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Sales, Quantity Surcharge, and Consumer Inattention*

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Abstract

Quantity surcharges occur when firms market a product in two sizes and offer a promotion on the small size: the large size then costs more per unit than the small one. When quantity surcharges occur the sales of the large size decrease only slightly despite the fact that the small size is a cheaper option – a clear arbitrage opportunity. This behavior is consistent with the notion of rationally inattentive consumers that has been developed in models of information frictions. We discuss implications for consumer decision making, demand estimation, and firm pricing.

Keywords: quantity surcharge, sales, promotions, consumer inattention, quantity discounts, nonlinear pricing.

JEL Classification: L12, L13, D4.

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1 Introduction

A standard assumption of empirical models of consumer choice is that consumers are fully informed about all relevant products and their prices, and that they make the utility-maximizing choice every time they decide on a purchase.¹ Cognitive and behavioral research has produced many examples – mainly through survey evidence – where consumers are not fully aware of available products and their prices. More recently, a flourishing literature in macroeconomics and financial economics has developed the notion of *rational inattention*.² The idea is that the processing of price information is costly and that consumers need to decide the extent to which they engage in that activity. This is related to the old notion of search costs (Stigler, 1961) and is therefore not entirely new. The novelty is the emphasis on the explicit modeling of the choice to process price information to re-optimize decisions.³ Models of information frictions can rationalize behavior that would seem irrational in a world of perfectly informed consumers. Terms like consumer inattention or limited attention have been used to describe the fact that consumers may not be fully attentive to (freely available) prices because the cost of doing so exceeds the expected benefit.

Empirical evidence of consumer inattention, as defined above, is not easy to come by. Alternative explanations of non-standard behavior are difficult to rule out, even with highly detailed data. In this paper we present evidence of consumer behavior that we believe can only be reasonably explained by some notion of consumer inattention. We exploit the occurrence of *quantity surcharges* in the pricing of detergent products in Dutch supermarkets. A quantity surcharge is the opposite of a quantity discount; it occurs when the same physical product is sold in two packages of different size and the large size has a lower price per unit than the small size.⁴ Standard nonlinear pricing theory predicts that price per unit should be decreasing in quantity sold, meaning that we should observe quantity discounts. Indeed, quantity discounts are the norm in our data as they are in many other datasets. Crucially however, we also observe many instances of quantity surcharges and these are typically associated with sales promotions. Promotions in our data are usually for a specific size: when a product is available in two sizes, either the small or the large size might be discounted in a given week, but not both. When the small size is promoted, the result is almost always a quantity surcharge: the unit price of the

¹There are a few exceptions, such as models of informative advertising (Sovinsky Goeree, 2008)), but the focus is on different departures from the standard model than the one of this paper.

²Sims (1998, 2003) is credited with starting this literature. More recent work includes Reis (2006), Mackowiak and Wiederholt (2009) and Mondria (forthcoming).

³An important difference with the search literature is that price information can be freely available in models of rational inattention.

⁴We borrow the term *quantity surcharge* from the marketing literature (Agrawal, Grimm, and Srinivasan, 1993; Sprott, Manning, and Miyazaki, 2003).

small size after the promotional discount drops well below the unit price of the large size.⁵

Quantity surcharges are extremely useful to the researcher because they give rise to an arbitrage opportunity. Since the small size has the lowest unit price, all buyers of the large size should switch to the small size, as long as they can approximate the desired quantity by purchasing multiple small packs. Switching away from the large size does not happen in our case study. In the raw data, sales of the large pack size during a quantity surcharge decrease by only 14.4% in the median case relative to the week preceding the surcharge. Formal econometric analysis yields the higher but still surprisingly low figure of 20.5%. We argue that the limited substitution away from the large size in the face of a quantity surcharge is evidence of consumer inattention. Since the small and large pack sizes contain the same physical product, a fully informed consumer seeking to purchase a certain amount of product at the lowest possible cost should never buy the large pack size if she can get the same amount of product by buying multiple units of the small pack size.⁶ If consumers are attentive to promotions, we would expect the sales of the large size to decrease by close to 100%. The 20.5% drop we find seems surprisingly small by comparison.⁷

Why do consumers select an option that is clearly dominated? It is difficult to come up with a reasonable explanation why they would *consciously* choose to do so. Rather, it seems that this behavior may be the result of consumers not checking prices systematically every time they go to the store, which leads to them missing out on some good deals. Cognitive research on decision-making in grocery purchases has demonstrated that the majority of consumers are not aware of point-of-purchase prices (Monroe and Lee, 1999). Such behavior is not necessarily irrational. A recent literature in macroeconomics and financial economics revolves around the idea that consumers can not possibly keep track of all available information and have to allocate their attention to collecting and processing the information that would be most valuable to them. In these models, not paying attention to all prices at all times is fully rational because the costs of doing so outweigh the benefits. This behavior has been labeled “rational inattention” and it can arise through a variety of mechanisms. One notion that is relevant to our study is that of “sticky information”, where consumers only update their information (such as prices) periodically, leading to information being “sticky” during the time between updates.

⁵Throughout the paper we use the terms “sales”, “promotions” and “sales promotions” interchangeably to refer to temporary price reductions, a common and well-documented pricing practice; see Pesendorfer (2002); Hendel and Nevo (2006b); Berck, Brown, Perloff, and Villas-Boas (2008) and a large marketing literature.

⁶This is the case in our data. For 65% of the products the small pack is exactly half the size of the large one and for the remaining products it is close to it.

⁷It may be argued that the two options (two small packs versus one large pack) are not perfect substitutes even if the amount of product is the same. While this argument has merit, in section 3 we argue that it does not suffice to explain our data.

In our context, we hypothesize that consumers are aware of the fact that many grocery store items are promoted from time to time but the exact timing of promotions is difficult to predict.⁸ A consumer needs to keep track of the prices of many products every week if she is to fully exploit promotional discounts. This clearly has a cost in terms of time, and possibly other costs as well (boredom comes to mind). We refer to all costs related to the collection and processing of price information as *monitoring costs*. If consumers have different monitoring costs, then some consumers will likely determine that the cost outweighs the savings from buying at a discount and will choose not to check prices every week. On the other hand, consumers with low monitoring costs will find it beneficial to check prices regularly and buy on promotion whenever possible. We call the latter consumers attentive and the former ones inattentive. The large responses to promotions together with the absence of arbitrage during promotions offer support to this typology.

If consumers with low monitoring costs are also more price sensitive and if buyers of premium brands are less price sensitive than buyers of value brands – both of which seem very plausible – then we would expect premium brand buyers to be less attentive than value brand buyers. The empirical implication is that we should observe more substitution away from the large size when a quantity surcharge occurs for a value brand than when it occurs for a premium brand. This is exactly what our econometric analysis finds. When we estimate separately the response to promotions of premium versus value brands we find that all the action is in the latter. A quantity surcharge for a value brand is associated with a 48% decline in the sales of the large size. On the contrary, a quantity surcharge for a premium brand has no discernible impact on the sales of the large size.

The idea that consumers choose to be inattentive to prices has some intuitive appeal but may have undesirable implications if taken to extreme. If consumers *never* check prices, this would lead to zero long-run demand elasticities, an implication that is difficult to accept. We use our data to estimate simple demand functions that seek to measure consumer response to permanent price changes, as opposed to temporary promotions. We find that demand for premium brands is less elastic than demand for value brands but is not perfectly inelastic. This indicates that premium brand buyers do respond to permanent changes in the relative price of the two pack sizes (as assumed by nonlinear pricing theory). The evidence is consistent with inattention being a temporary phenomenon. Consumers do not decide to never check prices but rather to do so periodically. This means that they will miss out on some temporary promotions, but when a price changes permanently they will eventually notice and adjust their behavior accordingly. The

⁸This is the general consensus in the literature; see, for example, Swait and Erdem (2002). In section 2 we present evidence to that effect from our own dataset.

departure from the standard paradigm is noteworthy because the cost of acquiring information is very small.

To our knowledge, our study offers the most direct evidence consistent with the rational inattention hypothesis that a significant fraction of consumers do not behave as if they were perfectly informed. The only empirical works on limited attention that we are aware of are behavioral studies of information opacity (see DellaVigna (2009) for a review).⁹ Two papers have considered consumer goods as we do. They show that consumers respond less to opaque information that is more difficult to process, such as nontransparent taxes (Chetty, Looney, and Kroft, 2009) or shipping costs (Hossain and Morgan, 2006). In our application there is no opaque component to the price that may confuse consumers. On the contrary, manufacturers and retailers go to great lengths to draw consumers' attention to the promotional offers and the fact that consumers still miss them seems striking.¹⁰

A possible interpretation of the behavior we document is that it represents a departure from the rational paradigm and provides support to the literature on behavioral biases. Although we can not rule out this interpretation, we think that the lack of arbitrage in our case study, and in particular the difference in substitution responses for premium and value brands and between the short and long run, are better explained by models of rational inattention. The rational inattention interpretation provides a bridge between the cognitive research on grocery decision making, which shows that a significant fraction of consumers is not aware about prices, and the large literature on demand estimation that assumes that all consumers are aware of all prices at each point in time. The key implication of inattention is that some consumers will respond less to price changes than if they were fully informed; there will be less substitution than in a full information world. A demand model that assumes only fully informed consumers will attribute the limited degree of substitution to other factors that are included in the model, with the possible implication, for example, of overestimating the impact of intangible variables such as brand loyalty.

Our evidence comes from a single product and a single country. One might legitimately be concerned about the extent to which our findings generalize to other products in other countries. On the other hand, laundry detergent is one of the most commonly studied consumer grocery

⁹Violation of rationality is also found when decision-making involves inter-temporal payoffs. DellaVigna and Malmendier (2006) show that some gym users could save by switching from a monthly subscription to pay-per-visit. They rationalize this by questioning rational expectations and inter-temporal commitment and do not consider consumer attention.

¹⁰This literature argues that, among other things, opacity depends negatively on salience. Salience increases during promotions due to advertising and more visible price tags. This should increase substitution; not limit it. Change in salience cannot explain our results.

product in economics and marketing. It is an ideal product for studying the impact of promotions because it has a near-constant usage rate and we do not have to worry about consumption effects. The Netherlands has a developed retail sector with many similarities with the US one,¹¹ and our data comes from *Nielsen*, the source of many US datasets. Most of the patterns we observe in our data (such as the frequency and depth of promotions and the magnitude of own demand response to promotion) are similar to those found in other studies, and in particular studies of laundry detergent using data from the United States.¹² This is confirmed when we compare our evidence on quantity surcharge with what is found using the widely used IRI Marketing Dataset. There is no reason to believe that the phenomenon we document is specific to either the country or the dataset. The magnitude of inattention, however, may be specific to our product. Rational inattention depends, among other things, on the depth and frequency of promotions and on the repeat purchase intensity, and these could change for other grocery products.

The rest of this paper is organized as follows. The next section describes the market and the dataset. Section 3 presents the findings of our econometric analysis and addresses their robustness and generality. Section 4 outlines a model of consumer behavior that is consistent with our findings and discusses its implications. Section 5 concludes.

2 Industry, data, and quantity surcharge

Our analysis is based on data from the laundry detergents market in the Netherlands. The dataset is similar in nature to the several other supermarket datasets that have been widely explored in the literature. It was obtained from the *Nielsen* marketing company and covers a period of 120 weeks between September 2002 to December 2004. We observe every size of every brand sold in each of the country's four major chains, Albert Heijn, Super de Boer (formerly Laurus), Schuitema and Superunie. For each size we observe the total quantity sold and the sales-weighted average price. The detergent market is dominated by three multinationals (Henkel, Procter & Gamble, Unilever) but private labels also have a significant presence. Each manufacturer markets several brands and each brand name is carried by several products.

A shortcoming of our data is that our information is at the level of the chain, not the individual store. The reported sales are aggregated over all stores and the price is a weighted average. A possible problem with this is that some items might not be available in all stores

¹¹The chain we will focus on, Albert Heijn, is in fact owned by Ahold, a Dutch firm that is a major international operator of supermarket chains owning, among others, the Stop & Shop chain in the US.

¹²Pesendorfer (2002); Hosken and Reiffen (2004); Hendel and Nevo (2006b); Berck, Brown, Perloff, and Villas-Boas (2008).

and thus will not be in the choice set of all consumers. Indeed, preliminary analysis of the data suggests that this is likely to happen in the case of Superunie and probably also Schuitema. In order to be conservative we will limit our analysis to the Albert Heijn chain for which the data are most reliable.¹³ Albert Heijn is the market leader with 750 stores and a 27% market share. The chain carries the major multinational detergent brands and its own private label. Each product is typically offered in either one or two pack sizes (containing the same physical product), respectively 45% and 54% of the times, and very rarely in three sizes or more. When two sizes are offered, sales are roughly balanced between them. For the median case during non-promotion weeks, sales of the small size are 61.5% of total sales.

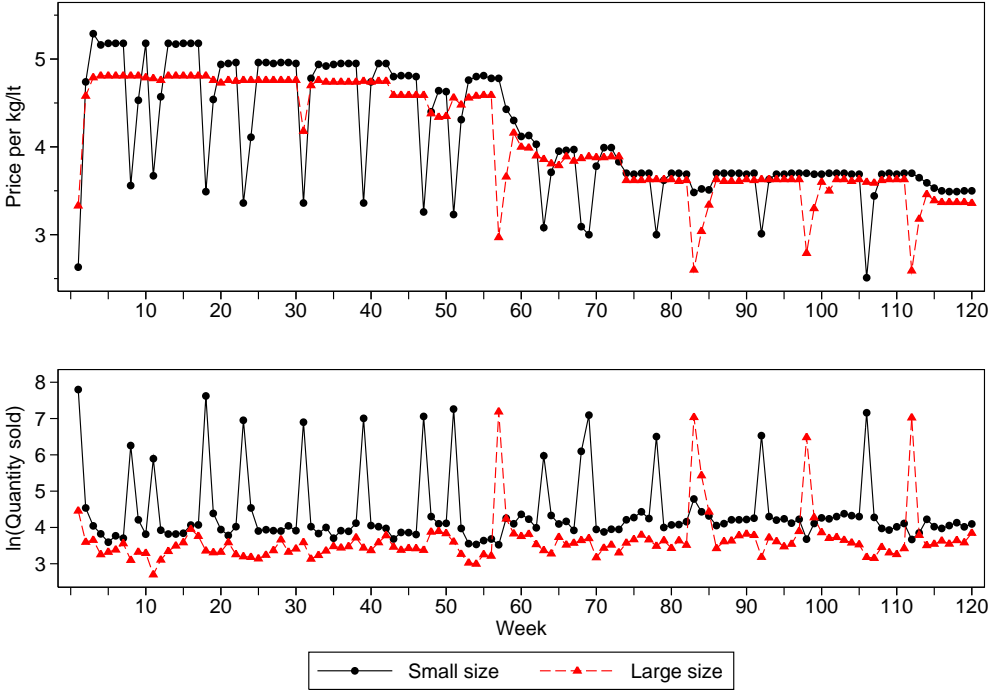


Figure 1: Prices and quantities sold for packs of a selected product line

Figure 1 illustrates the nature of the data variation we seek to leverage. The top graph plots the temporal evolution of price per unit for each of the two pack sizes of a selected product.¹⁴ Promotions are easy to identify as large and temporary downward deviations from the regular unit price. In each promotion the unit price drops sharply for a week, partially recovers in the

¹³We discuss this issue in greater detail in section 3.1.
¹⁴All prices in this study are measured per unit of product. Because there is no risk of confusion, we use interchangeably the terms price per unit, unit price, or more simply price.

following week and returns to its original level the week after that. Thus promotions last for between one and two weeks. In the first week all units are sold at the discounted price while in the second week some units are sold at the discounted price and others at the regular price, leading to a sales-weighted price lying somewhere between the two. The bottom graph plots the volume of sales for each size (in logarithms). The impact of promotions is quite striking, with a large spike in sales for the promoted pack. Sales increase by a factor of 5-10 relative to periods with regular price.

Figure 1 indicates that although promotions happen fairly regularly it is difficult to predict when they will happen next. The mean number of weeks between successive promotions of the same product is 10.3, with a standard deviation of 10.5. When we limit the sample to products that were promoted at least 10 times during the observed period, the mean drops to 6.5 and the standard deviation to 5.2. Even with this sample of frequently promoted products, there is large variation in the time between promotions. As a further test, we estimated a linear probability model of the event of a promotion, using pack fixed effects and a full set of dummy variables identifying the time since the product's last promotion as explanatory variables. The R^2 from this regression was 0.0875, reflecting the difficulty of precisely predicting promotions. A consumer who wants to buy on promotion has to check prices regularly.

During regular (non-promotion) periods, the price of the small pack is usually higher than the price of the large pack. This corresponds to quantity discounting, a practice that is consistent with standard nonlinear pricing theory. When the small pack is promoted, however, the price order is reversed: the price is lower for the small pack. When this happens, we say that there is a quantity surcharge. Quantity surcharge almost always happens when the small pack is promoted and the price differential between the small and large pack can be substantial (of the order of 20-40%). There is no obvious explanation for why quantity surcharges take place. One possibility is that the small pack is a more attractive choice for those firms who want to lure consumers to experiment and eventually switch brands. Whatever the reason, we would expect that consumers would exploit the promotion and buy two small sizes rather than one large one.

Figure 1 displays two other features we will leverage in the analysis. First, note that the large pack size is also occasionally promoted and the price difference between the large and small pack increases substantially when this happens. Second, there are also some permanent changes in the level of prices and in relative prices. In particular, the price series exhibit a structural break around week 60. At that time (November 2003) the Albert Heijn chain initiated an aggressive pricing strategy and sharply cut prices on a large number of products. As is clear from the plot, laundry detergents were among those products. There are additional occasions of smaller permanent price changes (all decreases) around weeks 20, 44, 73 and 112. The mean regular

Table 1: Descriptive statistics on promotions

	Total proms	Promotions per item			% time on prom.		% prom. discount	
		Mean	Median	Max.	Mean	Median	Mean	Median
Firm 1	152	5.5	4	14	6.9	5.4	26.5	28.9
Firm 2	105	7.4	8	12	7.3	7.0	28.2	30.3
Firm 3	110	5.5	5	11	6.6	7.4	25.7	28.0
Firm 4	32	3.7	4	7	5.1	3.9	25.9	27.7
Overall	399	5.8	5	14	6.7	6.7	26.7	29.1

price was 13.4% lower in the last 50 weeks of the sample relative to the first 50 weeks. The figure is 16.6% when comparing the last 20 weeks to the first 20 weeks.

We also note that the price differential between the two packs changed as a result of the price war, resulting in a lower quantity discount in the second sub-period. In section 3.2 we will leverage these incidents of non-promotional price variation to compute demand substitution across pack sizes in response to permanent price changes.

In order to proceed with our analysis we need to provide an operational definition of what constitutes a promotion. In the spirit of the literature, we identify a promotion as a temporary decrease in price of at least 10%.¹⁵ In practice this is implemented by looking at a six-week window around any given price. If the price in the current period is at least 10% lower than the modal price during the six-week window, then the current period is labeled as a promotion period. Promotions lasting more than one week are counted as one event. The use of the six-week window to define promotions means that we cannot identify promotions in the first and last three weeks of the sample, leaving us with 114 weeks of data.

This procedure identifies 399 promotions, the properties of which are summarized in Table 1. In the rest of this paper, we call the weeks without a promotion the regular periods for that pack. Firm 1 does the most promotions (152), but it also has the most products. Firm 2 is actually the most frequent promoter in relative terms. Its products are on promotion 7.3% of the time on average. Firm 4 (the private label) is the least frequent promoter. The depth of promotional discounts is in the range 25-30% and is very similar across firms. These price patterns are consistent with those reported elsewhere using detergent in other countries (United States, UK) or other grocery products (Hosken and Reiffen, 2004, among others).

Out of the 399 promotions we identify, 197 involve single-item product lines. Of the 202

¹⁵Some authors use a 5% threshold. We prefer to be more conservative on what constitutes a promotion.

Table 2: Quantity surcharge and promotions

	Periods with no promotions	Periods with promotions	All periods
Quantity discount	1,231	66	1,297
Quantity surcharge	90	110	200
Total	1,321	176	1,497
% of time with quantity discount	93.2%	37.5%	86.4%

Note: this table considers only products coming in two or more sizes.

instances when two sizes are available, the large size is promoted 76 times and the small size 126 times. On 26 occasions both sizes are promoted, meaning that we have 50 solo promotions of the large size and 100 solo promotions of the small size. The frequency of quantity surcharges is summarized in Table 2. The pricing schedule displays quantity discounts 93.2% of the time during periods without promotions, which is broadly consistent with nonlinear pricing theory. In promotion periods, this percentage drops to 37.5%. This is quite striking, and it demonstrates that quantity surcharges occur frequently when a promotion takes place. Out of the 100 solo promotions of the small size, 97 result in a quantity surcharge.

One may wonder whether quantity surcharges are specific to our data on a single product from a single retailer. Marketing studies have found that “quantity surcharges occur in 16% to 34% of supermarket brands that are available in two or more package sizes” (Sprott, Manning, and Miyazaki, 2003). As supplementary evidence, we turn to the comprehensive IRI Marketing Dataset, which covers a large array of products in a large number of US retailers over several years (Bronnenberg, Kruger, and Mela, 2009). We randomly selected ten stores from this dataset and looked at the prices of detergent product lines in 2005. There were 7,670 instances of detergents products available in more than one size and in 2,141 of those (27.9%) there was a quantity surcharge rather than a quantity discount.¹⁶ The frequency of quantity surcharges in the US data is even greater than what we observe in our Dutch data (13.6%).

The large discounts on offer during promotion periods suggest that there is substantial incentive to substitute. When the small pack is promoted, for example, the median surcharge for the large pack is 28.2%. In absolute terms, this corresponds to a median saving of €0.83 per kilogram. The savings exceed one euro per kilogram in 45% of promotion events. Quantity surcharges occurring during non-promotion periods are substantially smaller, with a median of 5.0% or €0.21 per kilogram. Because quantity surcharges outside promotions are small and

¹⁶To avoid counting minor discrepancies, we used a 2% threshold to define a quantity surcharge.

infrequent, we do not consider them further and focus on demand response during promotion-induced quantity surcharges only.

Promotions of the large size also provide opportunities for substantial savings. The price of the large size decreases by 27.9% during the median promotion. In contrast, the median quantity discount during non-promotion periods for the large pack is only 6.3%. Promotions of the large pack increase the quantity discount to 28.3%.¹⁷ The savings obtained from buying the large size increase substantially during promotions.

3 Econometric analysis

This section presents the results of our econometric analysis. We first analyze demand responses to promotional events, breaking down the response for premium versus value brands. We then estimate demand response to permanent price changes and obtain long-run elasticities. Finally, we address the robustness of the findings and discuss their generality.

3.1 Substitution during promotions

We use regression analysis to study substitution patterns during promotion periods. We follow a reduced-form approach that links the quantity sold of a particular pack to whether there is currently a promotion of either the pack itself or other packs of the same product. Our basic model is the following:

$$\begin{aligned} \ln(q_{it}) = & \alpha_i + \theta_{bt} + \beta_1 \cdot \text{BothPromLarge}_{it} + \beta_2 \cdot \text{BothPromSmall}_{it} \\ & + \beta_3 \cdot \text{OwnPromSolo}_{it} + \beta_4 \cdot \text{OwnPromLarge}_{it} + \beta_5 \cdot \text{OwnPromSmall}_{it} \\ & + \beta_6 \cdot \text{CompPromSmaller}_{it} + \beta_7 \cdot \text{CompPromLarger}_{it} + \beta_8 \cdot \text{AfterProm}_{it} + \varepsilon_{it}, \end{aligned} \quad (1)$$

where q_{it} denotes the quantity sold of pack i at time t . The right-hand side includes a set of dummy variables designed to capture the impact of different promotional events. The *BothProm** variables capture the impact of a promotion when both sizes are promoted at the same time, allowing the impact to vary by pack size. The impact of a promotion of a single pack size on its own sales is captured by the variables *OwnProm** and it is allowed to vary depending on whether the item is the only one in the product line (*OwnPromSolo*) or whether there are

¹⁷The 28.3 figure may seem small and this is due to the fact that there is variability around the different medians. If there were no variability around the medians, the quantity discount during promotion should increase by $1 - (1 - 0.279)(1 - 0.063)$ which gives the higher figure of 32.4%.

two products, in which case we allow the impact to differ for the large size (*OwnPromLarge*) and the small one (*OwnPromSmall*). The dummy variables *BothProm** and *OwnProm** are exclusive and they describe all promotions: exactly one of these variables will be equal to one for a given pack size in a week that it is being promoted.

The impact of a promotion of the competing size is captured by the *CompProm** variables and is allowed to vary according to whether the size being promoted is larger or smaller. The *AfterProm* variable is a dummy for periods immediately following a promotion and it is included as a control variable for promotions lasting for more than a week.¹⁸ The specification also includes a pack fixed effect α_i that controls, among other things, for the selection rule determining which products are promoted. If more popular products were more likely to be promoted, for example, the omission of such controls would lead to overestimating the impact of promotion on sales.¹⁹

Endogeneity of the promotion variables is typically a cause for concern in specifications similar to ours. This would be an issue, for example, if promotions were offered in response to demand shocks. But it is hard to imagine why product-specific demand shocks would occur every few weeks. Another possibility is that promotions are offered to boost sales of products losing market share. Again, this is not borne out either in the sales data or in the observed promotion patterns. The most plausible explanation for the timing of promotions and the choice of item to be promoted may be that provided by Hosken and Reiffen (2007), who argue that promotions are part of retailers' ongoing efforts to keep customer visits high and have little to do with the particular product that is being promoted. Endogeneity of promotions is not considered a problem in this literature (see, for example, the discussion on page 1645 in Hendel and Nevo (2006a)).

A limitation of our data is that we do not have any information on advertising or other non-price related marketing campaigns. This could affect our results in the following way. Suppose a promotional discount on a particular pack is accompanied by an advertising campaign that promotes the brand in general. The discounted pack will benefit from both of those practices. For non-discounted packs belonging to the promoted brand, there will be opposing effects: a positive impact due to the advertising campaign and a negative impact as consumers switch to the discounted pack. A specification that does not fully account for the campaign will attribute the gain in sales of the non-discounted pack to the discount. The result will be that the impact

¹⁸As a robustness check we also estimated the model excluding all observations for which *AfterProm* = 1. There was no difference in the coefficients of interest.

¹⁹We do not control for promotions of other *products* (as opposed to sizes) because we have found in other work that their impact is small and does not affect the coefficients of interest.

Table 3: Impact of sales

Promotion of large when both promoted (β_1)	0.616** (0.116)	0.465** (0.115)	0.463** (0.115)
Promotion of small when both promoted (β_2)	2.604** (0.117)	2.165** (0.116)	2.185** (0.116)
Own promotion when no other size exists (β_3)	2.414** (0.044)	2.145** (0.050)	2.143** (0.050)
Own promotion of large size (β_4)	1.367** (0.088)	1.387** (0.084)	1.386** (0.084)
Own promotion of small size (β_5)	2.434** (0.062)	2.334** (0.058)	2.332** (0.058)
Promotion of smaller alternative (β_6)	-0.114 [†] (0.061)	-0.191** (0.058)	
Promotion of smaller alternative with QS			-0.229** (0.059)
Promotion of larger alternative (β_7)	-0.023 (0.084)	-0.042 (0.081)	-0.042 (0.081)
Brand-week fixed effects	No	Yes	Yes
Obs.	5,828	5,828	5,828
F-stat	647.4	16.97	16.99

Estimates from fixed effect estimation at the individual item level. Estimates of the constant term and the coefficient on the *AfterProm* variable are not reported. Significance levels: † : 10%, * : 5%, ** : 1%.

of the discount on competing products will be underestimated.²⁰

We can partially control for this possibility by including brand-week fixed effects θ_{bt} . There are 14 different brands and 220 packs in our sample. We get identification from the fact that different packs of the same brand are promoted in different weeks. Thus we control for marketing and advertising campaigns or other interventions that affect a specific brand in a particular period. On the other hand, we can not control for product-specific marketing campaigns. Our results are then valid to the extent that most advertising campaigns, or other actions that are part of the marketing mix, are at the brand level rather than at the product level.²¹

Estimates from equation (1) with and without brand-week fixed effects are reported in Table 3. We first note that adding the fixed effects causes the coefficients on own promotion to fall

²⁰Failing to account for advertising will also overestimate the impact of own promotion.

²¹This is consistent with the marketing literature on advertising, promotion, or display which is always conducted at the brand level without distinguishing different products.

(except β_4 which increases slightly) and the coefficients on a competing promotion to rise (in absolute terms). This is consistent with the argument above and confirms that brand-week fixed effects are effective in soaking up promotional activity at the brand level. Our discussion of the results will therefore focus on the coefficients in the second and third columns. The difference between the latter two columns is in the definition of the variable *CompPromSmaller* and will be made clear below.

The first two variables listed in Table 3 capture the effect of promotions when both sizes are promoted. They are included primarily as control variables but it is worth noting that, when both sizes are simultaneously promoted, sales of the small size increase by much more than those of the large size. The next three variables capture the impact of a single promotion on own sales for solo, large and small packs respectively. A substantial impact is estimated in all three cases; sales of promoted items multiply by factors of 4 (large size) to 10 (small size). We note that again the impact is greater on the small size. These magnitudes are broadly consistent with past studies of promotion (Pesendorfer, 2002; Hendel and Nevo, 2006b) and bode well both for our data and for our empirical specification. The last two coefficients test our main hypotheses. The impact of a promotion of the small size on sales of the large size is estimated at -0.191, corresponding to a 17.4% drop in sales. This is higher than the 14.4% that comes out of the raw data but still surprising low.

In interpreting the -0.191 estimate, it should be borne in mind that promotions of the small size do not always lead to a quantity surcharge. The correct interpretation of this coefficient is that it measures the response to a promotion of the small size. This should be smaller than the response to a quantity surcharge if some promotions are so small that they do not generate a quantity surcharge. The response to a quantity surcharge can be estimated by focusing on promotions of the small size that lead to a quantity surcharge.²² Out of the 100 promotions of the small size in our data, 97 lead to a quantity surcharge. We therefore re-estimated equation (1), replacing *CompPromSmaller* with a new variable that flags instances when the small size is promoted *and* a quantity surcharge results. The results are presented in the third column of Table 3. At -0.229, the coefficient on the new variable is higher than the -0.191 obtained with *CompPromSmaller*, as expected. The difference is not large, but we would not expect it to be since the two variables only differ in three observations. The estimate corresponds to a 20.5% drop in sales for the large size in the event of a quantity surcharge, still very far from full arbitrage.

The last coefficient measures the drop in sales of a small size when its large counterpart

²²We are grateful to Catherine Thomas for pointing this out.

is promoted. The estimate is a very small and statistically insignificant -0.042 . This seems surprising given the substantial savings made possible by a promotion of the large size.

The findings presented thus far make a strong case that some consumers do not take advantage of promotions and instead buy dominated options. We are able to identify this lack of arbitrage by focusing on substitution during promotion between carefully selected pairs of products. Previous studies of promotions did not identify this behavior because they aggregated sales over products or focused on specific sizes. By examining the entire product line we are able to identify patterns of behavior that are masked by aggregation or selective analysis.

While our emphasis is on the limited substitution across product sizes during quantity surcharges, we cannot ignore the fact that promoted products register large increases in sales. This suggests that many consumers do take advantage of promotion opportunities. We next examine whether propensity to switch during a promotion can be related to other consumer characteristics, and in particular to price sensitivity.

Branded versus value products

Is the propensity to substitute during promotions correlated with other consumer characteristics? In the absence of consumer level data, it is difficult to make definite progress on the issue. We can, however, investigate whether consumer inattention depends on the type of product. An important distinction in the context of groceries is between branded products and value products (such as store brands). We can indirectly investigate whether inattention is related to consumer characteristics because price sensitive consumers are more likely to buy value brands rather than the premium brands sold by the big multinationals. This raises the question: are buyers of value brands more likely to identify and exploit arbitrage opportunities than buyers of premium brands?

Our data allow us to test this hypothesis. We split the brands in our sample into value brands and premium brands on the basis of their prices. Value brands are the store brand plus Henkel's Witte Reus and Unilever's Sunil. The latter two brands sell at a substantial discount relative to other brands sold by the three multinationals. The results from estimating separate responses to sales for each group are presented in Table 4.²³ The impact of own promotion is greater for premium brands across the board and the difference is statistically significant at the 3% level or better. A possible explanation is that promotions of premium brands are more likely

²³We also estimated equation (1) with the pooled data, allowing the coefficients of interest to differ according to product type. The estimates were very similar to those obtained in the separate regressions. We prefer to report estimates from the latter as they are more general, and use the pooled regression estimates to conduct the equality tests reported below.

Table 4: Impact of sales by product type

	Premium brands	Value brands
Own promotion when no other size exists	2.207** (0.054)	1.608** (0.129)
Own promotion of large size	2.177** (0.110)	0.495** (0.125)
Own promotion of small size	2.408** (0.067)	2.081** (0.107)
Promotion of smaller alternative with QS	-0.077 (0.068)	-0.655** (0.110)
Promotion of larger alternative	-0.003 (0.105)	-0.132 (0.121)
Obs.	3,846	1,982
F-stat	19.56	8.74

Obtained from estimating equation (1) separately for premium and value brands. Item and brand-week fixed effects are included. Only selected coefficients are reported. Significance levels: † : 10%, * : 5%, ** : 1%.

to induce switching from consumers who would otherwise buy a different product.

Our main interest is in the four coefficient estimates on the two bottom lines. Comparing the two coefficients for the value brands with those for the premium brands, we note that the impact of a promotion on the competing size is much greater for value brands than it is for premium brands; the two coefficients on the right column are several orders of magnitude greater than those on the left column.²⁴ Most importantly, a promotion of the small size of value brands leads to a substantial 48% ($\approx 1 - \exp\{-0.655\}$) decrease in the sales of large sizes. For premium brands, however, there is no significant change in sales. All the substitution taking place during quantity surcharge is done by buyers of value brands.

3.2 Response to permanent price changes

Consumer inattention is by definition a short-run phenomenon. Consumers who do not check prices every time they go to a store might miss out on some good deals that are offered for short periods of time. An implication of inattention is that substitution across pack sizes should increase as consumer become aware of price changes. For example, if a promotion lasts several

²⁴The difference is statistically significant at the 1% level in the case of promotions of the small size but it is not significant in the case of the large size (see footnote 23).

weeks one would expect that more and more of the consumers who buy premium brands would gradually become aware of it and progressively change their purchasing behavior. This hypothesis would be testable if promotions of varying lengths were observed in the data. Unfortunately this is not the case, as the promotions in our sample typically run for just one week and rarely for more than two.

We formulate an alternative hypothesis that can be tested using the data at our disposal. If buyers of premium brands are not inattentive in the long-run, then we would expect to see substitution between sizes when relative prices change permanently. The extent of substitution that would be considered reasonable is of course hard to quantify, but certainly we would expect to see *some* substitution for premium brands. We test our hypothesis by leveraging changes in the overall level of prices during our two-year period – notably the price war that took place in November 2003 – to estimate demand substitution responses to non-temporary changes in price.

We estimate simple reduced-form demand functions by regressing sales on own price and on the price of the competing pack size (all in logarithms):

$$\ln(q_{it}) = \alpha_i + \theta_{bt} + \beta_1 \cdot \ln(p_{it}) + \beta_2 \cdot \ln(p'_{it}) + \varepsilon_{it}, \quad (2)$$

where p_{it} is own price of item i and p'_{it} is the price of the competing size.

There are two main differences between this analysis and the one presented in the previous section. We are now computing price elasticities, while Tables 3 and 4 presented demand responses to promotion events. In addition, the two types of demand response are estimated from two different sources of price variation in the data: variations in price over time in the current analysis and temporary price decrease of 10% or more in the promotion analysis.²⁵ As before, we include brand-week fixed effects that control for many sources of price variation that could be endogenous at the brand level (advertising, response to competitors, etc.).²⁶ This greatly reduces the concern for endogeneity. We also note that much of our non-promotion price variation comes the price war that brought prices down from week 55 to 75 (see Figure 1), and which was an exogenous event.

In order to be able to interpret the coefficients in equation (2) as responses to permanent price changes (long-term demand elasticities) we remove all observations for which any size of the product is promoted during the same week. This ensures that the price variation we leverage

²⁵We note that this is a different issue from the distinction between short- and long-run elasticities that is encountered in the demand literature. The latter deals with responses to a price change that are measured over two different horizons; see Bentzen and Engsted (1993) for an example.

²⁶In fact the addition of brand-week fixed effects in this specification did not change estimates much. This is consistent with our explanation of what these effects capture.

Table 5: Estimates of simple demand functions

	All data		Non-promotion data	
	Premium	Value	Premium	Value
Own price	-4.038** (0.504)	-4.207** (0.325)	-1.603* (0.644)	-3.169** (0.683)
Price of competing size	1.797** (0.498)	2.060** (0.394)	0.927* (0.447)	1.928** (0.619)
Obs.	2,992		2,443	

Item and brand-week fixed effects are included. Robust standard errors are reported. Significance levels: † : 10%, * : 5%, ** : 1%.

is non-temporary. In order to have a basis of comparison, we also estimate the same specification with all data. In both cases, single-pack products are necessarily excluded from the sample as there is no competing size.

The estimates are reported in Table 5. Looking first at estimates obtained using all data, we note that both own and cross price elasticities are quite high and they are not very different between premium and value brands (even though differences are statistically significant). When we remove promotion observations from the data, the picture is quite different. Estimated elasticities are smaller and more in line with what is considered normal for this type of product.²⁷ Demand for value brands is more elastic than demand for branded products. Both own and for cross price elasticities are higher for value brands and the differences are significant at the 1% level. This further demonstrates that the demand for value and branded products behave very differently in response to promotions and to permanent price changes.

The key finding in Table 5, however, is that the demand for premium brands does respond to relative price changes over the long-run. We can therefore reject the hypothesis that the demand for branded products does not depend on the price of other packs. For premium brands, this holds for the sub-sample with non-promotion data only but also for the entire sample. One does not find that the substitution patterns across pack sizes violate demand theory when promotion and non-promotion periods are aggregated.

One concern with the specification in (2) is that consumers may exploit promotions in order to build their inventory and this will lead to reduced sales in subsequent periods. In a specification that does not account for this possibility, this drop in sales (known in the literature as post-

²⁷As estimated, for example, in the structural models of Erdem, Imai, and Keane (2003) and Hendel and Nevo (2006a).

promotion dip) may be attributed to other factors leading to biased estimates. The evidence in the literature suggests that the post-promotion dip is actually quite small.²⁸ Nonetheless, we tried to account for this possibility by re-estimating equation (2) after removing observations from weeks following a promotion. All four coefficients of interest rise somewhat relative to those presented in the second column of Table 4 but statistical significance remains the same, even though the number of observations is reduced to 2,072.²⁹ We conclude that inventory effects do not seriously affect our estimates.

3.3 Robustness

The estimated demand responses to temporary price reduction present somewhat of a puzzle. If consumers are rational and fully informed, they should substitute to the small size during a quantity surcharge. Why would they not do so? Could our findings be a data artifact?

One possibility is that consumers cannot substitute because retailers run out of stock and the promoted size is not always available. This would lead to lower substitution than under unlimited supply. The possibility of stock-outs can not be completely ruled out, which is also true of almost the entire literature on promotions. But we argue that stock-outs are unlikely to be the explanation for at least three reasons. To start, stocking out does not explain why we find a substitution response for value brands but not for branded products; it would have to be that premium brands stock out but value brands do not. Second, we conducted a phone survey of store managers to clarify this issue as well as others. All managers we talked to said that stock-outs were not common. Third, stock-outs are inconsistent with the fact that we do find a very large increase in sales of the promoted product, similar or larger to existing estimates in the literature. As a further robustness check, we measured substitution using promotions that last more than one week. Because sales for these promotions (121 of them) are positive the in second week, stock-out is less likely to have happened in the first week. The results do not change when we restrict the analysis to (the first week of) these promotions; we find large own promotion responses and no substitution responses. The combined evidence above suggests that frequent stock-outs are unlikely to be causing the observed patterns.

A second explanation is that promoted products could be placed in different locations within each store. They might still be available in each store but consumers may not be able to easily

²⁸See Hendel and Nevo (2003) and references therein.

²⁹The new estimates are (by row) -1.685, -3.298, 1.147 and 2.092. This method of removing inventory effects has recently been proposed by Hendel and Nevo (2010). The results are also robust to decomposition by pack size as in Table 4. The estimated coefficients do not change but they become insignificant at conventional levels for the small pack size.

make unit pricing comparisons because the two packs of the same products are rarely located nearby. We have also addressed this issue in our survey of store managers. All managers responded that promoted items may be placed at the end of the aisle but they are usually left in the regular location. Hence promoted items would be easily seen by consumers.³⁰

Still another possibility is that consumers may have a strong preference for a particular size. For example, two small packs may not be considered equivalent to a large pack that is double the size because of environmental considerations (they use more packaging) or because consumers are used to a certain feel or handling experience. There could also be storage space considerations. Two small sizes may take more space than a large one, especially in the case of liquid detergents. This distinction has a testable implication. If powder detergents are easier to store because of their cuboid shape, then people would be more likely to switch to a different size than with liquid detergents. We split our sample between liquid and powder detergents and estimated separate demand responses for each type of product, but found no difference. An argument could also be made in the opposite direction: two small sizes provide more storage flexibility than one large one and may be preferred by at least some consumers. Overall, the case for strong preferences for size seems weak.

The observed patterns could also arise if no one buys large packs of premium brands during regular periods. The absence of substitution would occur for a trivial reason.³¹ We can easily rule this out by looking at the raw data; large packs of premium brands do record sales in regular periods. In fact, a larger fraction of large packs sales is recorded at the regular price than is the case for small packs. For the median product in our sample, 17.1% of sales of the large pack occur during promotions, compared to 50.5% of small packs. Splitting the sample into premium and value brands, the corresponding figures are 22.1% and 58.8% for premium brands and 11.0% and 43.4% for value brands.

The main cause for data-related concern is related to the fact that our data are aggregated to the chain level. This could cause problems if prices, promotional activity or product lines are not the same in all stores. There is solid evidence that this is definitely not an issue for prices and promotional activity. Albert Heijn advertises the use of national pricing on its website and all the store managers we surveyed confirmed that this is the case. We can therefore rule out the possibility of prices and promotions varying across stores.

The possibility of differences in product lines can not be dismissed as easily. The problem is

³⁰Even if it is the case that the promoted items are located elsewhere, it is still a puzzle. Consumers who visit the store often should know that this is the case and look for them.

³¹We thank Catherine Thomas and Aviv Nevo for pointing out this possibility.

that some stores may not carry both pack sizes. Suppose that the small size is only available in some stores but the large size is available in all stores. If the small size is promoted, consumers in stores where it is not available have no opportunity to substitute to it (unless they go to another store). In the extreme case where some stores carry one size and the remaining stores carry the other size (and are located away from the former stores), there would be zero substitution which would be entirely due to the lack of substitutes and not to consumer inattention. This extreme scenario is highly unlikely, but the possibility that not all stores carry both sizes can not be a priori ruled out. If many stores do not carry the small size, our main conclusion about the lack of substitution to the small size could be questioned, though it would not be completely invalidated at least for branded products: as long as both sizes appear in some stores, then we should observe *some* substitution.

Several pieces of evidence suggest that non-availability of the small size is unlikely to be a problem. The first piece of evidence comes from the managers in our survey. Most respondents reported that smaller stores typically carry the small size while larger stores carry both sizes (the rest of the managers reported that they were not familiar with what other stores are carrying). A second piece of evidence comes from the fact that we do find substitution in the case of value brands, suggesting that availability is not a big issue there. It is hard to imagine why the retailer would offer more sizes for value brands than for premium brands, given that the latter make up more than two thirds of the market.

For our final evidence we utilize some additional information on product availability from our dataset. *Nielsen* has provided us with two important pieces of data: (i) the fraction of stores carrying each pack in a given week and (ii) the fraction of stores carrying *any* pack of a given product line each week. In order to be explicit, suppose there are N stores. Let N_S denote the number of stores carrying the small size; N_L denote the number of stores carrying the large size; and N_{SL} denote the number of stores carrying at least one of the two. The variables we have are $\lambda_S \equiv N_S/N$; $\lambda_L \equiv N_L/N$; and $\lambda_{SL} \equiv N_{SL}/N$. Clearly, $\lambda_S + \lambda_L \geq \lambda_{SL}$. In addition, we also have sales-weighted versions of these fractions.

With this information we are able to confirm what store managers told us about availability of the different sizes: the median λ_S and λ_L are .89 and .52, meaning that the typical small and large pack are available in 89% and 52% of stores respectively. When weighted by sales, the corresponding figures are 92% and 61%. More importantly, by comparing λ_S with λ_{SL} we can assess the likelihood of the problem scenario described above. That is, how often do stores carry the large size but not the small size? Fortunately, the answer is not very often. The median ratio λ_S/λ_{SL} is .97; the ratio is at least 85% for 90% of the products in our data. The median ratio λ_L/λ_{SL} is .58, reflecting the fact that large sizes are generally less available. This information is

very important because it allows us to rule out the possibility that the lack of substitution from the large to the small size is driven by availability. The fact that the small size is carried in the large majority of stores carrying the large size is strong evidence that availability is not a major concern. Availability might play a bigger role in explaining limited substitution from the small to the large size since the latter is not available in a fairly large number of stores. This however does not affect our main finding.

4 Discussion

4.1 Rational inattention and grocery shopping

Empirical models of grocery shopping assume that consumers are fully informed about point-of-purchase prices. This is a simplification. Cognitive research has shown that the majority of consumers cannot correctly quote the price of items they have just placed in their shopping cart (Monroe and Lee, 1999). Dickson and Sawyer (1990) find that “more than half of the shoppers who purchased an item that was on special were unaware that the price was reduced.” In addition, consumers consider few alternatives for each item they purchase and spend little time doing so (Hoyer, 1984). Lennard, Mitchell, and McGoldrick (2003) report that only half of the consumers use unit pricing as an information source to find the best option.³² The other consumers find that the information is too complicated to use or report that they do not have the time to compare prices.

The cognitive evidence that many consumers do not systematically process point-of-purchase price information challenges the standard assumptions of models on consumer decision making. At the same time, there is ample evidence that actual consumer purchases are consistent with the “law of demand” (that sales are inversely related to prices) and empirical demand models that depend on rational choice assumptions produce reasonable estimates. As a result, the mainstream literature has largely regarded the evidence on behavioral biases as interesting but inconsequential and the two literatures remain separate. Our findings present a more direct challenge to full information models of rational choice because they question the outcome rather than the underlying assumptions. Any standard demand model will predict that consumers will exploit arbitrage opportunities when these are available and plainly obvious. By contrast, we

³²Unit price comparison was possible in our application because information on unit pricing was posted together with the product’s price. The European Parliament and the European Council (1998) established directive 98/6/EC on consumer protection, compelling stores to display unit prices in an unambiguous, easily identifiable, and clearly legible way.

find that when the small pack is promoted, buyers of regular brand do not arbitrage and only half of the buyers of value brands arbitrage.

The fact that consumers are not aware of all prices at all times has been recognized for a long time. The marketing notion of “consideration set”, that goes back to Howard and Sheth (1969), argues that consumers only look at a selected subset of products. More recently, Piccione and Spiegler (2009) have assumed that consumers follow procedural rules to decide what product to purchase (e.g. first choose a pack size and then select a product of that size). These models are useful ways of operationalizing consumer behavior but they do not actually address the issue of why consumers behave in that way. There are also other concerns that are specific to our application. For example, consumers would have to sometimes change procedural rules to accommodate the fact that substitution takes place in the long run.

Why is it that many consumers do not make simple unit price comparisons? After all, the cost of visually scanning the supermarket aisle for possible promotions seems quite small and the savings of close to €1 are not negligible. Dubé, Hitsch, and Rossi (forthcoming) have recently introduced the concept of psychological switching cost to explain inertia in consumer choice. Another explanation, recently developed in the literature on rational inattention, is based on the concept of costly information. A literal interpretation would say that the consumer optimization problem includes many products and it is costly to check all options at the store. As a result, some consumers may decide (rationally) to not compare prices each time they visit a store. The consumers who do not systematically compare prices may miss out on promotions. But they rationally check prices at contingent “planning dates” and this explains why demand responds to permanent price changes. Assuming that consumers vary in their monitoring costs could explain the large responses to promotions and the difference between branded and value brands. It would also explain both the evidence from the cognitive research on price knowledge and the difficulty of finding violations of the law of demand (due to lack of arbitrage).

But one may argue that the time cost of checking prices is too low in our application to justify inattention as optimal behavior. Consumers do not have to check many prices to take advantage of promotion opportunities. For example, consumers could follow simple rules such as “*buy the cheapest per-unit pack of product X*”. Consumers who would adopt such rules would do better than the consumers in our sample. This, however, is not the correct comparison. The potential savings have to be adjusted by the probability that a suitable substitute is on promotion on the particular day. An alternative way to think of this issue is to consider a consumer who prepares a shopping list for a trip to the grocery store. The consumer knows that some items on her list will be on promotion but she does not know which ones. She can either go through the retailer’s advertising leaflet in order to identify the weekly promotions or she can look for them once she

gets to the store. Either way, there is a cost involved with identifying promotions.

The point can be made somewhat more concrete. In our sample, a product is on promotion 6.7% of the time. The average savings from buying on promotion is around €1. If there is only one alternative, the expected savings from checking whether the alternative is on promotion is only 6.7 cents. To eliminate arbitrage, a consumer has to find out whether a smaller pack exists, locate it, make sure it is the same physical content, and then compare the unit prices. This may take several seconds. Hoyer's (1984) study of consumer in-store decision making for laundry detergents reports that the median consumer considered only 1.19 packages when making a purchase and spent 4.77 seconds per brand. Taking this literally, suppose that it takes about 5 seconds to check a price. Engaging in a price comparison requires checking two prices, which takes 10 seconds. A consumer with an opportunity cost of time greater than about €24 per hour ($=.067*3600/10$) should not look for promotion before buying a non-promoted item. This calculation accounts only for the time cost of checking prices. If some consumers get disutility from engaging in price comparisons would only reinforce the conclusion. Costly information seems like a reasonable explanation for the finding that some consumers do not arbitrage.

How many consumers are inattentive? Our data do not allow us to say anything definitive, but we can make some progress toward getting an answer. We first note that if attentive and inattentive consumers consume similar quantities of detergent – which seems plausible – then the fraction of inattentive consumers in the population will be equal to the fraction of purchases made by inattentive people. This is a useful observation because the latter figure may be easier to approximate. From the estimates in Table 3 we know that the sales of the large size drop by 20.5% when there is a quantity surcharge. The implication is that 79.5% of purchases of the large size during regular periods are made by consumers who do not check prices. If we assume that each unit sold corresponds to one individual (which is consistent with evidence reported in Hendel and Nevo (2006a)), this implies that 79.5% of consumers who usually buy large packs during non-promotion periods are inattentive.³³

A rough lower bound for the fraction of inattentive consumers in the entire population is 79.5% times the fraction of regular buyers of large sizes. This calculation yields an estimate of 27.0% of sales going to inattentive consumers, implying that the fraction of inattentive in the population is also 27.0%.³⁴ This probably underestimates the fraction of inattentive consumers

³³The results reported in Table 4 give a similar figure. According to the estimates, only 7.4% of premium brand buyers are attentive, versus 48.1% of value brand buyers. During regular periods, premium brands have an aggregate market share of 58.3%. Taking this as an estimate of the number of premium brand buyers, the implied proportion of inattentive in the population is 75.6%, not far from the 79.5% above.

³⁴We compute the fraction of regular buyers of the large sizes as follows. The denominator is total sales during the 120-week period. We obtain this by adding sales for each product during the entire period. For products that

because it only considers inattention (a) among buyers of the large size (b) to promotional prices. A deeper issue is that attention is probably not an all-or-nothing outcome. Consumers may be attentive to some prices and not to others. Our results only speak to inattention to arbitrage opportunities. The 27.0% figure is clearly a ballpark estimate but it suggests that the fraction of inattentive consumers is not negligible and their presence should be taken into account when constructing demand models.

4.2 Implications

Part of our evidence is inconsistent with most models of consumer decision making that have been used to explain firm pricing (nonlinear pricing or promotion) and to estimate consumer demand for grocery products. These models are based on assumptions that do not correctly capture consumer responses to short and long term price changes. We briefly discuss some implications.

Demand models that are used in empirical studies of nonlinear pricing (Cohen, 2008; Thomas, 2009) or consumer inventory (Hendel and Nevo, 2006a) typically assume that consumers know all prices, and most importantly, that they purchase the item with the lowest price. This is inconsistent with the finding that a significant fraction of consumers buy a dominated option. Short-run consumer inattention may wrongly lead us to conclude that there are strong preferences for specific pack sizes. Long-run demand responses show that this is not the case. Inattentive consumers are also likely to overlook promotion of competing products. If so, demand models that do not allow for consumer inattention may wrongly attribute the limited extent of cross-brand substitution during promotions to brand loyalty.

The common finding in the promotion literature that short-run demand elasticities are smaller than long-run ones has been attributed to inventory storage costs, commitment, adjustment frictions, or switching costs. Our evidence suggests that demand substitution may be small in the short run for entirely different reasons. There is no adjustment friction or switching cost in our application. The only friction that prevents consumers from switching is whether they process price information.

It might be argued that the evidence on quantity surcharge during promotion periods is a challenge to nonlinear pricing theory, which predicts quantity discounts and explains them as

are not available in all periods we apply the necessary correction to obtain a sales estimate for the entire period. To obtain the numerator, we calculate the median sales of the large size during regular periods and multiply by 120 to obtain total sales of the large size to regular-period buyers throughout the sample period. Note that in the calculation we only consider products that come in two sizes.

a mechanism for exercising price discrimination (Stole, 2007; Maskin and Riley, 1984).³⁵ But this is not the case once one accounts for the fact that inattentive consumers do not respond to promotion opportunities. The assumption at the heart of nonlinear pricing theory, that the buyers of the large pack would substitute to the low pack in the event of quantity surcharge does not hold for short term price decreases. Firms violate the concavity of their product lines for short periods of time in a promotion, but there is little cost doing so.³⁶ Everything else equal, firms should promote less often products for which there is more substitution. Interestingly, value brands, for which there is more substitution, are promoted less often than premium brands. The median value product is on promotion 4.4% of the time while the median premium product is on promotion 8.3% of the time, almost twice as often. This indicates that firms internalize the fact that promotions can come at the cost of losing sales from competing packs - the cannibalization effect.

5 Summary and conclusions

Consumers do not fully exploit arbitrage opportunities arising when a small pack size of a detergent product is heavily discounted. Looking specifically at value brands, we found that the large size of a value brand loses roughly half its sales when its smaller counterpart is promoted. This means that the other half of regular buyers of large size value products choose a dominated option during promotions of the small size. With premium brands, we pick up no impact at all on the sales of the large size in a similar situation. Essentially, all buyers of large size premium products choose a dominated option during promotions of the small size. We also find no statistically significant evidence of substitution away from the small size when the large size is promoted.

These findings come from estimating consumer responses to temporary price reductions. The fact that we find only partial substitution (or no substitution in the case of premium brands) is somewhat surprising but not shocking. What would be shocking is if consumers did not respond at all to *permanent* price changes. In order to examine this possibility we estimated simple demand functions designed to give us estimates of long-run price elasticities. We found that

³⁵Both the economic and marketing literatures have applied the theory of nonlinear pricing to consumer packaged goods and most empirical studies use grocery data. McManus (2007) applies the theory of nonlinear pricing to the market for coffee drinks, Cohen (2008) to the paper towel market, and Allenby, Shively, Yang, and Garratt (2004) to the beer market. In a review of nonlinear pricing for the *Handbook of Pricing Research in Marketing*, Iyengar and Gupta (2009) quotes consumer package goods as one of the leading applications of nonlinear pricing.

³⁶Another implication is that one should be careful in the conduct of empirical analysis of nonlinear pricing and distinguish promotion and non-promotion periods. Our results suggest that the nonlinear price schedule should be computed using long term substitution responses.

both own-price and cross-price elasticities were quite reasonable and – importantly – non-zero, even in the case of premium products. Consumers therefore do respond to permanent price changes.

We propose an interpretation of these findings based on the concept of costly information. Keeping track of the prices of every product and its close substitutes on a weekly basis is a time-consuming and, for many people, unpleasant task. Back of the envelope calculations suggest that it is quite plausible that the cost of time associated with the process of collecting and processing information might exceed the expected benefit from it, at least for some consumers. These consumers will choose to not be attentive to temporary price changes. Information complexity does not have to be great to generate significant deviations from the predictions of the standard rational, full-information model.

This explanation helps reconcile the cognitive evidence that many consumers are not aware about point-of-purchase prices with the wide body of evidence in support of empirical demand models. Violations of the ‘no arbitrage condition’ implied by these models can be found for temporary price reductions but disappear with time aggregation. We argue that the lack of substitution in response to promotion is not a mere curiosity. It is inconsistent with the consumer behavior assumed in discrete choice models that have been used in the context of grocery products to explain firm pricing practices (nonlinear pricing and sales) and to estimate consumer demand. Our findings point out some directions in which to generalize these models in order to obtain better demand estimates.

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