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QUANTITY SURCHARGE

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ABSTRACT

We explored the prevalence and the reason of quantity surcharge (QS), a counterintuitive pricing phenomenon where larger quantities of a product are sold at a higher unit price than smaller quantities. By using retail scanner data from NielsenIQ, we documented the prevalence of QS over 9 product categories. Also, by combining retail scanner data with consumer panel data, we found indirect evidence that consumer inattention could be one of the sources of QS. We applied a novel approach, so called flexible logit, to structurally capture consumer inattention and estimate underlying demand parameters robust to consumer search model. We also conducted counterfactual simulations to assess the impact of quantity surcharges on consumer surplus and firm revenue, suggesting that eliminating quantity surcharges or more attentive consumer behavior towards pricing could lead to a small increase in consumer surplus but big decrease in firm's revenue. The findings have implications for decomposition for the different rationales of quantity surcharges.

CHAPTER 1

INTRODUCTION

Quantity surcharge (hereafter, QS) is the phenomenon whereby the unit price of a large-packed item is higher than that of a small-packed item in terms of equivalent units. It can be understood as the opposite of a quantity discount.

The phenomenon of quantity surcharge (hereafter, QS) is intriguing in scholarly circles because it challenges standard microeconomic theory. In the Consumer Packaged Goods (CPG) industry, it is conventionally expected that the unit price of a large-packed item would be lower due to diminishing marginal returns. Nonlinear pricing, as explained by Iyengar and S. Gupta (2009), can be categorized into two types: increasing block and decreasing block schemes. In an increasing block pricing scheme, per-unit prices rise as the quantity purchased increases, while in a decreasing block scheme, per-unit prices decrease with quantity. Despite the prevalence of quantity discounts in the CPG industry, as investigated by several studies, including Granger and Billson (1972), Nason and Della Bitta (1983), and Wansink (1996), quantity surcharge contradicts these expectations. What's more intriguing is that QS is not just theoretical but also widely observed in the real world. Numerous studies have documented the existence and prevalence of QS using various data sources. We also confirmed the same phenomenon using retail scanner data provided by NielsenIQ.

Now, it raises a natural question: What is the driving force behind this unconventional phenomenon? We consider two hypotheses: consumer inattention and preference on size.

On the one hand, if consumers do not know the exact unit price, they might end up purchasing QS'ed products. This becomes more persuasive when we find ourselves standing in front of shelves in a market. We may not always examine the exact price per equivalent unit (hereafter, PPE). While some stores might suggest the unit price with the bundle price, there might be cases where units differ between products: some might be priced in dollars per ounce, some in dollars per pound, and others in dollars per milliliter. If consumers are not capable of converting units flexibly all the time, there is a chance that they are not paying attention to the price thoroughly. Consequently, consumers might rely on their prior belief that large-packed items would be cheaper in terms of PPE, whereas it might not always be the case. Many papers already document this consumer inattention. Hoyer (1984) found, for frequently bought products, consumers tend to apply simple choice rules without inspecting prices carefully, making decisions quick and effortless. Dickson and Sawyer (1990) found that shoppers in grocery stores tend to purchase products without checking the price of selected items. Firms might take advantage of this and set higher prices for large-packed items. Thus, our key hypothesis is that consumers may not be paying attention, and firms may be exploiting their inattention with their pricing.

On the other hand, consumers might prefer larger packs even though they have a higher unit price. This preference can stem from various factors. For instance, some consumers feel more comfortable when their pantry is well-stocked with larger quantities because it reduces the frequency of shopping trips and provides a sense of security. Additionally, larger packs may offer perceived value or convenience, especially for items that are frequently used or have a long shelf life. Furthermore, consumers may choose larger quantities as a solution to their own 'optimization problem.' For example, buying in bulk can be more cost-effective in the long run or may align with dietary preferences, such as meal planning or portion control. In some cases, consumers may prioritize convenience over price efficiency, especially if the difference in unit price between large and small packs is not substantial.

The innovative method we employed to explore this topic captures consumer inattention structurally. For descriptive and reduced-form analysis, we utilized promotion data to gauge consumer inattention. Specifically, our hypothesis posited that promotions impact consumer attention by enhancing the visibility of prices rather than altering consumer utility. We defined 'promotion' based on whether products were 'featured or displayed.' Previous research, such as that by Mehta, Rajiv, and K. Srinivasan (2003), supported the idea that promotions reduce search costs for consumers. Confirming our hypothesis, we found disparities between QS sales in descriptive analysis and differences in price elasticities in reduced-form analysis across various promotion statuses. These discrepancies suggest varying levels of attention among consumers based on different promotion statuses.

To delve deeper, we employed the flexible logit model, which is robust to consumer search behavior, as outlined by Abaluck, Compiani, and Zhang (2023). This method provides a semi-parametric structural test of inattention that doesn't rely on exclusion restrictions. If consumers are inattentive to certain product attributes, they may undergo a search process to uncover these attributes. However, while some attributes are visible to consumers, others remain invisible. This invisible-to-visible transition occurs during the search process. If this holds true, economists must model an explicit consumer search process for these invisible attributes. Our approach, however, estimates unbiased underlying demand parameters without explicitly modeling consumer search behavior. We achieve this by assuming the utility function is sufficiently flexible to span a range of potential search models. By comparing the results from our approach with those from the classical logit model, we can structurally test for consumer inattention.

The significance of this topic lies in its potential impact on the pricing and promotion strategies of firms. Our research revealed that consumers display heightened price awareness when a product is promoted, indicating greater price elasticity for promoted items. This finding implies that the QS pricing scheme may not be as effective if the item is subject to promotion. Through simulations of various hypothetical scenarios, we determined that discontinuing QS implementation or increasing consumer price awareness would result in decreased revenue for firms.

Moreover, this topic also holds importance due to its potential effect on consumer surplus. By conducting counterfactual simulations, we assessed how consumer surplus would be affected under different circumstances. Our analysis revealed that consumer surplus could increase if firms ceased QS implementation or if consumers exhibited greater price awareness. These findings shed light on how consumers stand to benefit if firms opt out of the QS pricing scheme.

In our analysis using reduced-form methods, we observed variations in consumer price elasticities based on the promotional status of items. Specifically, when an item was under promotion, the demand exhibited higher elasticity to price changes. This observation indirectly suggests that consumers engage in a costly search process for pricing information, with promotions serving to mitigate these costs. Essentially, promotions capture consumers' attention, indicating a level of inattention to price otherwise.

Moving forward, in our structural-form analysis, we employed an innovative approach to estimate the fundamental demand parameters, which accounts for consumer behavior related to information search. Using these estimates, we conducted a structural test for consumer inattention to price, affirming the presence of such behavior. Additionally, through various counterfactual simulations, we found that discontinuing QS implementation resulted in only marginal increases in consumer surplus, while adversely impacting firm revenue. However, in scenarios where consumers exhibited heightened price awareness, there was also a small increase in consumer surplus accompanied by a significant decline in firm revenue.

The following chapters are as follows: In the second chapter, we investigated various previous literature and how this paper is related to those previous literature. In the third chapter, we explained the data that we utilized for the analysis. In the fourth chapter, we explained what analyses were used. Especially, we explained the descriptive analysis, reduced-form analysis, and structural-form analysis in depth, and how they are related. In the fifth chapter, we explained counterfactual simulations that investigated how consumer surplus and firm revenue would change under various scenarios.

CHAPTER 2

LITERATURE REVIEW

2.1 Quantity Surcharge

The pioneering work of Widrick (1979) marked the first attempt to quantify the occurrence of quantity surcharge. Conducting research on 10 product categories across 37 grocery stores in upper New York State, the author identified a substantial prevalence of quantity surcharge incidents. For instance, in categories like canned tuna fish and laundry detergent, the findings revealed high percentages of occurrences (e.g., 84.4% for canned tuna fish and 33.3% for laundry detergent).

Cude and Walker (1984) also documented the prevalence of QS using 23 products in 15 grocery stores in rural Illinois community in October 1981. Throughout the paper, authors not only recorded the existence of QS over 19 products but also the amount of mean QS ranges from less than one cent to 65 cents.

O. K. Gupta and Rominger (1996) explores the ethical implications of quantity surcharges in retail pricing, where larger quantities of a product are priced with a higher unit cost than smaller quantities. Through empirical studies, including one in Northwest Indiana, the authors demonstrate that this practice is widespread and often goes against consumer expectations of receiving a discount for buying in bulk. The paper delves into the ethical considerations of such pricing strategies, examines relevant government regulations, and discusses the impact on consumers, particularly those who are less informed or economically disadvantaged. The authors argue that while quantity surcharges may be legally permissible, they raise significant ethical concerns regarding fairness and transparency in consumer transactions.

Agrawal, Grimm, and N. Srinivasan (1993) delve into the concept of quantity surcharge by viewing it as a form of price discrimination aimed at households with higher demand. They suggest that retailers may implement quantity surcharges to capitalize on the willingness of certain consumers to pay higher prices for larger quantities. Additionally, they explore how quantity surcharges can vary across different product categories and retail environments, shedding light on the complexities of pricing strategies in the grocery industry.

In contrast, Sprott, Manning, and Miyazaki (2003) proposed an alternative perspective on quantity surcharges. They argue that retailers may employ quantity surcharges strategically, particularly on products with small package sizes that generate significant sales volumes. Their analysis suggests that such surcharges could serve to reinforce the perception of low prices at the store level, thereby influencing consumer behavior and brand image. However, despite these insights, neither study provides a comprehensive analysis of household purchasing behavior in response to quantity surcharges.

Binkley and Bejnarowicz (2003) examined canned tuna and found out that failure to price search due to high time and information costs led to the purchase of QS'ed items. Authors used Salop and Stiglitz (1977) model of price search. The reduced-form analysis mainly focused on what affects the market share of small-size canned tuna, compared to large-size canned tuna. By including several independent variables related to time cost and time efficiency, they found that if time cost increased for consumers, then the market share of small-size can decreased, leading to QS.

Shreay, Chouinard, and McCluskey (2016) proposed that QS may stem from variations in product sizes within the same category. Specifically, it suggests that different sizes of identical products are not perfect substitutes, leading to the implementation of QS based on package size as a distinguishing product characteristic. Utilizing the methodology introduced by BLP and analyzing data spanning 10 stores over a 4-week period from Dominick's, the authors computed own-price and cross-price elasticities for each product and size variant. They then conducted counterfactual simulations based on observed and simulated substitution patterns. The findings indicated that while there was substitution observed among cans of tuna of the same size, there was limited to no substitution between cans of different sizes, underscoring the presence of size-based product differentiation in the canned tuna market.

Clerides and Courty (2017) conducted pioneering research on quantity surcharges, focusing on consumer behavior. They analyzed store-level data within the laundry detergents category in the Netherlands, revealing that a substantial proportion of households, ranging from 45% to 75%, displayed inattention by failing to take advantage of opportunities to switch from larger to smaller package sizes during quantity surcharge periods. The authors attributed this phenomenon of consumer inattention to varying search costs, suggesting that individuals differ in the costs associated with seeking out the best deals. They introduced the concept of 'rational' inattention, positing that it is rational for consumers with higher search costs to refrain from investing time in tracking quantity surcharges. However, the study faced limitations due to the nature of store-level data, which prevented the analysis of the behavior of 'attentive' households. Despite these limitations, Clerides and Courty's research provided valuable insights into consumer decision-making processes in response to quantity surcharges.

Within this quantity surcharge literature, we also confirmed that, by using RMS data from Nielsen IQ over 9 product categories, QS is a prevalent phenomenon. Furthermore, the novel contribution of our paper is that we used exclusion restriction to quantify the underlying driving force of QS, and performed counterfactual simulations to inspect how consumers and firms would be affected.

2.2 Consumer Search Model

The previous literature mainly focus on modeling consumer search explicitly. The main reason is that, without modeling consumer search, the estimates of underlying parameters would be biased.

In Weitzman (1979) search model, which assumes uniform search costs and prior beliefs about hidden attributes across goods (though these may differ among consumers), the optimal strategy involves searching goods in descending order of anticipated utility. At each stage, the decision to continue searching for the next good is determined by weighing the expected benefits against the associated search costs.

The directed cognition model by Gabaix et al. (2006) assumes that agents use partially myopic option-value calculations to select their next cognitive operation. Thus, consumers might make short-sighted decisions about whether to persist in their search by comparing the current utility they possess with the anticipated utility of the next option.

'Satisficing' search model, developed by Simon (1955), assumes that consumers engage in sequential searching, halting their search once they attain a level of reservation utility that satisfies their needs.

The novel method developed by Abaluck, Compiani, and Zhang (2023) overcomes modeling the search process. The authors propose a method to identify consumer preferences even when consumers are not fully informed about product attributes. Assuming consumers search in decreasing order of expected utility they outline conditions under which choice data alone can recover preferences by setting the utility specification flexible enough so that to utilize the second-order derivative of the market share function. Thus, by comparing the result from the model and the result from the classical naive logit model, it is possible to test consumer inattention structurally.

The method that we employed can encompass the above different consumer search models. The benefit of our approach is not only the explicit consumer search model is not required to estimate the underlying demand parameter but also the scope that the model can encompass is broad.

CHAPTER 3

DATA

The data source is NielsenIQ, provided by the Kilts Center for Marketing in Chicago Booth. We used Household Panel Data (HMS) and Retail Scanner Data (RMS) spanning from 2006 to 2018.

Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

3.1 Data for Descriptive Analysis

For descriptive analysis, we used only RMS data for 2016. Instead, we inspected over 9 product categories to calculate how prevalent QS sales was. The 9 product categories are baby food, baking mix, beer, cereal, cracker, deodorant, gum, laundry detergent, toilet paper.

	beer	babyfood	bakingmix	cereal	cracker	deodorant	gum	laundrydetergent	toiletpaper
number of weeks	53	53	53	53	53	53	53	53	53
number of stores	2,404	2,546	2,158	2,449	3,014	3,012	3,034	3,040	3,040
number of store * week	112,918	67,015	81,179	102,041	124,694	111,062	140,356	137,988	144,354
number of products	1,389	541	231	523	308	295	177	246	154
number of items	4,986	720	357	909	639	466	448	1,094	634
number of items per product	3.59	1.33	1.55	1.74	2.07	1.58	2.53	4.45	5.65
promotion percentage	19.71%	16.58%	8.17%	16.10%	25.55%	15.43%	7.84%	20.26%	18.07%

Table 3.1: Summary statistics for RMS data

The table 3.1 shows the summary statistics for RMS data. The number of weeks observed was 53. The number of observed stores varies between product categories, as some stores may not sell particular product categories or may lack promotion records, leading to dropped observations. It's worth mentioning that the number of items per product and promotion percentage differ across categories. Baby food had the lowest items per product (1.33), while toilet paper had the highest (5.65). This suggests that the unit of baby food may be quite standardized, while the unit of toilet paper is more diversified. The promotion percentage was lowest for gum (7.84%) and highest for crackers (25.55%). Across all product categories, the variation in promotion was sufficient to perform descriptive analysis capturing the QS sales ratio according to different promotion statuses.

3.2 Data for Reduced-form and Structural-form Analysis

We constructed a Choice Panel Data by combining Household Panel Data (HMS) and Retail Scanner Data (RMS) from NielsenIQ spanning from 2006 to 2018. Initially, we selected toilet paper for a detailed case study to explore mechanisms further. This enabled us to estimate discrete choice models and conduct counterfactual analysis to ascertain the presence of QS and consumer purchasing behavior. The detailed process for combining RMS and HMS is outlined below.

Process combining RMS and HMS

1. Remove trips from HMS where store code is missing.

2. Remove trips from HMS which purchased 2 or more different item (within the same product category).

3. Remove trips from HMS where households purchased the same item with 3 or more quantities (within the same category).

4. Remove store from RMS where promotion information is missing.

5. Inner join HMS and RMS on store code / week.

6. (Keeping in mind that there are trips which purchased the same item with 2 quantities) Add hypothetical alternatives into the original choice set, by doubling the bundle size, and make the choice with purchase quantity of 2 into purchase quantity of 1.

For steps 2 and 3, we identified cases in the HMS where households purchased multiple quantities or items within a single trip. If a household bought three or more quantities of the same item or purchased two or more different products, we excluded those trips. This decision was made because such instances were rare, and including mixed choices in the discrete choice structure could excessively expand the choice set, leading to unmanageable estimation times.

Regarding step 6, when a household purchased two quantities of the same item, we doubled the product space. For instance, if a household bought two packs of '10-roll toilet paper,' we created an artificial product called '20-roll toilet paper' and assigned the household to have purchased one pack of it.

In removing the product space, we excluded products that were infrequently observed or selected. Since these observations were sparse, their removal would not significantly alter the estimation results but would expedite the estimation process.

	value	mean	std
number of total households	19,915		
number of total trips	85,274		
number of total products	27		
number of total items	113		
number of trips per household		4.18	7.58
number of items per product		4.19	3.96
number of products per trip		10.51	2.5
number of items per trip		21.3	5.71
number of promoted items per trip		3.04	2.34
number of QS'ed items per trip		0.68	1.05

Table 3.2: Summary statistics for choice panel data

The table 3.2 show the key numbers of households, trips, products, and items. On average, a single product offers four different items distinguished solely by size. Consumers encounter an average of 11 products and 21 items per trip. During their trip, consumers typically encounter three promoted items and 0.68 quantity surcharged (QS) items on average.

After completing the aforementioned process, we scaled certain variables to ensure the coefficients remained at a reasonable magnitude. Specifically, for toilet paper, the unit of measurement was the 'sheet,' making the unit price the 'cent price per sheet.' However, the original values were quite small, often less than 2 or 3 decimal points. To address this, we multiplied the unit price by 1000, resulting in the unit price representing the 'cent price per 1000 sheets.' Additionally, the bundle size for each item, when measured in sheets, was excessively large due to variations in the number of sheets per roll across products. Comparing the number of rolls could therefore inaccurately reflect the number of sheets. To remedy this, we divided the bundle size (number of sheets) by 1000. Consequently, the bundle size now represents the 'number of 1000 sheets.'

CHAPTER 4

ANALYSIS

We utilized three different models: descriptive analysis, reduced-form analysis, and structural-form analysis.

In the descriptive analysis, we relied solely on RMS data to explore how promotions influenced QS sales. For the reduced-form analysis, we utilized the constructed choice panel data to observe how promotions altered the price elasticities of demand among consumers. In the structural-form analysis, we estimated the underlying demand parameters that remain resilient to variations in consumer attention.

We employed promotion as an exclusion restriction because it increased the salience of price, prompting consumers to pay more attention to it. Thus, the variation in QS sales ratios across different promotion scenarios in the RMS data suggests varying levels of consumer attention to price due to promotions. Additionally, the differences in price elasticities resulting from different promotion statuses imply that consumers engage in price search processes, with promotions reducing the costs associated with this search. Consequently, the structural-form model, utilizing flexible logit, estimates underlying consumer demand parameters that remain robust across different consumer search behaviors.

4.1 In-Depth Definition of Terminologies

Before diving into the analyses directly, we would define the terms that we used.

4.1.1 Quantity Surcharge

The concept of Quantity Surcharge (QS) revolves around the phenomenon where the price per equivalent unit (PPE) of a large-packed item exceeds that of a small-packed item. However, defining the relationship between large-packed and small-packed items based on bundle size can be complex. In our analysis, QS is defined by two criteria: first, within the same product, the large-packed item's units are multiples of the small-packed item's units, and second, the PPE of the large-packed item is higher than that of the small-packed item. For instance, consider toilet paper packs where item A contains 3 rolls and item B contains 12 rolls, with item B having a higher per-sheet-price. In this scenario, item B would be classified as a quantity surcharged item, termed as 'QS exact'.

To ensure robustness in our analysis, we also defined and examined other types of QS. 'QS margin' occurs when purchasing multiple quantities of the small-packed item can closely match the bundle size of the large-packed item, with a 15% margin. For instance, if purchasing 3 quantities of a 3-roll pack closely mimics a 10-roll pack with a 10% margin, then the 10-roll pack would be considered QS. 'QS half' occurs when the bundle size of the small-packed item is less than or equal to half of the large-packed item's bundle size. For example, if a 3-roll pack is less than half the size of a 10-roll pack, and the PPE of the 10-roll pack is higher, then it would be considered QS. 'QS any' applies when the bundle size of the small-packed item is strictly less than that of the large-packed item, allowing for comparisons across different pack sizes.

Our primary focus on 'QS exact' stems from its perfect substitutability, ensuring that the large-packed item is not the only feasible choice for consumers' optimization. For instance, if a consumer specifically wants a 10-roll pack but only 3-roll pack and 10-roll pack are available, purchasing multiple quantities of 3-roll pack may not provide the exact quantity desired. In other words, 10-roll pack is the only choice. However, if a 2-roll pack is available, purchasing 5 quantities would yield the exact quantity sought. Thus, consumer has two choices: 5 quantities of 2-roll packs or 1 quantity of 10-roll pack. By focusing on 'QS exact', we aim to eliminate potential issues with consumer choice optimization. Nonetheless, this narrowly defined concept may not fully account for all substitution patterns, as some consumers may opt for looser substitutes, such as purchasing multiple small packs to approximate a large pack.

While the four measures of QS yielded slightly different results, their differences were negligible, and their impact on estimation and simulations was consistent. Therefore, prioritizing 'QS exact' for analysis was deemed appropriate and did not compromise the robustness of our findings.

4.1.2 Promotion

We defined 'promotion' based on criteria provided by NielsenIQ, encompassing various forms of retailer advertisements such as those found in local newspapers, free-standing inserts (FSIs), circulars, and online ads on the retailer's website. While the majority of featured items typically include price discounts, it's worth noting that this isn't a strict requirement. Additionally, a 'display' refers to a non-permanent secondary location within the store intended for merchandising purposes.

It's crucial to understand that the concept of promotion in our analysis is solely focused on its impact on consumer attention, particularly by enhancing the visibility of prices, rather than affecting consumer utility directly. If our estimated results are influenced by the presence or absence of promotion, it serves as indirect evidence suggesting that consumers engage in a search process for price information, with promotions potentially lowering the associated search costs. Thus, incorporating promotion into our analysis allows us to gauge consumer attention levels based on promotion status, providing valuable insights into their decision-making behavior.

4.1.3 Product and Item

So far, we've been using the terms 'product' and 'item' interchangeably. However, moving forward, we'll differentiate between these two terms as follows:

A 'product' refers to the unique bundle that can be distinguished from other bundles by having different characteristics. For example, 'Charmin Strong' and 'Charmin Soft' are considered different products, because they have different attributes other than bundle size. Additionally, 'Charmin Strong' is distinct from 'Cottonelle.'

On the other hand, an 'item' refers to the unique bundle specific to its bundle size within a product. For instance, 'Charmin Strong 4-roll' and 'Charmin Strong 10-roll' are both considered items within the same product.

We've made this distinction between products and items to precisely measure quantity surcharge at the product level while avoiding the influence of choice conversion between different products, each with its own set of attributes. By maintaining this differentiation, we can effectively capture quantity surcharge without inadvertently including choice conversion between distinct product offerings.

4.2 Descriptive Analysis from RMS

Using RMS data for 2016 across 9 product categories, we calculated the ratio of QS items sold in volume over the total volume sales, as depicted in Figure 4.1. The highest ratio was 5.14% for beer, while the lowest ratio was 0.04% for baby food Note that the denominator of this ratio is the total volume sales.

Figure 4.2 illustrates a similar QS volume sales ratio, where the denominator is altered to the volume sales conditional on the week-store where QS'ed items were present. For instance, the QS sales ratio for baby food surged to 56%. This implies that, in the case of baby food, if consumers are presented with both QS'ed items and other items simultaneously, 56% of sales opted for QS'ed items. This trend was observed across other product categories as well. This suggests that although QS'ed items may not frequently occupy shelf space, when they are available, consumers tend to purchase them more frequently.

Further analysis across 9 product categories using 2016 RMS data suggests that consumer inattention to price and preference for size coexist. To assess how QS sales changed, we

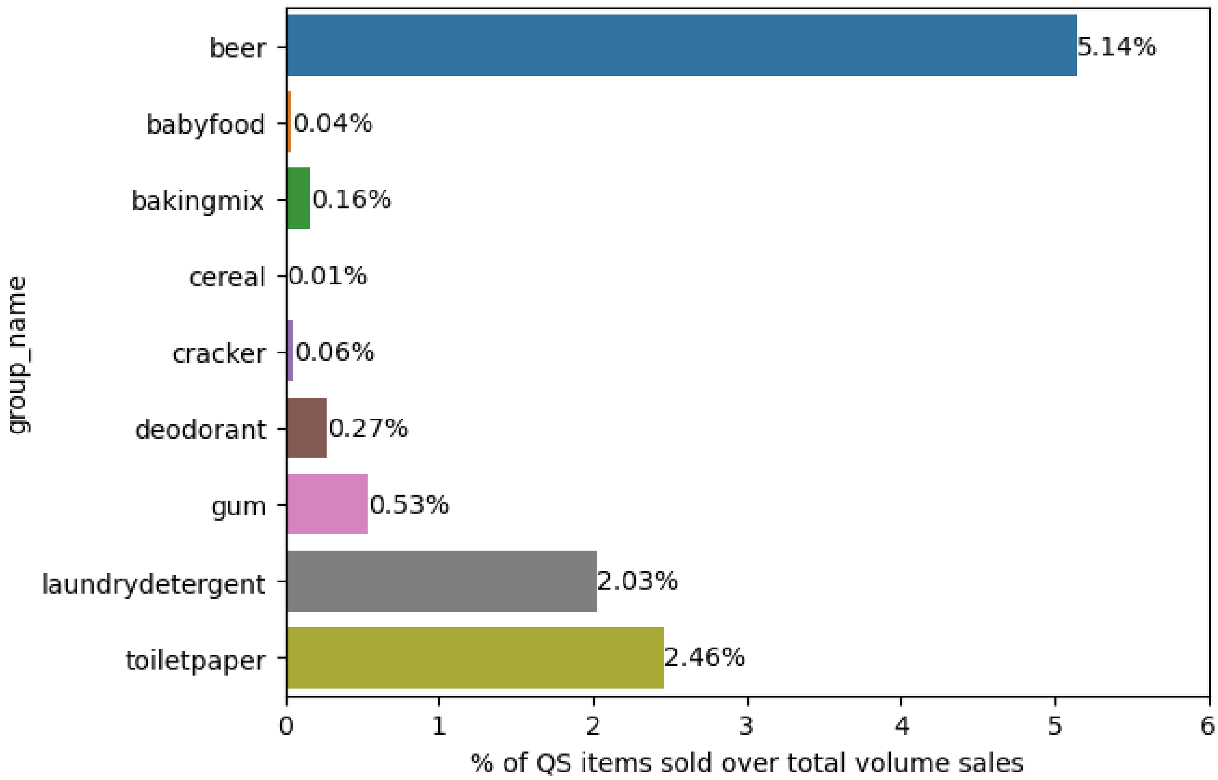

Figure 4.1: QS sales ratio over total volume sales

defined the QS sales ratio as follows:

$$\text{QS sales ratio} = \frac{\text{\$ sales where items were QS'ed}}{\text{total \$ sales}} \tag{4.1}$$

The above value was calculated under four different promotion scenarios: all items are not promoted, only QS'ed items are promoted, only non-QS'ed items are promoted, and all items are promoted.

Note that, during the analysis, we encountered the issue of 'partial promotion'. Partial promotion occurs when only some items within a product category are promoted, while others are not. For example, let's consider product A with three items: item 1, item 2, and item 3. If item 3 is a QS'ed item and is promoted, while item 1 and item 2 are not, it constitutes a partial promotion scenario where the Non-QS'ed items are partially promoted.

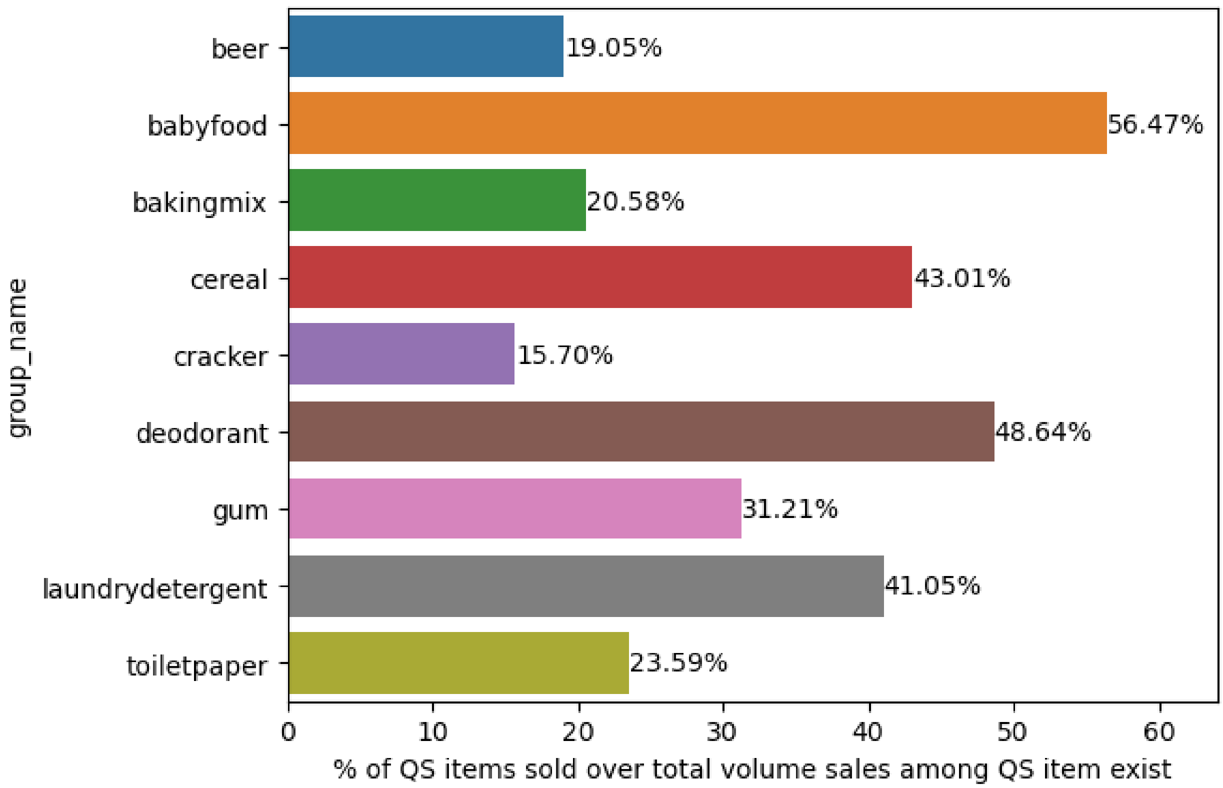

Figure 4.2: QS sales ratio over volume sales conditional on the existence of QS'ed items as alternatives

Conversely, if both item 1 and item 2 are promoted, it constitutes a full promotion scenario. To assess this partial promotion separately, we need to consider nine cases: no promotion, partial promotion, and full promotion for each QS'ed and non-QS'ed item. However, in some product categories, the number of observations was too limited to calculate the QS sales ratio effectively for each case. Therefore, we combined the partial promotion and full promotion cases into a single category labeled 'promotion'. In this merged category, whether a QS'ed or non-QS'ed item is partially promoted or fully promoted, we considered the case as promoted. Although the intensity of promotion may differ between partial promotion and full promotion, merging them into a single category allows us to distinguish promotion from no promotion at all. Since the insights gained from analyzing these four cases were deemed sufficient to understand the phenomenon, we treated partial promotion as equivalent to full promotion for our analysis.

If consumers are not paying attention to price, we would expect the QS sales ratio to be higher when no items are promoted compared to when non-QS'ed items are promoted. Conversely, the QS sales ratio would be lower when no items are promoted compared to when QS'ed items are promoted. This conjecture is based on the rationale that promotion increases the salience of price, prompting consumers to pay more attention to unit price.

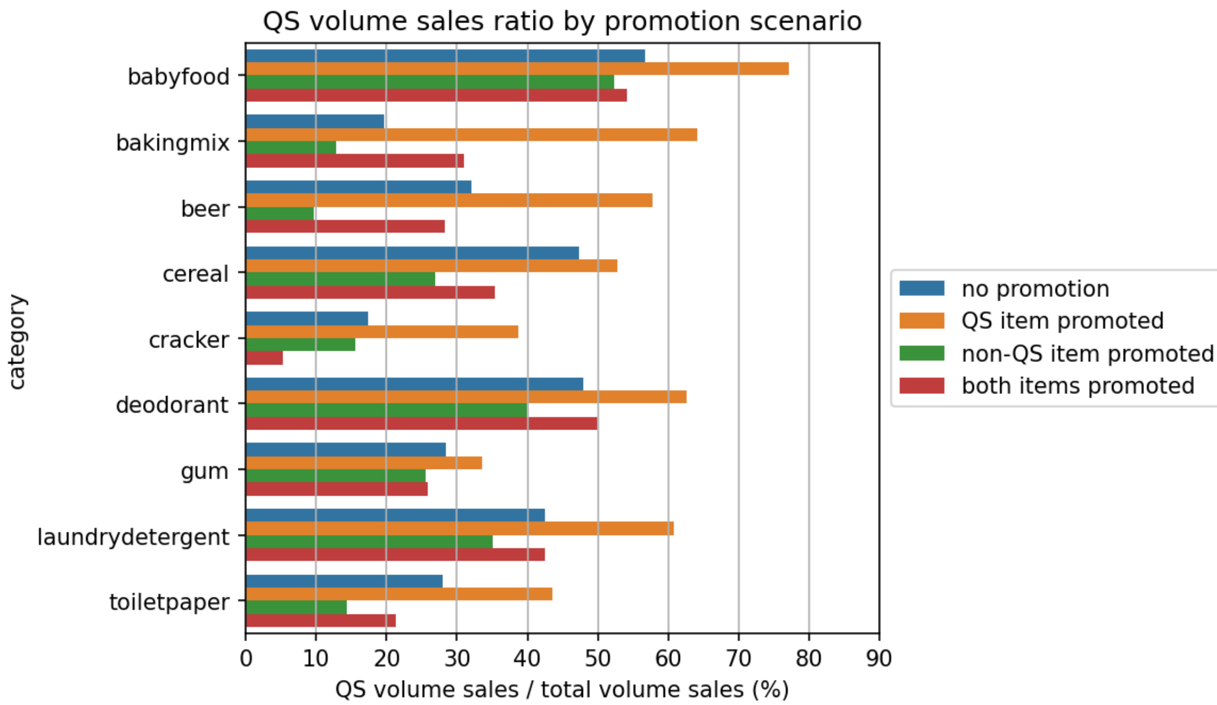

Figure 4.3: QS volume sales ratio by promotion scenario

The figure 4.3 shows the QS sales ratio under different promotion scenarios for each product category.

Across all categories, we observed that the QS sales ratio under 'no promotion' was consistently higher than that under 'non-QS'ed items are promoted'. Similarly, the QS sales ratio under 'no promotion' was consistently lower than that under 'QS'ed items are promoted'. These patterns provide indirect evidence suggesting consumer inattention to price. When consumers are inattentive to price, promotions on QS'ed items may incentivize consumers to purchase more of these items, thus driving up the QS sales ratio. Conversely, promotions on non-QS'ed items may lead consumers to purchase more of those items, resulting in a decrease in the QS sales ratio.

Moreover, we found that the QS sales ratio under 'both items are promoted' was generally higher than that under 'non-QS'ed items are promoted'. This trend could indirectly indicate heterogeneity in consumer preferences for product size. Even when consumers are attentive to both QS'ed and non-QS'ed items, a higher QS sales ratio under 'both items are promoted' suggests a potential preference for larger-sized items. This preference for size might influence consumer purchasing decisions, especially when both QS'ed and non-QS'ed items are promoted simultaneously.

4.3 Reduced-form Analysis: Random Coefficient Logit

To evaluate the impact of promotions on the price sensitivity of demand, under the exclusion assumption, we utilized the random coefficient logit model. This model incorporates consumer heterogeneity in preferences for product attributes, including price. By estimating price elasticities of items across various promotion statuses, we aimed to identify evidence indicating consumer inattention to price. Our analysis focused specifically on the toilet paper product category to apply this model.

4.3.1 Model Specification

Let households be $h = 1, ..., H$, trips be $t = 1, ..., T$, products be $j = 1, ..., J+1$ (outside good is $J+1$), and brands be $b(j) = 1, ..., B$. Products have three attributes: size ($q_j \in \mathcal{Q}$), price (p_{jt}), and promotion status ($f_{jt} \in \{0, 1\}$). Note that size is the same for the same product across trips, but price and promotion status can be different across trips. Let household's utility for trip t from product j be as follows.

$$u_{jth} = \lambda_{b(j)} + \sum_{q \in Q} \gamma_{hq} \mathbb{I}_{\{q_j = q\}} + p_{jt}\alpha_h + f'_{jt}\psi_h + p_{jt} f_{jt} \delta_h + \varepsilon_{jt} \tag{4.2}$$

From the above equation, note that the random coefficients are only applied to the product characteristics (bundle size, price, promotion, and interaction between price and promotion), and the coefficients of brand fixed-effects are non-random. For bundle size, I classified each product into decile. Assuming ε_{jt} follows Type I extreme value distribution, the choice probability can be expressed as follows.

$$\Pr\Big(y_{jt} = 1\Big) = \frac{\exp\Big(\lambda_{b(j)} + \sum_{q \in Q} \gamma_{hq} \mathbb{I}_{\{q_j = q\}} + p_{jt}\alpha_h + f'_{jt}\psi_h + p_{jt} f_{jt} \delta_h\Big)}{1 + \sum_{i=1}^{J} \exp\Big(\lambda_{b(i)} + \sum_{q \in Q} \gamma_{hq} \mathbb{I}_{\{q_i = q\}} + p_{it}\alpha_h + f'_{it}\psi_h + p_{it} f_{itk} \delta_h\Big)} \tag{4.3}$$

A single likelihood function of household h and trip t is as follows.

$$f(y^{ht}; \vartheta^h) = \prod_j \Pr\left(y_j^{ht} = 1; \vartheta^h\right)^{y_j^{ht}} \tag{4.4}$$

Since a single household can do multiple trips within the sample period, the likelihood of a household is as follows.

$$f(y^h; (\mu, \Sigma)) = \int \prod_t \prod_j \Pr\left(y_j^{ht} = 1; \vartheta^h\right)^{y_j^{ht}} \phi(\mu, \Sigma) \tag{4.5}$$

Multiplying the likelihood functions over households gives the overall likelihood funciton.

$$\mathcal{L}(\mathbf{y}; (\mu, \Sigma)) = \prod_h f(y^h; (\mu, \Sigma)) \tag{4.6}$$

name	est	s.e.	z score	p value
unit_price_mean	-1.4974	0.0136	-110.4322	0
promotion_mean	2.0592	0.0337	61.118	0
price*promotion_mean	-0.641	0.0154	-41.6054	0
size_decile_2_mean	0.144	0.0456	3.1547	0.0016
size_decile_3_mean	0.04	0.0409	0.9777	0.3282
size_decile_4_mean	0.8282	0.0296	27.9447	0
size_decile_5_mean	0.9432	0.0298	31.6753	0
size_decile_6_mean	0.752	0.0302	24.9308	0
size_decile_7_mean	0.4586	0.0331	13.8724	0
size_decile_8_mean	0.015	0.0314	0.4791	0.6319
size_decile_9_mean	-0.9365	0.0527	-17.7618	0
size_decile_10_mean	-0.8096	0.0489	-16.549	0
unit_price_std	0.8831	0.01	88.0734	0
promotion_std	0.8149	0.031	26.2866	0
price*promotion_std	0.2963	0.0157	18.8927	0
size_decile_2_std	1.6465	0.0418	39.4336	0
size_decile_3_std	1.4621	0.0374	39.1175	0
size_decile_4_std	1.3289	0.0239	55.7164	0
size_decile_5_std	1.19	0.0265	44.9755	0
size_decile_6_std	1.316	0.0282	46.6788	0
size_decile_7_std	1.7703	0.0282	62.7411	0
size_decile_8_std	1.4185	0.0294	48.2953	0
size_decile_9_std	1.771	0.0472	37.5103	0
size_decile_10_std	2.2908	0.0457	50.0902	0

Table 4.1: Estimates from random coefficient logit model

4.3.2 Model Result: Coefficients

Table 4.1 presents the coefficient results from the RC logit model. Variables labeled with 'mean' indicate the mean values of the coefficients, while those labeled with 'std' represent the standard deviations of the coefficients. Note that product fixed-effects are also included as non-random coefficients.

Analyzing the results, we observe that the coefficient of 'unit_price_mean' is negative, indicating that an increase in unit price leads to a decrease in the choice probability. Conversely, the coefficient of 'promotion_mean' is positive, suggesting that the promotion status increases the choice probability. However, what stands out in the results is the sign of ‘price*promotion_mean’. This coefficient is negative, implying that consumers become more sensitive to price when the item is promoted. This finding is particularly intriguing as it suggests a nuanced relationship between price sensitivity and promotional status.

4.3.3 Model Result: Price Elasticity

From the estimated results, we calculated the price elasticities of products and divided them into two categories: whether they are promoted or not.

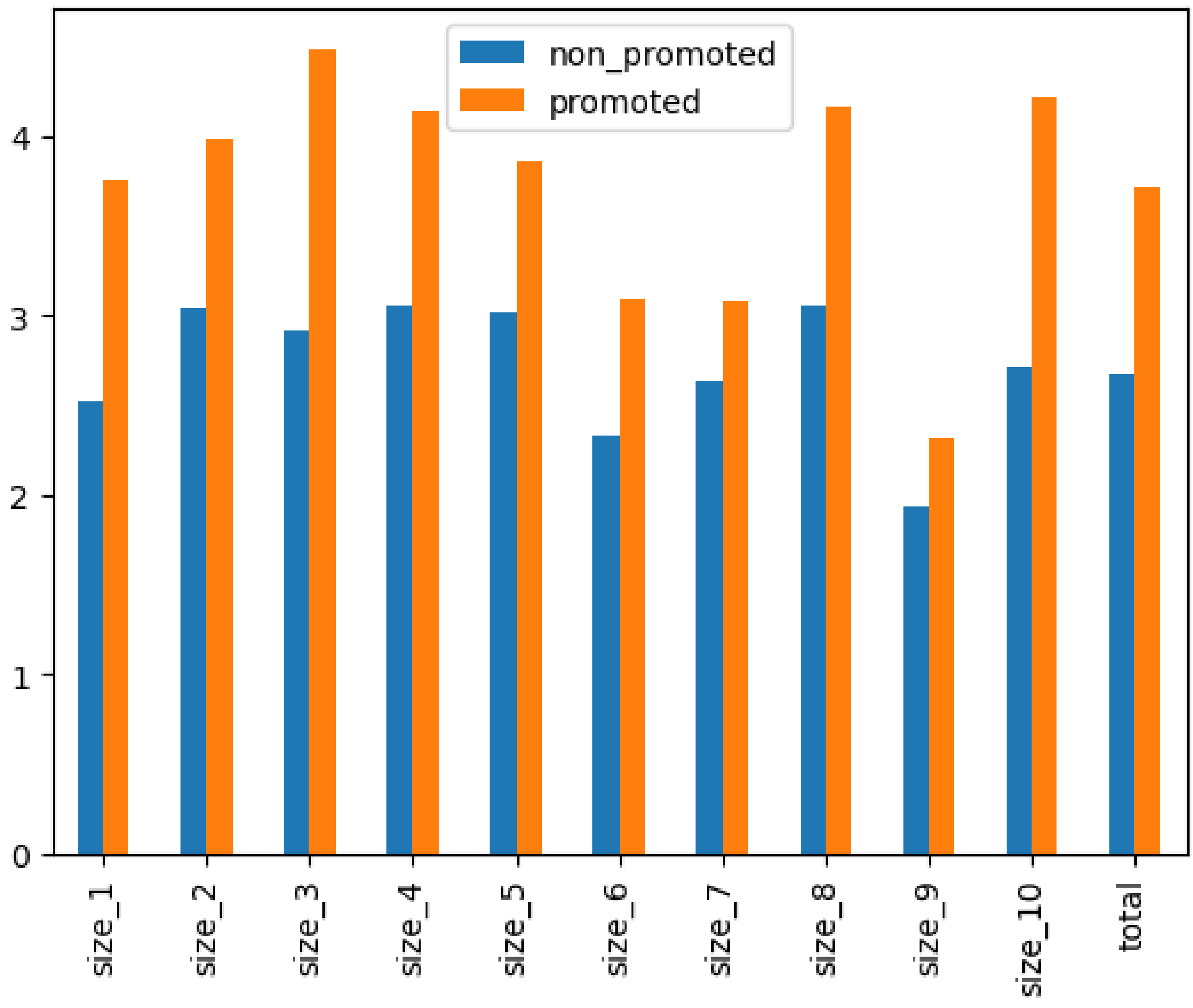

Figure 4.4: (negative) Price elasticities by promotion status and size decile

Figure 4.4 illustrates the price elasticities of products categorized by promotion status and size deciles. Across all size deciles, promoted products exhibit higher price elasticities (in absolute value) compared to non-promoted products. This suggests that promotional status influences consumers' responsiveness to price changes, with promoted items being more price elastic.

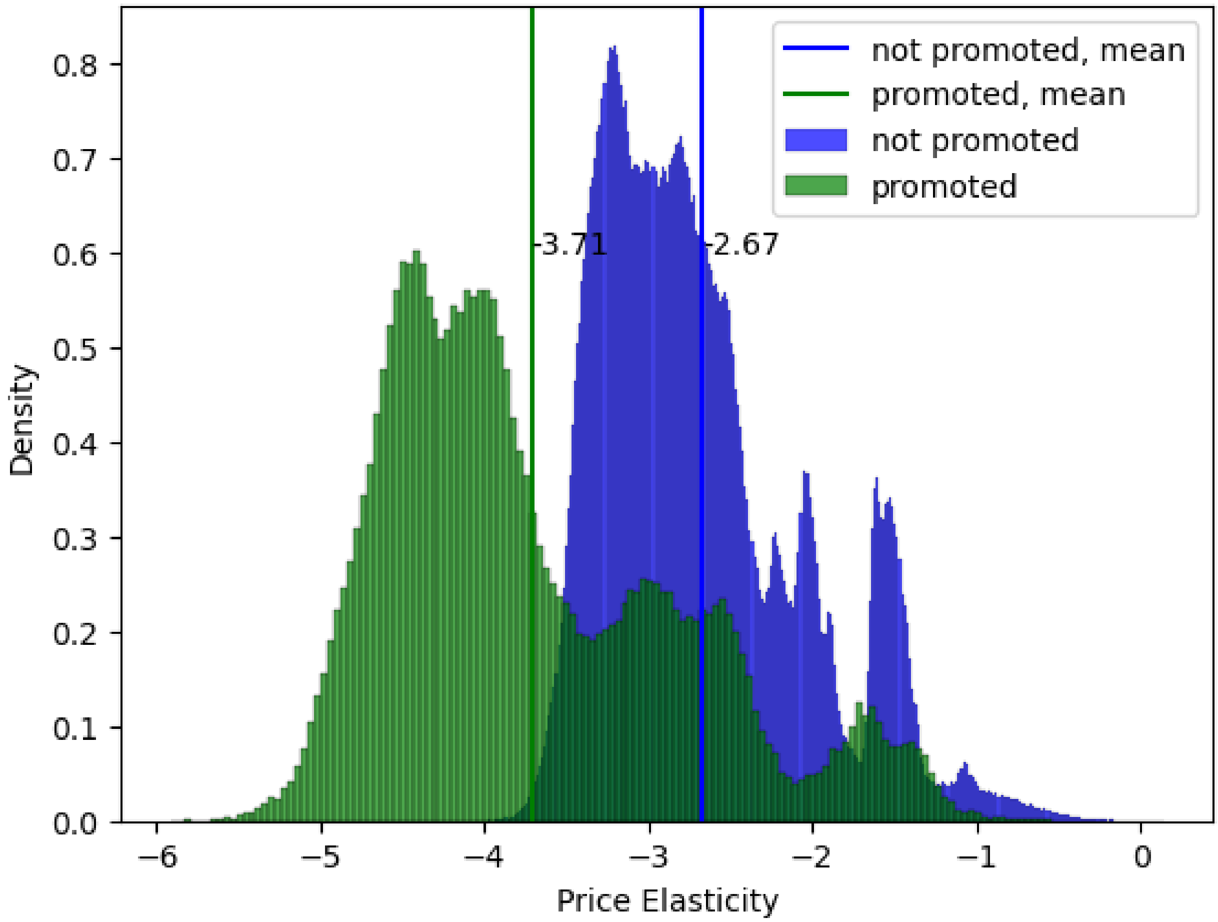

Figure 4.5: Distribution of price elasticities by promotion

The figure 4.5 shows the histogram of price elasticities for promoted and non-promoted products. In general, the promoted items have higher price elasticities (in absolute value) than unpromoted items.

These findings indirectly suggest that promotions attract consumers' attention to price, making them more price elastic. This observation hints at the likelihood of consumers engaging in a search process focused on price, with promotions potentially helping to reduce the cost associated with this search.

4.4 Structural-form Analysis: Flexible Logit

From the above analyses, it is conceivable that consumers undergo a search process. Previous literature has incorporated an explicit consumer search model to address this. The method we employed is the flexible logit model, developed by Abaluck, Compiani, and Zhang (2023), which enables us to estimate underlying parameters that remain robust despite variations in consumer search behavior. Thus, without explicitly implementing the consumer search model, we are not only able to estimate the consumer demand parameters but also to test whether consumers are fully attentive. We focused on the toilet paper product category to apply this model.

Note that the previous exclusion restriction on promotion that was used in descriptive and reduced-form analysis is not explicitly used within this flexible logit model. Rather, we used the second order derivative of choice probability with respect to product characteristics, in order to capture the true underlying demand parameters.

4.4.1 Intuition from the Method Paper

When we consider the ratio with the denominator being the sales conditional on the week-store where QS'ed items exist, the ratio Assume there are two types of product attributes: visible attributes and hidden attributes. Visible attributes are readily available for consumers. In contrast, hidden attributes require some cost of search or investigation to unveil. Researchers typically have access to data on all attributes and choice probabilities but lack information on individual-specific random errors.

The standard approach, which does not explicitly model the search process, can suffer from attenuation bias. This bias occurs when consumers are only informed about visible attributes of alternatives but remain unaware of hidden attributes. As a result, their valuation of products may be underestimated. This bias can lead to inaccurate estimations of consumer preferences and choices.

The above explanation can be written in equations. Consider a J-good model with linear utility $U_{ij} = \alpha x_j + \beta z_j + \varepsilon_{ij}$, where x_j and z_j are scalar, for simplicity, and $\alpha > 0, \beta > 0$. With full information, having $s_j = P(U_{ij} \geq U_{ij'}, \forall j' \neq j)$, the chain rule identifies the marginal rate of substitution: $\frac{\partial s_j}{\partial z_j} / \frac{\partial s_j}{\partial x_j} = \beta/\alpha$. However, if consumer goes through a search process and the hidden attribute, z_j are available only for some alternatives, then the above value will suffer from attenuation bias.

$$\left| \frac{\partial s_j}{\partial z_j} / \frac{\partial s_j}{\partial x_j} \right| \leq |\beta/\alpha| \tag{4.7}$$

The idea of overcoming the attenuation bias can be understood through the following example. In the context of purchasing items at a grocery store, where accessing nutritional information incurs a cost, there is a risk of failing to maximize utility if consumers choose not to examine labels. The underlying assumption is that consumers, when deciding to check the nutrition label for a specific item, initially evaluate the labels of other items that seem more promising based on expected utility. This implies that consumers who actively search for the most nutritious item consistently select the option that maximizes utility among all options considered. By analyzing the sensitivity of choices to the nutrient content of the most nutritious item, it becomes possible to identify consumers who behave as if they were fully informed.

The above intuition is implemented as follows. For each individual i and item j, let the expected utility before the search be as follows: $EU_{ij} = \alpha x_j + \beta E[z_j|x_j] + \varepsilon_{ij}$. Assume consumers search in decreasing order of expected utility. Define 'alternative 1' be the alternative with the largest value of unanticipated component of z_j, $\tilde{z}_j = z_j - E[z_j|x_j]$. Then, adding some more assumptions that will be stated below, it will be

$$\frac{\partial^2 s_1}{\partial z_1 \partial z_j} / \frac{\partial^2 s_1}{\partial z_1 \partial x_j} = \beta/\alpha \tag{4.8}$$

In other words, the cross-derivative ratio recovers the marginal rate of substitution for any models consumers search. The authors suggest two methods for estimation: approximating the demand function via Bernstein polynomials, and 'flexible logit', which adds more flexibility on utility function so that the mean utility for 'alternative 1' depends directly on attributes of rival alternatives.

So, the estimation of the whole coefficients is simple. First, estimate the coefficients with classical naive logit. Next, going through the flexible logit, it is possible to estimate β/α. Then, since α is estimated from naive logit, β can also be estimated.

After the estimation, comparing the ratio of first-order derivative and second-order derivative, $\frac{\partial s_j}{\partial z_j} / \frac{\partial s_j}{\partial x_j}$ and $\frac{\partial^2 s_1}{\partial z_1 \partial z_j} / \frac{\partial^2 s_1}{\partial z_1 \partial x_j}$, can work as a test for whether consumers are fully informed or not. If consumers are not fully informed, the ratio of first-order derivative will suffer from the attenuation bias, while the ratio of second-order derivative will not. Thus, if the two are statistically different, we can conclude that consumers are not fully informed. In the context of this paper, it can be said that consumers are inattentive to price and they go through a certain search process.

4.4.2 Model Assumption and Specification

Let's maintain the assumptions established in the previous section. Assume there are two types of attributes: visible variables and hidden variables. Consumers can observe visible attributes without any search effort but need to undergo an explicit search process to discover hidden variables. Only selected alternatives are searched, thus ensuring that hidden variables are fully revealed. In our model, the bundle price is considered a hidden variable, while other product attributes, such as bundle size and promotion status, are visible variables. Econometricians have access to both visible and hidden variables.

Note that we denote bundle size as x, other product attributes as $\tilde{\mathbf{x}}$. The reason of distinction between x and $\tilde{\mathbf{x}}$ is that x, the bundle size, is used for calculating the cross derivatives, while $\tilde{\mathbf{x}}$, other visible attributes, are not. We transformed the price into the negative price in order to make the coefficient to be positive. Thus, the hidden attribute, negative price, is z.

The assumption for specification is as follows.

1. utility: $U_{htj} = \tilde{\boldsymbol{\alpha}}\tilde{\mathbf{x}}_{tj} + \alpha x_{tj} + \beta z_{tj} + \varepsilon_{htj}$

2. expectation:

$$E[z_{tj}|x_{tj}, \tilde{\mathbf{x}}_{tj}] = \gamma_0 + \gamma_1 x_{tj} + \boldsymbol{\gamma_2}\tilde{\mathbf{x}}_{tj}$$

$$EU_{htj} = \tilde{\boldsymbol{\alpha}}\tilde{\mathbf{x}}_{tj} + \alpha x_{tj} + \beta E[z_{tj}|x_{tj}, \tilde{\mathbf{x}}_{tj}] + \varepsilon_{htj}$$

The utility specification notes that attributes are additive. The expectation specification notes how consumers form expectation on the hidden variable. Consumers form expectation on hidden variables using the visible attributes.

The assumption for consumer search is as follows.

1. revelation: household observes $x_{tj}, \tilde{\mathbf{x_{tj}}}, \varepsilon_{htj}$ for all j prior to search, but need to search good j to fully uncover z_{tj}

2. order: household searches goods in decreasing order of EU_{htj}

3. reservation: household searches j if and only if $g_h(\tilde{\mathbf{x_{tj}}}, x_{tj}, \varepsilon_{htj}, \overline{u}) \geq 0$

4. consideration set: household chooses the good which maximizes utility among searched goods

Define 'good 1' to be the product with highest $\tilde{z}_j = z_j - E[z_j|\tilde{\mathbf{x}}_\mathbf{j}, x_j]$. Then, the following ratio of second order derivatives will reflect the ratio between the coefficients of price over size.

$$\frac{\partial^2 s_1}{\partial z_1 \partial z_j} / \frac{\partial^2 s_1}{\partial z_1 \partial x_j} = \beta/\alpha \tag{4.9}$$

The above second-order derivative might not be captured through the classical naive logit model. Thus, to add more flexibility, let the mean utility for good 1 depend directly on attributes of rival goods as follows.

$$v_1 = a_1 x_1 + b_1 z_1 + c_1 \tilde{\mathbf{x}}_1 + \sum_{k \neq 1} (\gamma_k \omega_{z1k} z_k + \gamma_{2k} \omega_{x1k} x_k + \omega_{z2k} \delta_k z_k z_1 + \omega_{x2k} \delta_{2k} x_k z_1) \tag{4.10}$$

where $\omega_{z1k}, \omega_{x1k}, \omega_{z2k}$ and ω_{x2k} are known weights, and $b_1, \gamma_k, \gamma_{2k}, \delta_k$ and δ_{2k} are coefficients to be estimated. The above equation is the source of the name of the method: the functional form is 'flexible' enough to capture the cross-derivate ratio. It is a convenience functional form that allows us to back out the relevant preference parameters. Thus, the coefficients from the above equation does not have any causal meaning. It will only help to identify β/α, which is the cross-derivative ratio. With weights chosen appropriately, after recovering the coefficients by estimating the above equation, the cross-derivate ratio can be calculated as follows:

$$\frac{\partial^2 s_1}{\partial z_1 \partial z_{j'}} / \frac{\partial^2 s_1}{\partial z_1 \partial x_{j'}} = \frac{-b_1 + \gamma_{j'} + \delta_{j'}}{-a_1 + \gamma_{2j'} + \delta_{2j'}} \tag{4.11}$$

The specific estimation procedure for β is as follows.

Estimation procedure of flexible logit

1. Estimate the equation in utility assumption, including α, via standard logit, restricting to choice sets where the variance of z_j across j is below a cut-off (and check robustness to cut-off choice).

2. Create initial naive estimates (α^*, β^*) and associated choice probabilities s_j^* by estimating a naive logit model. Use these to construct the weights ω_{ij}.

3. Estimate equation 4.10 given these weights to recover the coefficients.

4. Use equation 4.11 to compute $\frac{\partial^2 s_1}{\partial z_1 \partial z_{j'}} / \frac{\partial^2 s_1}{\partial z_1 \partial x_{j'}}$.

5. Multiply the estimate from step 4 by that from step 1 to obtain an estimate of β.

Since β is estimated from the above procedure, and other coefficiens are estimated by classical naive logit, the whole coefficients are estimated.

4.4.3 Model Results: Estimates

If consumers have a partial information on the hidden variable, then the estimate for the hidden variable will be attenuated. This is evidenced by the results.

The estimate for first-order derivative ratio 1.211 from the naive logit, while the estimate for second-order derivative ratio 1.356 from the flexible logit.

The figure 4.6 depicts the distribution of differences between estimates from the flexible logit and the naive logit. Each observation is generated from 250 bootstrap samples, and 95% confidence intervals are calculated using the bias-corrected bootstrap method. Note that the 95% confidence interval was $[0.001278, 0.3956416]$.

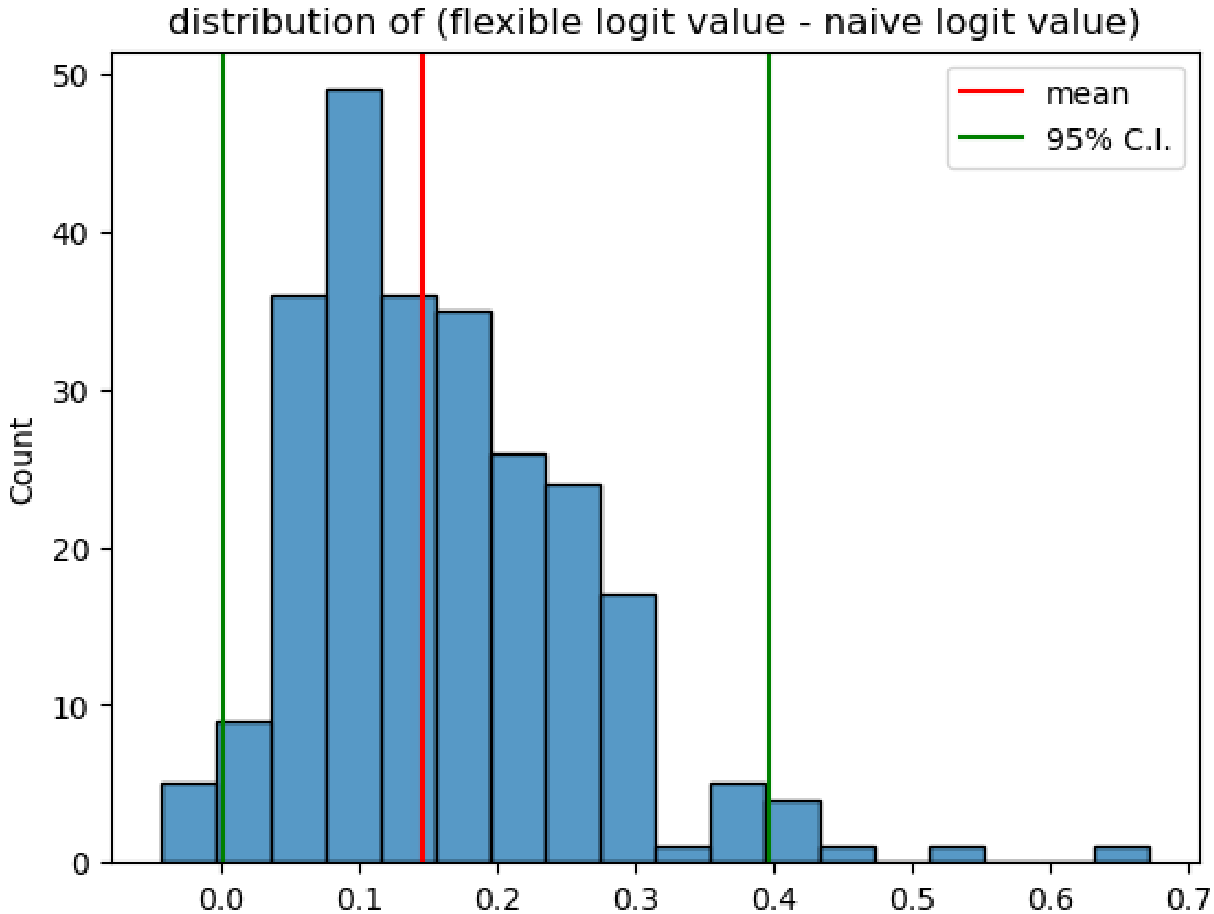

Figure 4.6: Distribution of difference between second-order derivative ratio and first-order derivative ratio

From the above result, it is evident that the estimate for β/α from the flexible logit is statistically different from that of the naive logit. In other words, we performed the structural test and concluded that consumers have inattention to price.

Then, we were able to retrieve the parameters for the utility specification.

The table 4.2 shows the estimates from the structural-form model. The pack price is retrieved from the flexible logit procedure, while other estimates are from naive logit. Note that pack price is the negative pack price, so the estimate is positive. Also, product fixed-effects are included during estimation.

	est	s.e.	z score	p value
bundle_size	0.2167	0.0024	90.2141	0
(negative) pack_price	0.2939	0.0005	605.1269	0
promotion	1.0060	0.0086	116.7862	0
ply	1.0328	0.0182	56.6111	0
soft	0.3821	0.0152	25.0596	0
strong	0.4315	0.0182	23.7653	0
recycled	-0.0578	0.0280	-2.0615	0.0196

Table 4.2: Estimates from flexible logit

CHAPTER 5

COUNTERFACTUAL SIMULATIONS

By utilizing the estimated results from the structural-form model, we conducted simulations to evaluate the influence of size preference and price inattention. The aim of these simulations is to dissect the extent to which consumer inattention and size preference affect QS, particularly concerning consumer surplus and firm revenue. Additionally, we aimed to assess the impact of discontinuing the QS pricing scheme on firm revenue and consumer surplus. The results revealed significant variations in firm revenue and consumer welfare across different scenarios.

Note that the utility specification is $U_{htj} = \tilde{\boldsymbol{\alpha}}\tilde{\mathbf{x}}_{tj} + \alpha x_{tj} + \beta z_{tj} + \varepsilon_{htj}$. The only difference between naive logit and flexible logit is the estimate on β. Thus, other coefficients, $\tilde{\boldsymbol{\alpha}}$ and α are from naive logit, and the estimates for price, β is from flexible logit.

5.1 Calculating Methods

To assess the impact of simulations, we employed two key measures: dollar sales for firms and consumer surplus. Dollar sales quantifies how firms' sales would change due to the simulation, while consumer surplus measures the impact on consumers' overall satisfaction and welfare.

It's important to note that the calculated values are projected to represent US households using a projection factor. Given that the constructed choice panel data only covers a subset of households from the entire household panel data, we scaled the original projection factor accordingly. This scaled projection factor for each year is derived by multiplying the 'scale factor' with the original projection factor. The scale factor is computed as the sum of all projection factors in the panel year divided by the sum of projection factors of the selected households in the choice panel data.

Additionally, since the data spans from 2006 to 2018, we calculated the firm's revenue and consumer surplus for each year and then took the average.

For dollar sales, we straightforwardly computed the sum of all prices sold under both the baseline scenarios and counterfactual simulations. It's important to highlight that for the baseline scenario, we also estimated the choice probability from the estimated parameters. Subsequently, utilizing these estimated choice probabilities for each item, we multiplied them by the pack price and summed up the values. The same calculation method was applied for counterfactual scenarios.

Regarding consumer surplus, we used the method provided by Appendix F in Abaluck, Compiani, and Zhang (2023). The consumer surplus under the partial information on price would be as follows:

$$E[CS] = \frac{1}{\beta_f}\left[\sum_j (\beta_f z_j - \beta_n z_j) s_j(\beta_n) + \ln \sum_j \exp(\tilde{\boldsymbol{\alpha}}_n \tilde{\mathbf{x}}_j + \alpha_n x_j + \beta_n z_j)\right] \tag{5.1}$$

The consumer surplus under the full information on price would be as follows:

$$E[CS] = \frac{1}{\beta_f} \ln \sum_j \exp(\tilde{\boldsymbol{\alpha}}_n \tilde{\mathbf{x}}_j + \alpha_n x_j + \beta_f z_j) \tag{5.2}$$

5.2 Scenarios

Note that the baseline scenario reflects the conditions faced by consumers in the original dataset. It encompasses the presence of QS'ed items among alternatives, partial price information requiring consumers to engage in a search process, and a positive consumer preference for size.

In the first counterfactual simulation, we explore the scenario where the firm discontinues the implementation of quantity surcharges (QS). The objective is to gauge the impact on firm revenue and consumer surplus resulting from the cessation of QS. If QS is deemed excessive, discontinuing it would lead to a decrease in firm revenue but a notable increase in consumer surplus. In this scenario, for items identified as QS'ed, we assign the minimum unit price among the alternatives within the same trip. Consequently, only the prices of QS'ed items are adjusted, while the prices of quantity-discounted items remain unchanged.

In the second counterfactual simulation, we investigate a scenario where consumers become more attentive to price. The goal is to assess how changes in consumer price sensitivity impact firm revenue and consumer surplus, without altering the firm's QS implementation. Assuming heightened consumer price attention, as indicated by descriptive and reduced-form analyses reflecting increased price sensitivity during promotions, we simulate a scenario where all products are promoted. This simulation provides insights into the effect of consumer inattention on QS sales.

The third counterfactual simulation explores a scenario where consumers exhibit no preference for size. Its purpose is to examine potential changes in consumer surplus and firm revenue in the absence of size preference. Although the structural-form model suggests consumers have a positive size preference, we set the preference parameter to zero for this simulation. The results shed light on the extent to which QS sales are influenced by size preference.

Finally, the fourth counterfactual simulation combines both attentive consumers and the absence of size preference. This scenario integrates elements from the second and third simulations to investigate the joint effects on consumers and firms when different conditions are simultaneously imposed.

5.3 Results

The table 5.1 illustrates how firm revenue changes with each counterfactual simulation. The first column displays the original firm revenue values, while the second column indicates the percentage change for each scenario compared to the baseline.

	firm revenue	% change from base
base	$9,863,307,318	
scenario 1	$9,915,955,770	0.53%
scenario 2	$9,462,303,389	-4.07%
scenario 3	$8,741,440,185	-11.37%
scenario 4	$8,419,407,606	-14.64%

Table 5.1: Counterfactual simulations: impact on firm's revenue

In the first scenario, where the firm ceases to implement QS, firm revenue increases by 0.54%. This increase could be attributed to the reduction in prices for QS'ed items, leading to an uptick in quantity demanded. Consequently, while the firm may miss out on the opportunity to charge higher unit prices through QS, the potential for increased revenue arises from the higher quantity demanded.

In the second scenario, if consumers become more price attentive, firm revenue decreases by 4.07%. This decline suggests that approximately 4% of the current revenue stems from QS charges due to consumer inattention to price.

In the third scenario, where consumers have no preference for size, firm revenue decreases by 11.37%. This outcome may occur if consumers not only refrain from purchasing QS'ed items but also avoid quantity discounted items. Essentially, if consumers exclusively purchase small-packed items, firm revenue could drop by 11%.

In the fourth scenario, where consumers are more price attentive but have no size preference, firm revenue decreases by 14.64%. This scenario combines the effects observed in the second and third scenarios.

	consumer surplus	% change from base
base	$22,829,225,830	
scenario 1	$22,871,994,865	0.19%
scenario 2	$22,851,021,253	0.10%

Table 5.2: Counterfactual simulations: impact on consumer surplus

The table 5.2 presents the change in consumer surplus for each scenario. It aims to assess how consumers are impacted by the presence of QS'ed items and increased attention to price. Note that we only calculated consumer surplus for the first and second scenarios.

In the first column, the original consumer surplus values for a given year are displayed, while the second column indicates the percentage change in consumer surplus compared to the baseline.

In the scenario where the firm ceases to implement QS, consumer surplus increases by 0.19%. Conversely, if consumers become more attentive to price, consumer surplus increases by 0.1%. The reason why the first scenario shows a higher increase than the second scenario is primarily due to the change in price. In the first scenario, we reduced the unit price of QS'ed items to the lowest unit price within the same trip. This price reduction likely contributes to the larger increase in consumer surplus observed in the first scenario.

	QS sales ratio
base	2.01%
scenario 2	1.83%
scenario 3	1.48%
scenario 4	1.33%

Table 5.3: Counterfactual simulations: impact on Qs sales ratio

The table 5.3 illustrates the QS sales ratio under the original data and various simulation scenarios mentioned earlier. Notably, the scenario where the firm ceases to implement QS is intentionally omitted from this table. This decision is made because if the firm stops QS, the QS sales ratio will be zero since there are no QS'ed items. Additionally, it's important to clarify that the QS sales ratio in this context follows the definition used in the descriptive analysis. The denominator represents the total sales under the baseline scenario or each simulation, while the numerator represents the dollar sales attributed to QS'ed items.

In the baseline scenario, the QS sales ratio stood at 2.01%. However, it decreased to 1.83% when consumers became more attentive to price. Furthermore, the QS sales ratio dropped even further to 1.48% when consumers lacked a size preference. Interestingly, when consumers were both attentive to price and lacked a size preference simultaneously, the QS sales ratio decreased to 1.33%.

Using these results across different scenarios, it becomes possible to deconstruct the QS sales ratio based on various rationales. Approximately 9% of the QS sales ratio can be attributed to consumer inattention, calculated by comparing the QS sales ratio of the baseline scenario with that of the second scenario ($\frac{2.01-1.83}{2.01}$). Additionally, a further 25% can be attributed to size preferences, calculated by comparing the QS sales ratio of the second scenario with that of the fourth scenario ($\frac{1.83-1.33}{2.01}$). The remainder is attributed to logit shocks.

CHAPTER 6

CONCLUSION

This paper presents empirical evidence to elucidate the different factors contributing to QS. Through a comprehensive descriptive analysis encompassing nine product categories, we document the widespread occurrence of QS. Our findings reveal that when consumers are presented with QS'ed items alongside alternatives, they exhibit a notable propensity to purchase QS'ed items.

To delve deeper into the underlying mechanisms driving QS, we conduct descriptive tests leveraging promotions as a proxy for consumer inattention. By assuming that promotions do not directly influence consumption utility, we aim to shed light on the extent of consumer attention to price. Our analysis suggests that consumers may indeed engage in a search process for price, and promotions could serve to alleviate the associated search costs.

Furthermore, we employ a structural model of demand that is robust to various commonly used search models. This enables us to estimate demand parameters and elucidate the factors contributing to QS. Through counterfactual simulations, we aim to measure the impact of different scenarios on QS, offering valuable insights into its drivers and implications.

By doing the decomposition of the QS sales ratio, we have concluded that around 9% is due to inattention and 25% is due to preference in size. The consumer surplus increased less than 1% if consumers were more attentive, but firm's revenue decreased by 5%. If firm stopped implementing QS, consumer surplus increased less than 1% and firm's revenue increased less than 1%.

REFERENCES

Abaluck, Jason, Giovanni Compiani, and Fan Zhang (2023). *A method to estimate discrete choice models that is robust to consumer search*. Tech. rep. Working Paper.

Agrawal, Jagdish, Pamela E Grimm, and Narasimhan Srinivasan (1993). "Quantity surcharges on groceries". In: *Journal of consumer affairs* 27.2, pp. 335–356.

Binkley, James K and John Bejnarowicz (2003). "Consumer price awareness in food shopping: the case of quantity surcharges". In: *Journal of Retailing* 79.1, pp. 27–35.

Clerides, Sofronis and Pascal Courty (2017). "Sales, quantity surcharge, and consumer inattention". In: *Review of Economics and Statistics* 99.2, pp. 357–370.

Cude, Brenda and Rosemary Walker (1984). "Quantity surcharges: are they important in choosing a shopping strategy?" In: *Journal of Consumer Affairs* 18.2, pp. 287–295.

Dickson, Peter R and Alan G Sawyer (1990). "The price knowledge and search of supermarket shoppers". In: *Journal of marketing* 54.3, pp. 42–53.

Gabaix, Xavier et al. (2006). "Costly information acquisition: Experimental analysis of a boundedly rational model". In: *American Economic Review* 96.4, pp. 1043–1068.

Granger, Clive WJ and Andrew Billson (1972). "Consumers' attitudes toward package size and price". In: *Journal of Marketing Research* 9.3, pp. 239–248.

Gupta, Omprakash K and Anna S Rominger (1996). "Blind man's bluff: The ethics of quantity surcharges". In: *Journal of Business Ethics* 15, pp. 1299–1312.

Hoyer, Wayne D (1984). "An examination of consumer decision making for a common repeat purchase product". In: *Journal of consumer research* 11.3, pp. 822–829.

Iyengar, Raghuram and Sunil Gupta (2009). "Nonlinear pricing". In: *Handbook of pricing research in marketing*. Edward Elgar Publishing, pp. 355–383.

Mehta, Nitin, Surendra Rajiv, and Kannan Srinivasan (2003). "Price uncertainty and consumer search: A structural model of consideration set formation". In: *Marketing science* 22.1, pp. 58–84.

Nason, Robert W and Albert J Della Bitta (1983). "The incidence and consumer perceptions of quantity surcharges". In: *Journal of retailing* 59.2, pp. 40–54.

Salop, Steven and Joseph Stiglitz (1977). "Bargains and ripoffs: A model of monopolistically competitive price dispersion". In: *The Review of Economic Studies* 44.3, pp. 493–510.

Shreay, Sanatan, Hayley H Chouinard, and Jill J McCluskey (2016). "Product differentiation by package size". In: *Agribusiness* 32.1, pp. 3–15.

Simon, Herbert A (1955). "A behavioral model of rational choice". In: *The quarterly journal of economics*, pp. 99–118.

Sprott, David E, Kenneth C Manning, and Anthony D Miyazaki (2003). "Grocery price setting and quantity surcharges". In: *Journal of Marketing* 67.3, pp. 34–46.

Wansink, Brian (1996). "Can package size accelerate usage volume?" In: *Journal of marketing* 60.3, pp. 1–14.

Weitzman, Martin L. (1979). "Optimal Search for the Best Alternative". In: *Econometrica* 47.3, pp. 641–654.

Widrick, Stanley M (1979). "Measurement of incidents of quantity surcharge among selected grocery products". In: *Journal of Consumer Affairs* 13.1, pp. 99–107.