peanut butter category using the definition of a product. First I merge all the sister brands into one: for example, I consider Skippy, Skippy Natural and Skippy Super Chunk as the same brand "Skippy" with different product characteristics [3]. Then I focus on the four leading brands: Skippy, Jif, Private Label, and Peter Pan. Lastly, I group UPCs with the same observable characteristics (texture, flavor, salt contents, sugar contents, and process) except for the package size.

The list of products identified is presented in Table 3. 17 products are identified. 12 of them have a single package size, and five of them have two package sizes. A smaller package size ranges from 15 oz to 18 oz, and the larger one is 28 oz. I call a UPC that belongs to a product as an item. 17 products combined together have a market share of 86.26%.

In order to study quantity surcharges, I focus on five products with multiple package sizes. Both Skippy (product 1 and 2) and Jif (product 9 and 10) have two products with multiple package sizes, one with creamy texture and another with chunky texture. Private Label also has one product with two package sizes, product 14.

Quantity surcharges are determined by the price dynamics between small and large size items. Figure 1 provides an illustrative example of how the price difference between the two sizes varies over time, and how quantity surcharges are identified. In the Figure 1a, the solid line represents the small size item (item 1) and the dash line represents the large size item (item 2). The two items belong to product 1 identified in Table 3 and the price is normalized to 16 oz.

Quantity surcharges exist whenever the dashed line stays above the solid line. That is equivalent

[3] In addition, I combine Jif, Jif Natural, and Simply Jif as "Jif", and Peter Pan, Peter Pan Plus, and Peter Pan Smart Choice as "Peter Pan".

Table 3: Products Identified

Item ID	Prod ID	Brand ID	Oz	Jars	Share	Ave Price (per 16 oz)	Feature Freq.	Display Freq.	Creamy	Flavor	Salt	Sugar	Natural	Red Fat
1	1	1	16.3	6,433	0.1831	2.1837	0.0940	0.2041	1	0	1	1	0	0
2	1	1	28.0	983	0.0280	2.3241	0.0359	0.0207	1	0	1	1	0	0
3	2	1	16.3	2,225	0.0633	2.1611	0.0865	0.1816	0	0	1	1	0	0
4	2	1	28.0	387	0.0110	2.3385	0.0215	0.0161	0	0	1	1	0	0
5	3	1	16.3	397	0.0113	2.2467	0.0900	0.0171	1	1	1	1	0	0
6	4	1	16.3	356	0.0101	2.2144	0.0675	0.0166	0	1	1	1	0	0
7	5	1	16.3	1,416	0.0403	2.2727	0.0940	0.0128	1	0	1	1	0	1
8	6	1	16.3	498	0.0142	2.2802	0.0891	0.0129	0	0	1	1	0	1
9	7	1	15.0	708	0.0202	2.5039	0.0476	0.0075	1	0	1	1	1	0
10	8	1	15.0	445	0.0127	2.5305	0.0552	0.0048	0	0	1	1	1	0
11	9	2	18.0	4,933	0.1404	2.0600	0.0630	0.1827	1	0	1	1	0	0
12	9	2	28.0	1,362	0.0388	2.1085	0.0192	0.0107	1	0	1	1	0	0
13	10	2	18.0	1,342	0.0382	2.0755	0.0534	0.1026	0	0	1	1	0	0
14	10	2	28.0	240	0.0068	2.1162	0.0203	0.0118	0	0	1	1	0	0
15	11	2	18.0	1,213	0.0345	2.1160	0.0662	0.0214	1	0	1	1	0	1
16	12	2	17.3	430	0.0122	2.2638	0.0299	0.0021	1	0	0	0	0	0
17	13	3	18.0	2,204	0.0627	1.6606	0.0427	0.2746	1	0	0	1	0	0
18	14	3	18.0	308	0.0088	1.5364	0.0000	0.0104	1	0	1	1	0	0
19	14	3	28.0	350	0.0100	1.6844	0.0075	0.0011	1	0	1	1	0	0
20	15	3	18.0	663	0.0189	1.6880	0.0350	0.1883	0	0	1	1	0	0
21	16	4	16.3	2,556	0.0728	2.0568	0.0302	0.1524	1	0	1	1	0	0
22	17	4	16.3	852	0.0243	2.0987	0.0322	0.0766	0	0	1	1	0	0

Note: Brand ID is 1 if Skippy, 2 if Jif, 3 if Private Label, and 4 if Peter Pan.

to those weeks where the price difference is positive in the Figure 1b. In the figure, price difference is defined as price of the small size item subtracted from price of large size item. Quantity discounts exist whenever the dashed line is below the solid line, or equivalently, whenever the price difference is negative. The pricing alternates frequently between quantity surcharges and quantity discounts in the earlier weeks. Quantity surcharges last for a while afterwards, and then mostly quantity discounts in the later weeks.

The price gap between the two sizes, which determines the magnitude of quantity surcharges, fluctuates over time. The small size item show more frequent and deeper price drops, especially during the first 70 weeks, and those drops increase the price gap. Around week 70 and 100, the price gap stays at a somewhat moderate level. In later weeks, the gap becomes slip, except for the two big spikes of quantity surcharges.

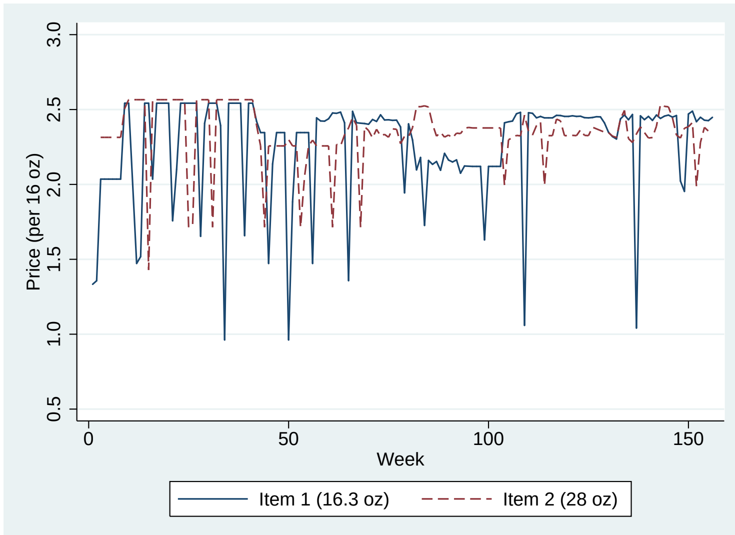
For each of the five products, I count the frequency of quantity surcharges and quantity discounts as follows: 1) at each store, I determine whether the product is quantity surcharged or quantity discounted in each week; 2) I count the number of quantity surcharge weeks and quantity discount weeks at a store; 3) I sum up the number of quantity surcharge weeks and quantity discount weeks across the six stores; 4) I divide both numbers by the total number of weeks that both items were sold. The results are presented on the second and fourth columns on Table 4.

Table 4: Frequency and Magnitude of Quantity Discounts and Quantity Surcharges

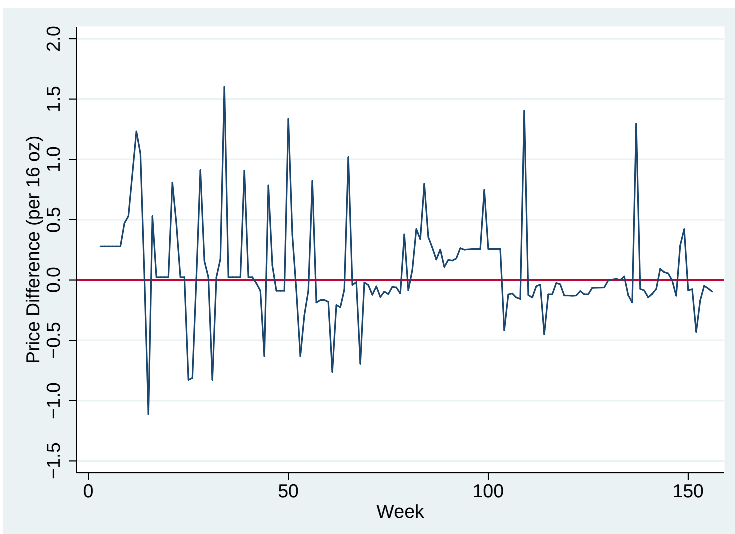
	QD ($p_S > p_L$)		QS ($p_S < p_L$)	
Prod ID	% of weeks	Ave $p_L - p_S$ ($)	% of weeks	Ave $p_L - p_S$ ($)
1	36.38	-0.1807	63.64	0.3105
2	36.62	-0.1754	63.38	0.3577
9	44.95	-0.1387	55.05	0.1998
10	47.99	-0.1440	52.01	0.2109
14	13.29	-0.4364	86.71	0.1785

Note: A product is defined as a group of UPCs with the same observable characteristics but package size. The five products are the products identified in Table 3 that has two different package sizes, small and large; p_S and p_L are the price per 16 oz of the small and large size item, respectively. A quantity discount (QD) exists for a product at a certain week at a store if $p_S > p_L$ holds, and a quantity surcharge (QS) exists if the opposite ($p_S < p_L$) holds. % of weeks is the percentage of weeks at the six grocery stores combined when quantity discounts or quantity surcharge existed; Ave $p_L - p_S$ is the average price difference per 16 oz between the small and the large items across weeks and stores. It measures the average magnitude of quantity discounts and quantity surcharges. The difference is negative in quantity discount weeks and positive in quantity surcharge weeks.

Figure 1: Price of Product 1 at Store 2



(a) Price per 16 oz of Product 1 at Store 2



(b) Price Difference Between Two Items of Product 1 at Store 2

Note: Panel (a) shows weekly prices (per 16 oz) of the two items, item 1 and item 2 an panel (b) shows the price difference between the two items (price of item 1 subtracted from price of item 2). The two items belong to product 1 identified in Table 3. The price information is obtained from store 2, one of the six grocery stores in the market, from 2008 to 2010.

The results show that quantity surcharges are more frequent than quantity discounts across products. The two Skippy products (product 1 and 2) have quantity surcharges for around 63% of the weeks. Quantity surcharges are less frequent for the two Jif products (product 9 and 10), compared to the Skippy products, but still more frequent than quantity discounts. Product 14 shows the highest frequency of quantity surcharges among the five products, which goes up to 87%. It can be possibly explained by the fact that the product belongs Private Label, which is a store brand. Stores can have more direct influence on prices of their own brands. Stores might have wanted to keep the price of the small size item, which is more popular than the large size item, at a low level. As a result, quantity surcharges became highly frequent.

Large size items are more expensive by \$0.20 to \$0.36 per 16 oz than small size items in quantity surcharge weeks. The third and the last columns in Table 4 show the average magnitudes of quantity discounts and quantity surcharges of each product. The magnitudes are measures by the price difference between the two sizes. I subtract the price per 16 oz of a small item from the price per 16 oz of a larger counterpart. The magnitude of quantity surcharges are bigger than that of quantity discounts except for Product 14. Again it can be possibly explained by the fact that Product 14 belongs to Private Label verses the other four products belong to leading national brands. Among the four products, the two Skippy products (product 1 and 2) show bigger magnitudes of quantity surcharges than the two Jif products (product 9 and 10).

Quantity surcharges are related to temporary price reductions on small size items, but that is not the main cause. Table 5 shows the relationship between quantity surcharges and sale. I follow Hendel and Nevo (2003)'s approach and define a sale for an item as follows: I first define the regular price as the modal price, which is the most frequent price for the item at a store. Then sale is defined as any price at least 5% lower than the regular price.

There are four possible sale states: only the small size item is on sale, only the large size item is on sale, both items on sale, and none of them is on sale. Table 5 shows that quantity surcharges are the most common when neither of the items is on sale. The second most frequent state is sale on the small size item only, except for product 10. Hence quantity surcharges are more of consistent phenomena for peanut butter products than side effects of sale on small size items.

Table 5: Quantity Surcharges and Sale on Each Package Size

Prod ID	Sale on Small Size Only	Sale on Large Size Only	Sale on Both Sizes	No Sale on Both Sizes
1	33.75	0.90	18.95	46.39
2	31.59	5.43	19.11	43.86
9	24.26	3.55	23.47	48.72
10	19.03	20.13	29.20	31.64
14	8.29	0.00	1.51	90.20

Note: A sale is defined as a price at least 5% less than the modal price at each grocery store for the period analyzed.

3.2 Quantity Surcharge and Households' Heterogeneous Behavior

Small size jars are cheaper than large size jars in quantity surcharge weeks. If all households were aware of the substitution opportunity, the two following purchasing patterns would be expected during quantity surcharge weeks: 1) no large size jar purchase during quantity surcharge weeks, and 2) more frequent multiple small size jar purchases than during quantity discount weeks. In other words, all the households who would demand a large quantity should have purchased multiple small size jars. Here I assume no preference towards large package size and no stock-outs of small size items. Those two possibilities are discussed later in this chapter.

In order to test households' awareness, I analyze how multiple jar purchases of each size vary during quantity discount and quantity surcharge weeks. The results are presented in Table 6. A purchase is "single" when a household purchases a single jar on a trip, and "multi" when the household purchases more than one jar on a trip.

Table 6: Quantity Surcharges and Multiple Jar Purchases

	Small			Large		
	Single	Multi	Total	Single	Multi	Total
QD($p_S > p_L$)	571	922	1,493	513	560	1,073
QS($p_S < p_L$)	2,981	3,786	6,767	598	261	859
Total	3,552	4,708	8,260	1,111	821	1,932

Note: "single" represents single jar purchases and "multi" represents multiple jar purchases on a trip

There is heterogeneity in households' awareness of quantity surcharges. Multiple small size jar purchases are significantly more frequent in quantity surcharge weeks. However, the number of large size jar purchases in quantity surcharge weeks is not negligible. Multiple small size item purchases are roughly four times more frequent in quantity surcharge weeks compared to quantity discount weeks. This implies that some households are aware of the existence of quantity surcharges and chose to buy multiple small size jars rather than a large size jar.

The number of single small size item purchases jumps up in quantity surcharge weeks compared to quantity discount weeks also. This could be because small size items are on sale roughly half of the times (including sale on small size item only and sale on both sizes) during quantity surcharge weeks, as shown in Table 5.

On the other hand, there is a positive number of purchase observations of large size items during quantity surcharge weeks, both single and multiple. This founding is consistent to the concept of consumer inattention that Clerides and Courty (2017) argues: there exist inattentive households who are unaware of the existence of quantity surcharges and miss the opportunities to substitute. I define a miss as a purchase incident of large size items in quantity surcharge weeks.

There could be alternative explanations for the positive sales of large size items during quantity surcharge weeks. One possible explanation is strong preference on large size jars. However, it is hard to reason that when small size jars has relative advantages to large size jars: a smaller jar can keep peanut butter more fresh than a larger jar does, and it is also more convenient to carry around.

Another alternative explanation could be a stock-out. That is, some households purchase large size items in quantity surcharge weeks just because small size items are not available upon their visits. Conlon and Mortimer (2013) argue that ignoring incomplete product availability may bias demand estimates. I cannot verify this argument, as the store level data are recorded at weekly level.[4] However, the five small size items that I focus on to analyze quantity surcharges are more popular than most of the other UPCs on the market. Thus, they are relatively less likely to be stocked out at stores. Hence, it is hard to argue that strong preference on large size jars or stock-outs of small size items is the main reason for those large size purchases in quantity surcharge weeks.

Almost 20% of households made at least one miss purchase. Table 7 shows the number of households

[4]The household level data have information on checkout time. However, this information allows me to observe product availability only when there exists a household who purchased the item of interest.

who did not make any miss purchases to one, two, and three or more miss purchases. 1,908 households made zero miss [5]. However, there are 272 households who made one miss purchase. 272 households made two misses and 87 households made three or more.

Table 7: Number of Misses Each Household Made

Num of Misses	Freq.	Percent	Cum.
0	1,908	80.57	80.57
1	272	11.49	92.06
2	101	4.27	96.33
3+	87	3.67	100.00
Total	2,368	100.00	

Note: A miss is defined as an incident of purchasing a large size item in quantity surcharge weeks.

What makes inattentive households inattentive? There could be several reasons. Some households might have a limited ability to calculate price per ounce at grocery stores. High search costs could hurry some households and keep them from comparing prices of different size items. Clerides and Courty (2017) call this case rational inattention. Some households might have a strong belief that quantity discounts always exist. Those reasons are not mutually exclusive.

In this section, I found that quantity surcharges are more frequent than quantity discounts in the peanut butter category. During quantity surcharge weeks, households show heterogeneous behavior. I explain the heterogeneity using the concept of consumer inattention. Inattentive households are unaware of the existence of quantity surcharges and purchase large size jars. On the other hand, attentive households are aware of the existence of quantity surcharges and purchase multiple small size jars instead of one large size jar when they want to purchase a large quantity.

[5] Among them, 355 households did not purchase any of the five products with multiple package sizes, and 1,553 households purchased at least one jar of the five products but did not purchase large size jars in quantity surcharge weeks.

4 Model

In this section, I present a series of three discrete choice models for packaged goods. I start with the basic model, and then extend the model in two different ways in order to capture a key purchasing pattern found from the data.

4.1 Basic Model

The basic model is adopted from Allenby, Shively, Yang, and Garratt (2004). A consumer has the Cobb-Douglas utility function

$$\ln u(x,z) = \alpha_0 + \alpha_x \ln u(x) + \alpha_z \ln(z), \tag{4.1}$$

such that she enjoys both the inside good of our interests and an outside good. $x = (x_1, \ldots, x_K)$ is a vector of the amount of each product purchased, where K is the number of products available for the inside good. K products are differentiated in characteristics, and some of them have multiple package sizes. z represents the amount of the outside good consumption, and $u(x)$ indicates a subutility function.

The subutility function has a linear structure:

$$u(x) = \psi\prime x, \tag{4.2}$$

where ψ_k denotes the marginal utility for product k. Let $\ln(\psi_k) = \nu_k + \epsilon_k$, where ϵ_k is a stochastic element. The non-stochastic factor of the log marginal utility is determined as

$$\nu_k = \beta_{0b}\text{brand}_k + \beta_c \text{char}_k', \tag{4.3}$$

where brand_k represents the brand which product k belongs to, and char_k is a vector of product characteristics.

The consumer determines her consumption on each of K products and the outside good to maximizes her utility function in (4.1) subject to the budget constraint

$$\Sigma_{k=1}^{K} p_k(x_k) + z = T, \tag{4.4}$$

where $p_k(x_k)$ is the price of x_k units of product k and T represents the consumer's budgetary allotment. Price of the outside good is one. The price is a function of quantity in order to accommodate any kind of pricing schemes, including linear pricing, quantity discounts, and quantity surcharges.

The quantity choice of product k, x_k, is a discrete number, as products are offered in certain package sizes. Suppose product k is only available in 16 oz jars. Then x_k should be one of the multiples of 16, such as 16, 32, 48, ... oz. If the product is available in two package sizes, 18 and 28 oz jars, then x_k should be a combination of the two package sizes.

I assume consumers choose only one product (i.e. only one element of x is nonzero) and evaluate the utility function at all possible combinations of package size bundles of each product. Restricting the utility maximization solutions to corner solutions is a key assumption to make the evaluation feasible. Allenby, Shively, Yang, and Garratt (2004) prove that the C-D utility maximization solution subject to a convex budget constraint is actually at a corner. A budget constraint is convex when quantity discounts exit, and on the other hand, it becomes concave when quantity surcharges exit. Thus, the proof fails when both quantity discounts and quantity surcharges exit. However, the corner solution assumption is supported by the data, as multiple product purchases are rarely observed.

The solution strategy involves two steps when only one element of x is nonzero. In the first step, a consumer determines the optimal quantity for each of the products. The optimal quantity for a product is chosen from all possible combinations of the package sizes available. I substitute $z = T - \Sigma_k p_k(x_k)$ for the outside good, and the first stage optimization problem can be written as

$$\begin{aligned} &\max_{a \in A}\{\alpha_0 + \alpha_x \ln u(x_{ka}) + \alpha_z \ln(T - p_k(x_{ka}))\} \\ &= \max_{a \in A}\{\alpha_x \ln x_{ka} + \alpha_z \ln(T - p_k(x_{ka}))\}, \end{aligned} \tag{4.5}$$

where x_{ka} and $p_k(x_{ka})$ represent the quantity and the price of package bundle a of product k. A is the set of all possible combinations of the package sizes that are available for product k. A depends on product k

but here I drop the subscript k for convenience. Note that the stochastic factor of the log marginal utility, ϵ_k, cancels from the expression, as it is the same for any possible package bundles within a product. Hence, the optimal quantity of each product in the first stage is deterministic.

In the second step, the consumer decides which product to purchase. In the first step, the consumer searched for the optimal quantity, given that product k is chosen. In the second step, the consumer lines up the optimal quantity of each product, and compares the utilities. The second step product choice problem can be written as:

$$\begin{aligned}
&\max_{ka}\{\ln u(x_{ka}, T - p_k(x_{ka}))\}\\
&= \max_k[\max_{a|k}\{\ln u(x_{ka}, T - p_k(x_{ka}))\}]\\
&= \max_k[\alpha_0 + \alpha_x \ln u(x_k^*) + \alpha_z \ln(T - p_k(x_k^*))], \qquad (4.6)
\end{aligned}$$

where x_k^* is the optimal quantity for product k in the first step.

Substituting the subutility expression in equation (4.2) yields

$$= \max_k[\alpha_0 + \alpha_x(\nu_k + \epsilon_k) + \alpha_x \ln(x_k^*) + \alpha_z \ln(T - p_k(x_k^*))]. \qquad (4.7)$$

Assume ϵ_k follows the Type I extreme value distribution, EV(0,1). The choice probability can be written as

$$\Pr(x_i) = \frac{\exp[\nu_i + \ln(x_i) + (\alpha_z/\alpha_x)\ln(T - p_i(x_i))]}{\Sigma_{k=1}^{K} \exp[\nu_k + \ln(x_k^*) + (\alpha_z/\alpha_x)\ln(T - p_k(x_k^*))]}, \qquad (4.8)$$

where x_i is the observed demand. Note that x_i replaces x_k^* for the selected product in the estimation procedure.

The model ideally captures the nature of discrete choices consumers make for packaged goods, by searching through all feasible package bundles for each product. However, one critical limitation of Basic model is that it cannot explain the miss purchases observed in the data. Unless the price difference between the small and the large package sizes is negligible, the first stage optimal quantity choice yields one or multiple small package size purchases.

I extend the Basic model in two different ways to incorporate the miss purchases. Extension 1 allows consumers to have preference on package sizes, in order to test whether it is the strong preference on large package sizes that drives the miss purchases. Extension 2 incorporates the concept of consumer inattention and impose some restrictions on the set of package size bundles to consider in the first stage optimization problem.

4.2 Extension 1

I assume that consumers have certain preference on package sizes, in a sense that two different package sizes of the same product offer different marginal utility to consumers. That is, the marginal utility of a product depends on the package size a consumer chooses. I also assume that the preference on package sizes only affects the deterministic part of the marginal utility, and not the stochastic part. The deterministic part is defined as

$$\nu_{ka} = \beta_{0b}\text{brand}_k + \beta_c\text{char}'_k + \beta_s\text{small}_{ka}, \tag{4.9}$$

where small_{ka} is a dummy variable indicating whether the package bundle consists of small package sizes or not. Note that ν_{ka} now includes a subscript a to indicate that it depends on the package bundle a. Let ψ_{ka} denote the marginal utility of package bundle a of product k, where $\ln(\psi_{ka}) = \nu_{ka} + \epsilon_k$.

As the package size affects the marginal utility, it affects the choice of which package bundle to purchase also. The first stage optimal quantity choice problem can be written as

$$\begin{aligned}
&\max_{a\in A}\{\alpha_0 + \alpha_x \ln u(x_{ka}) + \alpha_z \ln(T - p_k(x_{ka}))\} \\
=&\max_{a\in A}\{\alpha_0 + \alpha_x(\nu_{ka} + \epsilon_k + \ln x_{ka}) + \alpha_z \ln(T - p_k(x_{ka}))\} \\
=&\max_{a\in A}\{\alpha_x(\beta_s\text{small}_{ka} + \ln x_{ka}) + \alpha_z \ln(T - p_k(x_{ka}))\}.
\end{aligned} \tag{4.10}$$

The stochastic factor of the marginal utility, ϵ_k, cancels as in equation (4.5), and thus the solution is still deterministic. However, there is an additional term, $\beta_s\text{small}_{ka}$, that hasn't been cancelled out as the package size matters.

Let x^*_{ka} be the quantity of the optimal package bundle a of product k identified in the first stage. In the second stage, the consumer compares the optimal quantities of each product chosen in the first stage, and decides which product to purchase. The second stage problem is the same as in Basic model, since the comparison is across products. The choice probability can be written as

$$\Pr(x_{ia}) = \frac{\exp[\nu_{ia} + \ln(x_{ia}) + (\alpha_z/\alpha_x)\ln(T - p_i(x_{ia}))]}{\Sigma_{k=1}^{K}\exp[\nu_{ka} + \ln(x^*_{ka}) + (\alpha_z/\alpha_x)\ln(T - p_k(x^*_{ka}))]}. \tag{4.11}$$

4.3 Extension 2

The second extension of Basic model focus on the consideration set that a consumer searches through in the first stage in order to find her optimal quantity for each product. In Basic model, the consideration set is A, the all possible combinations of package sizes available. Let A' be a subset of A that excludes all multiple small package size bundles. I assume that a consumer's consideration set is restricted to A', instead of A, when she makes a miss purchase. In those cases, the first stage optimal quantity problem becomes

$$\begin{aligned} &\max_{a\in A'}\{\alpha_0 + \alpha_x \ln u(x_{ka}) + \alpha_z \ln(T - p_k(x_{ka}))\} \\ =&\max_{a\in A'}\{\alpha_x \ln x_{ka} + \alpha_z \ln(T - p_k(x_{ka}))\}. \end{aligned} \tag{4.12}$$

Let $x^{*\prime}_{ka}$ be the quantity of the optimal package bundle a of product k identified in the first stage when the consideration set is A'. The second stage problem is the same as in Basic model. The choice probability can be written as

$$\Pr(x_{ia}) = \frac{\exp[\nu_i + \ln(x_{ia}) + (\alpha_z/\alpha_x)\ln(T - p_i(x_{ia}))]}{\Sigma_{k=1}^{K}\exp[\nu_{ka} + \ln(x^{*\prime}_{ka}) + (\alpha_z/\alpha_x)\ln(T - p_k(x^{*\prime}_{ka}))]} \tag{4.13}$$

when the purchase observation x_{ia} is a miss. Note that the consumer restricts her consideration to A' for not only the product i that is chosen, but all the other products k that are available. For the regular (non-miss) purchase occasions, the first stage problem and the choice probability are the same as in equation (4.5) and (4.8), respectively.

5 Estimation

The Cobb-Douglas utility function in equation (4.1) under three different model specifications is estimated as hierarchical Bayes models (Gelfand and Smith (1990)), which allows household heterogeneity. Not every parameter can be identified in equation (4.1), so I set $\alpha_0 = 0$ and $\alpha_x = 1$. α_z represents a household's relative preference of outside good to inside good after the normalization, and should be positive in economic theory. Hence I set $\alpha_z = \exp(\alpha_z^*)$ and estimate α_z^* unrestricted. In addition, I set $\beta_{03} = 0$, which is the preference parameter of brand 3 (Private Label), in equation (4.3) and (4.9).

Hierarchical bayes models allow household heterogeneity for all parameters $(\theta, T) = (\alpha, \beta', T)$. According to the Bayes theorem, the posterior is proportional to the product of the likelihood and the prior:

$$\pi(\theta_h, T_h) \propto \Pi_j \Pr(x_{ij}|\theta_h', T_h) \times \pi(\theta_h|\bar{\theta}, V_\theta) \times \pi(T_h|a, b), \tag{5.1}$$

where j denotes a purchase occasion of an household h. Hierarchical Bayes models impose a hierarchical structure to beliefs on parameters and involve two stages of priors:

$$\begin{aligned} \text{first-stage:} \quad & \pi(\theta_h|\bar{\theta}, V_\theta) \times \pi(T_h|a, b) \\ \text{second stage:} \quad & \pi(\bar{\theta}, V_\theta|\tau). \end{aligned} \tag{5.2}$$

I assume the normal prior model specified as

$$\begin{aligned} \theta_h &\sim N(\bar{\theta}, V_\theta), \quad T_h \sim N(a, b) \\ \bar{\theta} &\sim N(\bar{\bar{\theta}}, A^{-1}) \\ V_\theta &\sim IW(\nu, V), \end{aligned} \tag{5.3}$$

where V_θ follows the Inverted Wishart distribution with degrees of freedom ν and a scale parameter V.

The posterior distribution is simulated by generating sequential draws using Markov Chain Monte Carlo methods with Metropolis-Hastings Algorithm (Chernozhukov and Hong (2003)). I executed 50,000 iterations of the Markov chain and convergence was checked.

Table 8: Aggregate Coefficient Estimates

Parameters	(1)		(2)		(3)		(4)	
$\alpha^* = \ln(\alpha_z/\alpha_x)$	0.8268	(0.0642)	0.8570	(0.0716)	0.8078	(0.0648)	0.8323	(0.0674)
Skippy	1.8147	(0.1360)	1.7242	(0.1347)	1.8081	(0.1312)	1.6769	(0.1339)
Jif	1.8494	(0.1395)	1.7519	(0.1351)	1.8526	(0.1351)	1.7105	(0.1237)
Peter Pan	0.5660	(0.1599)	0.5118	(0.1418)	0.5645	(0.1605)	0.4702	(0.1662)
Creamy	1.6891	(0.1091)	1.6903	(0.1000)	1.6661	(0.1035)	1.6911	(0.1054)
Flavor	-2.7281	(0.2528)	-2.5760	(0.1888)	-2.5934	(0.2193)	-2.5377	(0.1773)
Salt	-0.4499	(0.1728)	-0.4059	(0.1532)	-0.5016	(0.1632)	-0.3571	(0.1617)
Sugar	3.7987	(0.3070)	3.6431	(0.2425)	3.8854	(0.3469)	3.5630	(0.2955)
Natural	-1.7324	(0.1797)	-1.6881	(0.1576)	-1.6868	(0.1739)	-1.6441	(0.1866)
Reduced Fat	-2.0798	(0.1241)	-2.0199	(0.1270)	-2.0375	(0.1286)	-1.9866	(0.1218)
Small Size	-	-	0.2103	(0.0796)	-	-	0.2427	(0.0793)
T	10.952	(0.2049)	10.945	(0.2064)	10.934	(0.2075)	10.9309	(0.2082)
Log Likelihood	-2688.70		-2671.20		-2683.50		-2669.50	

Note: Estimation was conducted with a subsample of 200 households. Standard deviations are reported in parentheses. Column (1) shows the estimation results of the basic model. Column (2) and (3) present the estimation results of extension 1 and 2 of the basic model, respectively. Column (4) shows the estimation results of the model in which extension 1 and 2 are combined. The log likelihood is evaluated at the household level parameter estimates $(\hat{\theta}_h, \hat{T}_h)$.

6 Results

The later half of the chain is used to estimate model parameters. The estimation results of different model specifications are reported in Table 8. Column (1)-(3) show the estimation results of Basic Model, Extension 1, and Extension 2, respectively. In addition, I estimate the model that combines Extension 1 and Extension 2, and the results are reported in column (4).

Here I interpret the estimation results of Extension 2 (column (3)). The aggregate estimate of α^* equal to 0.8078 means the aggregate estimate of α_z is equal to 2.2430. As α_x is normalized to 1, this means households enjoy the outside good 2.2430 times more than peanut butter products. Households prefer all three national brands to Private Label, and Jif is the most preferred brand among the three. Households prefer creamy texture over chunky texture, and regular sugar level over no sugar added. Households dislike peanut butter products that are flavored, salted, and naturally processed. Also, they dislike the products with reduced fat contents either.

Extension 2 fits the data the best. I calculate expected demand each model predicts, and compare it to the observed demand from the data. The results are shown in Table 9. The observed demand is calculated as sum of the total number of jars each household purchased multiplied by the size of the

Table 9: Expected Demand

Item ID	Oz	Observed Demand (Oz)	Expected Demand (Oz) (1)	(2)	(3)	(4)
1	16.3	7,665	9,489	9,889	9,013	9,820
2	28.0	2,632	2,676	1,697	2,861	1,652
3	16.3	2,191	2,034	2,160	1,983	2,134
4	28.0	420	483	249	526	248
5	16.3	521	672	760	733	767
6	16.3	326	122	137	136	137
7	16.3	1,958	1,778	1,829	1,786	1,853
8	16.3	281	286	293	292	295
9	15.0	1,558	1,883	1,907	1,896	1,933
10	15.0	648	354	363	363	374
11	18.0	9,756	10,793	12,194	10,246	12,297
12	28.0	5,376	5,375	3,194	5,774	3,045
13	18.0	1,458	2,816	3,099	2,738	3,066
14	28.0	364	901	456	982	441
15	18.0	1,800	2,048	2,076	2,046	2,105
16	17.3	502	411	437	388	450
17	18.0	3,258	4,670	4,707	4,728	4,662
18	18.0	414	1,469	1,524	1,381	1,565
19	28.0	1,400	1,402	1,304	1,489	1,406
20	18.0	666	321	334	321	343
21	16.3	3,204	3,183	3,202	3,117	3,179
22	16.3	793	574	577	579	575
Root Mean Square Error (RMSE) (%)			31.74	47.82	28.11	48.68

Note: Expected demand is calculated using the estimation results obtained from each model specification. Column (1) represents the basic model. Column (2) and (3) represent extension 1 and 2 of the basic model, respectively. Column (4) represents the model in which extension 1 and 2 are combined.

jars in ounces. Expected demand is calculated for each purchase observation, using household level parameter estimates $(\hat{\theta}_h, \hat{T}_h)$. First I solve the first stage optimization problem, according to the model, and find the optimal package bundle x^*_{ka} for each product. In the second stage, I calculate the probability for each product to be chosen, and then multiply it by the quantity of the optimal package bundle.

Extension 2 has the smallest root mean square error, which means that it predicts the demand which is closet to the actual demand observed, compared to the other model specification. Extension 1 performs poorly, such that it has root mean square error of 47.82%, which is even larger than the one from Basic model. This comparison supports that consumer inattention better explains households' purchasing behavior than preference on package sizes.

Table 9 also shows potential problems of using the models that are wrong-specified for prediction. Structural demand models are widely used to study policy implications and evaluate potential mergers. Thus, it is critical whether the model can predict the demand accurately. When packaged goods is of interest and quantity surcharges are common, it is important to understand consumer behavior and consider consumer inattention properly. Not considering it (Basic model) or wrong interpretation of consumer behavior (Extension 1) would result poor predictions.

7 Concluding Comments

I study quantity surcharges at grocery stores and consumers' heterogeneous behavior. The paper has three main contributions. The first is to reconfirm the existence of quantity surcharges, which is often forgotten when packaged goods and nonlinear pricing are of interest. Using the peanut butter category scanner data, I found strong evidence of quantity surcharges. It existed in 52% to 64% of the weeks between 2008 and 2010 at grocery stores in Eau Claire, Wisconsin. During those quantity surcharge weeks, small size peanut butter items were cheaper than the corresponding large size items by $0.20 to $0.36 per 16 oz on average.

The second contribution of this paper is to identify heterogeneity in consumer attention to quantity surcharges. The current literature focuses on the existence of inattentive consumers who are unaware of quantity surcharges and purchase large size items during quantity surcharge weeks. However, taking advantage of the rich household panel data available, I also identify attentive consumers, who actively respond to quantity surcharges and purchase multiple small size jars.

The last and most important contribution of this paper is to develop a demand model that can capture the heterogeneity in consumer attention. The model allows consumers to choose a product and its optimal quantity, as a combination of possible package sizes available. This can capture attentive consumers purchasing multiple small size items when quantity surcharges exist. In addition to that, the model restricts the choice set in case of miss purchases, which accommodates consumer inattention. The model can be solved as a two stage optimization problem.

I estimate the model using the MCMC methods. The objective function to maximize is complicated as the model features two stage optimizations and the number of package bundles to consider is huge. The Bayesian approach has advantages in this setting. I compare the estimation results to the two alternative model specifications: first, Basic model that does not consider quantity surcharges, and then an extension of Basic model that explains miss purchases as a result of strong preference on large package size. The estimation results support the model with consumer inattention.

A Appendix: Data

A.1 Data Set Descriptions

In this paper, I use five different data sets from IRI scanner data from 2008 to 2010 for the analysis. The first data set is product attributes data recorded at UPC level. The product attributes data originally contain 1,018 UPCs of peanut butter and peanut butter related products. For each UPC listed, information on its parent company, brand, product type, texture, flavor, and few other product characteristics is provided. As for product type, approximately 85% of UPCs belong to peanut butter and the rest belong to five other peanut butter related product types, such as peanut butter combo and peanut butter spread. There are 17 different textures and, ranging from super chunky and chunky to smooth and creamy.

The second data set is store level data containing information on weekly sales at UPC level at each store in Eau Claire. The available variables are store ID assigned by IRI, week, UPC, number of jars sold, total sales in dollars, and promotional activities such as feature and display. There are three types of stores in the market: two mass, three drug, and six grocery stores.[6] I focus on grocery stores only for the following reasons: 1) household level store visit observations from mass stores are missing; 2) drug stores have minimal sales volume compared to grocery stores [7]; 3) grocery stores also have somewhat different pricing strategies and promotional activities than grocery stores. Dropping observations from mass stores and drug stores, the data contain six stores, 31 brands, 159 UPCs, and 42,634 sales observations. In the rest of paper, I call grocery stores as stores.

The rest of three data sets are household level: household trip data, household demographic characteristics data, and household peanut butter purchase data. Household trip data contain records of trips to stores each household made for the period 2008-2010. For each household I can tell the store visited, the checkout time, and the total dollar amounts spent on the trip. This trip data originally contain 5,727 households and 719,711 trip observations. There are two types of stores, grocery stores and drug stores. Only 34,784 out of 719,711 trip observations are from drug stores, so I focus on the observations from grocery stores only. There are 5,702 households and 684,927 trip observations left after dropping the ob-

[6] One of the three drug stores opened in 2009

[7] The sum of sales in dollar amount of all the drug stores during the three year time period in Eau Claire takes roughly 1% of the total market sales.

servations from drug stores. Not every household has complete three-year trip records: some have trip observations from one year and no record for the next year. Those households are not appropriate for the analysis to understand household purchase behaviors with dynamic inventory holdings, so I keep the households with at least one trip observation each year. As a result, 4,076 households and 680,851 trip observations remain.

Next, household demographic characteristics data provide information on household income, family size, age and education level of household head, and few other characteristics. For the period 2008-2010, the demographic information was collected in Summer 2012, so the demographic characteristics for each household stay the same over the three years I analyze. There are 2,994 households listed on the data with at least one year observation. Using the fact that the demographic characteristics do not vary over the three years, I filled up the missing observations.

The last and the most important household level data are household purchase data. The data include the complete peanut butter product purchase records of the household panels during the time period analyzed: UPC of the peanut butter product and the number of jars purchased, dollar amount paid, and the store, week, and minute where and when the purchase occurred. Each observation is at household-store-week and minute-UPC level. Thus, if a household visited a store at a certain time and purchased two peanut butter jars with different UPCs, this purchase event is recorded as two separate purchase observations. However, if a household purchased two jars of the same peanut butter product (same UPC), then this purchase event is recorded as a single purchase observation. There are initially 2,713 households with 27,838 purchase observations in the data. Those purchases occurred at three different types of stores: mass, drug, and grocery stores. However, the purchase observations from mass stores and drug stores are very minimal.[8] Due to this negligible number of observations, and also in order to maintain the coherence with the other data sets, I keep the purchase observations from grocery stores only. This leaves 2,713 households and 27,661 purchase observations.

[8] Only 149 and 28 purchase observations occurred at drug stores and mass stores, respectively.

A.2 Merging Data Sets

I merged the five different data sets into one data set in the following order: 1) household trip data and household demographic characteristics data; 2) household peanut butter purchase data and peanut butter product attributes data; 3) results of merge 1 and merge 2; 4) result of merge 3 and store peanut butter sales data. In the process of merging, I dropped some observations that were not matched from one to another. Here are some details of each merge.

Merge 1: First, I merged the household demographic characteristics data to the household trip data. I dropped 88 households from the demographic characteristics data who do not have any matching trip observation in the trip data. Also 1,170 households (with 53,625 corresponding trip observations) from the household trip data have no demographic characteristics information available, so I dropped all of their trip observations. In addition, one household (with 45 trip observations) has most of demographic characteristics information available but no income information. Household income is one of the most important characteristics, so I dropped all of the household's trip observations. As a result 2,905 households and 605,688 trip observations are left.

Merge 2: The second step is merging the household product purchase data and the product attributes data. All the purchase observations from the household purchase data are successfully matched to the UPCs listed in the product attributes data. Households purchased four different kinds of product type: peanut butter, peanut butter combo, peanut butter spread, and peanut spread. I kept purchase observations of peanut butter and peanut butter spread types only. The reason is as follows: peanut butter combo is a type of products that has peanut butter and jelly or peanut butter and chocolate spread together in one jar. Peanut spread is usually flavored with honey or chocolate. However, peanut butter spread has no difference in observable characteristics than peanut butter. Also, the number of peanut butter jars that the household purchased during the time period analyzed, peanut butter combo and peanut spread product types together take a small share.[9] After dropping the purchase observations of those two product types, the same number of households remain, but the number of purchase observations are reduced to 27,527.

[9] Households purchased 42,425 jars in total, and among those, 125 jars are peanut butter combo type and 20 jars belong to peanut spread type.

Merge 3: The third step is to combine the two merged data sets, the household trip and demographic characteristics data set merged in step 1, and the household peanut butter purchase and peanut butter product attributes data set merged in step 2. I dropped 1,229 purchase observations with no matching trip observations. This yields 2,905 households in total with 606,833 trip observations. Among 2,905 households, 2,638 households bought at least one peanut butter jar during the time period analyzed. The total number of purchase observations is 26,298, and they include 28 brands and 129 UPCs. However, there is an additional grocery store in this merged data set other than the six grocery stores listed in the store level peanut butter sales data. 22 households visited the additional store during the time period analyzed, and the households made 54 trips and 2 peanut butter product purchases. In order to make it compatible to the store level peanut butter sales data, I dropped those 22 households. 2,883 households with 601,114 trip observations remain. Among them 2,616 households purchased at least one peanut butter product, and these households made 26,024 purchase observations in total.

Merge 4: The last step is to merge the store level peanut butter sales data and the combined household level data obtained by the merge 3. The final data set contains 42,634 sales observations at 6 different stores in the Eau Claire market for the period 2008-2010, including 31 brands and 159 UPCs. There are 2,883 households in total with 601,114 trip observations. Among them, 2,616 households purchased peanut butter products at least once, and those households made 26,024 purchase observations in total. Those purchase observations include 27 brands and 128 UPCs.

A.3 Data Summary Statistics

There are six stores in the Eau Claire market, and those stores carry 31 brands and 159 UPCs in total. Table 10 shows the top 30 selling UPCs. The best selling UPC for the period 2008-2010 is Skippy's 16.3 oz peanut butter with creamy texture, and Jif's 18 oz peanut butter with creamy texture is a close runner-up. Overall we can see that households prefer regular size jars to large or super size jars, and creamy texture to the chunky.[10] Another interesting pattern is that regular size UPCs tend to be less expensive per ounce than large size UPCs on average. For example, the rank 2 UPC, Jif's 18 oz creamy peanut butter, has average

[10]Here I group peanut butter UPCs to four sizes, small, regular, large, and super, for convenience. The small size jar ranges from 12 oz. to 15 oz, and the regular size jar is between 16 oz. and 18 oz. The large size jar varies from 26 oz. to 28 oz. and anything larger than 36 oz. is classified as the super size.

Table 10: Top 30 Selling UPCs at Store Level

Rank	Brand	oz	Texture	Sales ($)	Num of Jars	Market Share (%)	Ave Jar Price ($)	Ave Volume Price ($)
1	Skippy	16.3	CR	115,737	64,601	12.59	1.79	1.76
2	Jif	18.0	CR	124,288	59,353	11.56	2.09	1.86
3	Private Label	18.0	CR	43,418	28,130	5.48	1.54	1.37
4	Jif	28.0	CR	86,029	23,991	4.67	3.59	2.05
5	Skippy	16.3	CH	39,636	22,869	4.46	1.73	1.70
6	Peter Pan	16.3	CR	29,750	21,986	4.28	1.35	1.33
7	Skippy	16.3	CR	32,655	16,249	3.17	2.01	1.97
8	Jif	18.0	CR	33,505	15,364	2.99	2.18	1.94
9	Jif	18.0	CH	29,498	14,659	2.86	2.01	1.79
10	Skippy	28.0	CR	53,184	13,940	2.72	3.82	2.18
11	Smuckers	16.0	CR	32,631	12,915	2.52	2.53	2.53
12	Jif	40.0	CR	58,019	11,483	2.24	5.05	2.02
13	Smuckers	16.0	CH	25,063	9,923	1.93	2.53	2.53
14	Peter Pan	18.0	CR	17,349	9,775	1.90	1.77	1.58
15	Private Label	18.0	CH	12,934	8,340	1.63	1.55	1.38
16	Skippy Natural	15.0	CR	16,259	7,370	1.44	2.21	2.35
17	Private Label	18.0	CR	9,914	6,215	1.21	1.60	1.42
18	Private Label	40.0	CR	24,690	6,009	1.17	4.11	1.64
19	Skippy	16.3	CH	12,332	5,939	1.16	2.08	2.04
20	Simply Jif	17.3	CR	13,465	5,727	1.12	2.35	2.17
21	Jif	28.0	CH	20,447	5,666	1.10	3.61	2.06
22	Jif	40.0	CR	24,291	5,655	1.10	4.30	1.72
23	Private Label	28.0	CR	15,253	5,519	1.08	2.76	1.58
24	Skippy Super Chunk	28.0	CH	20,918	5,428	1.06	3.85	2.20
25	Skippy Natural	15.0	CH	11,554	5,185	1.01	2.23	2.38
26	Skippy	40.0	CR	26,028	5,010	0.98	5.20	2.08
27	Private Label	18.0	CR	8,545	4,607	0.90	1.85	1.65
28	Jif	18.0	CH	10,272	4,532	0.88	2.27	2.01
29	Jif	40.0	CH	21,368	4,278	0.83	4.99	2.00
30	Skippy Natural	26.5	CR	16,876	4,133	0.81	4.08	2.47

Note: The data used are store level peanut butter product sales data from six grocery stores in the Eau Clare market, 2008-2010. Rank and market share are based on the total number of jars sold for the three years. Texture is either creamy (CR) or chunky (CH). Sales is the sum of dollar values of peanut butter jars sold in the market. Ave jar price is the average price per jar and ave volume price is average price per 16 oz. across weeks and stores.

volume price \$1.86, which is lower than \$2.05, average volume price of Jif's 28 oz creamy peanut butter. This pattern indirectly suggests quantity surcharges.

Table 11 shows the summary statistics of demographic characteristics of households and trips to stores those households made for the period 2008-2010 in the Eau Claire market. The upper panel shows that the median income household earned annual income between \$35,000 and \$44,999. The family sizes are relatively small, as the median household consists of two family members and more than 75% of the households have no children. The lower panel shows the summary statistics of trips households to stores. The median number of trips is 179, which is more than once a week on average, considering that there are 156 weeks in three years. The majority of households visited multiple stores during the time period analyzed, that 75% of households visited greater than equal to three different stores and 50% of households visited greater than equal to four different stores. The median average number of trips in a week is above 1, and the median of the average number of weeks since last trip is less than a week. The two numbers together suggest that roughly 50% of households made regular weekly trips to stores. The median of the average expenditure is approximately \$37 per trip and \$62 per week.

Among the total number of 601,114 trip observations, 24,894 observations include peanut butter product purchases. The top panel in the table 12 shows the summary statistics of households' peanut butter purchases on a single trip. The average number of jars purchased is 1.61, which is significantly larger than 1, while the average number of UPCs and the average number of brands purchased are close to 1. These suggest that the households frequently purchased multiple jars at a single trip, and most of those cases were exactly the same UPCs, rather than purchasing multiple UPCs.

The middle panel in the table 12 shows the summary statistics when the purchases are combined in a weekly level. In only few cases the households purchased peanut butter products through multiple trips in a week. Hence, the summary statistics at a weekly level are not far from those of a trip level presented in the top level. During the time period analyzed, 2,616 households purchased peanut butter products at least once, and the summary statistics of those households' purchases are presented in the bottom panel. Roughly half of households purchased more than 10 jars, and more than 190 oz. in terms of volume, conditional on purchase. Even though households usually purchased a single UPC on a trip, they sought for varieties in the long term and purchased multiple UPCs and brands during the time

Table 11: Summary Statistics of Demographic Characteristics and Trips (updates needed)

Variable	Obs	Mean	SD	Min	P25	P50	P75	Max
Income	2,883	7.22	3.23	1	5	7	10	12
Fam Size	2,883	2.35	1.23	1	2	2	3	8
Num of Children	2,883	0.26	0.58	0	0	0	0	3
HH Age	2,870	4.78	1.17	1	4	5	6	6
HH Educ	2,870	6.79	15.57	1	3	4	5	99
Race	2,883	1.50	6.57	1	1	1	1	99
Num of Trips	2,883	208.50	133.08	5	122	179	261	1,927
Num of Stores	2,883	4.14	1.40	1	3	4	5	6
Ave Num of Trips	2,883	1.78	0.72	1.00	1.34	1.59	1.99	12.35
Ave Num of Weeks Since Last Trip	2,883	0.99	0.80	0.08	0.59	0.84	1.21	15.71
Ave Expend ($)	2,883	41.48	22.81	5.34	24.99	36.97	53.00	233.25
Ave Weekly Expend ($)	2,883	67.53	32.14	10.34	44.19	62.40	85.06	387.37

Note: The data used are household level panel data from the Eau Clare market, 2008-2010. The upper panel shows the summary of demographic information of households and the lower panel shows the summary information of the trips households made from six grocery stores in the market. Income is a categorical variable representing the combined pre-tax income of the head of household (HH). Income is equal to 1 if the combined pre-tax income of HH is in the range of $00,000 to $9,999 per year, 2 if in the range of $10,000 to $11,999, 3 if in the range of $12,000 to $14,999, 4 if in the range of $15,000 to $19,999, 5 if in the range of $20,000 to $24,999, 6 if in the range of $25,000 to $34,999, 7 if in the range of $35,000 to $44,999, 8 if in the range of $45,000 to $54,999, 9 if in the range of $55,000 to $64,999, 10 if in the range of $65,000 to $74,999, 11 if in the range of $75,000 to $99,999, and 12 if greater than or equal to $100,000. Fam size and num of children represent the number of family members and the number of children in the household, respectively. HH age is a categorical variable representing the age of HH. HH age is equal to 1 if the HH's age lies in the range of 18 to 24, 2 if 25 to 34, 3 if 35 to 44, 4 if 45 to 54, 5 if 55 to 64, and 6 if greater than equal to 65. Race is a categorical variable representing the HH's ethnicity. Race is equal to 1 if the HH is white and 96.94% of 2,883 households in the data have white HHs.

period analyzed.

B Appendix: Estimation

Table 12: Summary Statistics of Household Peanut Butter Purchases (updates needed)

Variable	Obs	Mean	SD	Min	P25	P50	P75	Max
On a Trip								
Num of Jars	24,894	1.61	0.89	1	1	1	2	16
Volume (oz)	24,894	31.76	19.12	12	18	33	36	336
Num of UPCs	24,894	1.05	0.21	1	1	1	1	3
Num of Brands	24,894	1.01	0.12	1	1	1	1	3
In a Week								
Num of Jars	23,502	1.70	1.08	1	1	1	2	18
Volume (oz)	23,502	33.65	21.74	12	18	33	36	336
Num of UPCs	23,502	1.07	0.28	1	1	1	1	6
Num of Brands	23,502	1.03	0.17	1	1	1	1	4
For Three Years								
Num of Jars	2,616	15.29	17.09	1	4	10	20	166
Volume (oz)	2,616	302.27	343.42	12	81	189	388	2,977
Num of UPCs	2,616	4.44	3.18	1	2	4	6	25
Num of Brands	2,616	2.62	1.39	1	1	2	4	10

Note: The data used are household level panel data from the Eau Clare market, 2008-2010. There are three groups of summary statistics of peanut butter purchases the household panels made, conditional on purchase: 1) on a single trip; 2) in a week (possibly multiple trips combined); 3) for the three years combined.

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