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WORKING PAPER

Implicit Contracts and Price Stickiness: Evidence from Customer-Level Scanner Data

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Implicit Contracts and Price Stickiness: Evidence from Customer-Level Scanner Data *

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Abstract

This paper uses scanner data at the individual customer level, compiled from the loyalty card database of a European retailer, to determine the importance of implicit contracts as a source of price stickiness. Drawing from Customer Relationship Management (CRM), we use segmentation techniques and cluster analysis to split up the customer base in three groups according to their behavioural loyalty to the retailer. We then perform a demand analysis on the loyal and non-loyal segments in parallel, discarding the large middle cluster. Our results from estimating a Behavioural Almost Ideal Demand System (B-AIDS) for numerous product categories reveal that loyal customers have a considerably more concave demand curve than non-loyals. This result holds true in the aggregate, and for all but some individual product categories. The more pronounced asymmetry in the price elasticity of demand for loyal customers is a major incentive for the retailer to commit to a sticky price.

JEL: C33, C38, D12, L14
Keywords: Customer loyalty, Clustering, Curvature of demand

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1 Introduction

Price stickiness is key to explain the real effects of monetary policy. It is therefore incorporated in most theoretical macro models. Despite its importance in explaining business cycle movements, the empirical assessment of the sources of price stickiness has until now been relatively limited. Menu costs or sticky information are traditionally the go-to sources of sticky prices in macroeconomics, although they can hardly explain the extent of price rigidity or the abundance of small price changes found in micro data (Klenow and Kryvtsov, 2008).

Okun (1981) conjectures that price rigidity originates from an invisible handshake between a firm and its customers, both gaining from a long-term relationship in customer markets. Through a stable pricing policy, the firm can discourage its regular customers from shopping elsewhere, whereas these customers can minimize their shopping costs. In other words, the firm commits to an implicit agreement with its regular customers not to increase prices when market conditions are tight (Nakamura and Steinsson, 2011). In exchange, the firm does not decrease its prices when demand is weak, because this would only attract less interesting bargain hunters. This implicit contract theory of price stickiness is backed up by survey results of Blinder (1991, 1994) and Blinder *et al.* (1998) for the United States, Hall *et al.* (2000) for the United Kingdom, Apel *et al.* (2005) for Sweden, and Fabiani *et al.* (2005) for the Euro Area [1].

The purpose of this paper is to empirically investigate the relevance of implicit contracts as a source of price stickiness in retailing, using customer-level scanner data from a large European retailer [2]. We do so by establishing a link between the price elasticity and curvature of demand and the loyalty of the customer. Our results confirm two key components of Okun's theory of customer markets. Firstly, the price elasticity of demand of loyal customers is lower than that of non-loyals. Firms choose stable prices in order to increase customer loyalty, which in turn decreases the price elasticity of demand and increases their profit margins. Secondly, loyal customers have a considerably more concave demand curve than non-loyals. Consumption of repeat customers is more elastic at high relative prices, presumably because they are very responsive to price levels that exceed what they experienced previously (Okun, 1981). Random buyers react less strongly to high relative prices because they only observe the current price and therefore have no terms of reference. On the other hand, consumption of the random shoppers is more

[1] These survey results are based on interviews and questionnaires, completed by a large sample of firms. Implicit contracts systematically outweigh all other declared sources of price stickiness, including menu costs and sticky information.

[2] An analytical approach to this issue is important as the available survey evidence may be sensitive to the wording of questions, the order in which they appear, and the setting in which they were answered (Blinder *et al.*, 1998).

elastic at low relative price levels because they are typically bargain hunters that search actively for low prices. Repeat customers were ready to buy at the previous price, so their reaction to a price reduction is bound to be low (Okun, 1981).

If a firm or retailer increases its price when demand is high, it risks to lose its high-value loyal customers. Cutting the price in the wake of depressed demand mainly attracts less interesting bargain hunters, who will shop elsewhere when demand picks up and the price returns to its original level. The asymmetrical price elasticity of demand for repeat customers is an important assumption at the basis of the implicit contract theory of price stickiness. It provides the retailer with ample incentive to keep prices stable in the wake of demand fluctuations, preventing the market from clearing. Sticky prices are the natural outcome of this process.

We use point-of-sale scanner data of an anonymous European retailer with a unique availability of price and quantity data at the level of the individual customer. Through the compulsory nature of the retailers' loyalty card program, we can perfectly detect for every individual at any point in time which products he or she buys in what quantity and at what price. To allow for a comparison of the price elasticity and curvature of demand between loyal and non-loyal customers, the individual card holders have to be divided according to some loyalty metric. In this paper, we will focus exclusively on behavioural loyalty because supermarket scanner data are less appropriate for studying the attitudinal dimension of loyalty (Allaway *et al.*, 2006).

Using segmentation techniques and clustering analysis, we divide the customer base into three loyalty segments. Discarding the large middle cluster, a comparative demand analysis of the top and bottom segment of the customer base highlights potential loyalty-induced differences in consumer behaviour. To obtain elasticity estimates for both segments in parallel, we estimate the Behavioural Almost Ideal Demand System (B-AIDS) of Dossche *et al.* (2010) with Stone price index approximation on a large number of different product categories. This model is an extension of the standard AIDS model developed by Deaton and Muellbauer (1980), capable of fully capturing potential non-linearities in the demand curves for individual product categories. It is of the utmost importance to be able to freely estimate the curvature of demand if we want to test for loyalty-induced effects of price change.

Although we find wide variation in the estimated elasticities and curvatures across product categories, the recurring image from the data is a more concave demand curve for the loyal customer segment compared to the non-loyals. Loyal shoppers value a stable price, whereas this is less important for infrequent customers. This result supports implicit contracts as a source of price stickiness, as price setters will want to commit to a stable price in order to preserve the relations with their loyal customers. Our results can serve as a useful input for the calibration of macro models with heterogeneous customers.

The remainder of the paper is organized as follows. Section 2 describes the scanner data in more detail. Section 3 introduces the loyalty concept used in this paper and presents the segmentation analysis that divides the customer base according to the level of loyalty. In section 4, we estimate a demand model and derive elasticity and curvature estimates for a large number of product categories, and perform a comparative analysis of the loyal and non-loyal customer segments. Section 5 concludes.

2 Data

We use point-of-sale scanner data, gathered from six stores of an anonymous euro area retailer. Whenever a product is scanned at the counter of one of these stores, the scanning device registers the purchase transaction and saves it in a transactions database. The retailer offers a very wide range of approximately 15000 stock-keeping units, covering 40% of euro area CPI. They are registered at a very detailed level through their Universal Product Code (UPC). In this project, we use daily transactions data running from January 2002 until November 2004.

This dataset has been used before by Dossche *et al.* (2010) and Verhelst and Van den Poel (2010), albeit at a more aggregate level. Their results confirm a number of stylized facts of price setting: regular prices are sticky, although the frequency of price change is extremely heterogeneous across products; price decreases are quite common, even after filtering out temporary sales promotions, providing no proof of downward rigidity in retail prices; the size of price changes is large compared to aggregate inflation, although many small price changes do occur. These findings are in line with previous results on price setting in the Euro Area based on broader CPI-data (Dhyne *et al.*, 2005).

This paper explores for the first time the individual customer dimension of the data. Through a system of compulsory loyalty cards, each purchase transaction is linked to an individual customer. Consequently, the invoice lines of the transactions database show us for each day of the considered data period who buys what product in what quantity and at what price. Our dataset contains slightly more than 1.3 million unique customers who visited one of the stores at least once during the period 2002-2004. Together, they paid approximately 72 million visits to one of the stores in the three-year period under consideration, during which they bought a total of nearly 658 million items in varying quantities. The extensive nature of the database and its level of detail offer a unique possibility to study differences in consumer behaviour according to individual characteristics, more specifically the behavioural loyalty of the customer.

As we discuss in section 4.2, this transactions dataset will be limited to 20 broad product categories based on market share and price variation requirements in order to keep estimation of the demand models manageable. The number of unique customers that consumes at least one item from those categories during the period 2002-2004 drops to slightly less than 1 million. The data period can be divided into 76 bi-weekly periods, during which the price is kept constant as a policy choice of the retailer. In other words, every two weeks there is a price review of all the items, at which point the retailer can choose for each individual item to change its price or not. Between price reviews, all prices remain unchanged, so the retailer does not continuously adapt its prices to changes in market conditions. It is important to note that price policy is centralized, so prices and price changes are identical across the different stores of the retailer.

Verhelst and Van den Poel (2010) show that temporary price markdowns are quite common in the dataset. It is important to take this into account when estimating elasticity and curvature parameters, because the promotional price elasticity is generally much higher than the regular price elasticity (Bijmolt *et al.*, 2005). Every temporary price markdown of an item is accompanied by the item being mentioned in the retailer's circular, and our dataset contains an indicator variable that is equal to 1 if it is included in the circular and 0 otherwise. When estimating our demand models, this indicator variable will be very useful as a dummy variable that captures the effect of price promotion and increased visibility of the item on the elasticity and curvature of demand.

3 Customer segmentation

The segmentation of the customer base in homogeneous groups according to the level of loyalty is a recurring subject in Customer Relationship Management (CRM). Customer value analysis is important, as retaining a loyal customer is much cheaper than attracting a new one (Cheng and Chen, 2009). Hence, it pays off for the retailer to concentrate marketing efforts on detecting and rewarding their most loyal customers to solidify their allegiance (Allaway *et al.*, 2006).

The RFM model, in which the behavioural loyalty of customers is measured by the recency, frequency and monetary value of past purchases, has been used extensively by marketeers over the past fifty years (Hughes, 2005) [3]. Once each customer is scored

[3] A good description of the RFM model can be found in Bult and Wansbeek (1995), Jonker *et al.* (2004), Pauler and Dick (2006) and Cheng and Chen (2009), among others.

on the three dimensions of the model, clustering techniques can be applied to split the customer base into segments based on some distance measure over the quantitative input attributes R, F and M. This procedure is generally used to find the optimal number of clusters with as much inter-cluster heterogeneity and intra-cluster homogeneity as possible (Jonker *et al.*, 2004). It usually serves direct marketing purposes, by distinguishing a limited number of highly loyal customers that are likely to react to targeted marketing programs, hence maximizing profit for the retailer (Pauler and Dick, 2006).

The aim in our analysis is slightly different, as we simply want to separate the loyal from the non-loyal customers in our dataset. We therefore discard the recency coordinate, as it does not convey the loyalty of a customer over a prolonged period of time. The frequency (F) and monetary value (M) of purchases are therefore the quantitative variables that we use as yardsticks to measure store loyalty [4]. To this end, we calculate for each individual customer the number of times he or she visited the store over the considered data period (F), and the total amount of money spent during that period, in euro (M). In other words, all customers are scored on the F and M attributes, and these numeric scores serve as the input for a clustering analysis that splits the customer base into a predetermined number of homogeneous and disjoint clusters, taking into account the different scale of the F and M scores and their correlation structure. The purpose of this procedure is to obtain a grouping in which customers are similar within the same cluster, but dissimilar to the customers in any of the other clusters (Cheng and Chen, 2009). Both attributes are given equal weight in the analysis that follows. Although there is a clear positive correlation between the frequency and monetary value of purchases in our data, with a correlation coefficient of 0.47, they do measure different dimensions of loyalty and deserve to be treated as two separate aspects of customer loyalty.

In order to measure the similarity or dissimilarity between customers with respect to F and M, we need to define a certain distance metric (Ryu and Eick, 2005). The most commonly used metric is the Euclidean distance, which is defined between two customers i and j as follows

$$d_E(i,j) = \sqrt{(i-j)^T(i-j)} \tag{1}$$

where in our two-variable case $i = (i_F, i_M)^T$ and $j = (j_F, j_M)^T$ and i_F, i_M, j_F and j_M are the scores of customers i and j on frequency and monetary value, respectively. However, this distance measure requires that the F and M scores are measured at the

[4] We assume that store loyalty and supermarket loyalty are equivalent, because the six stores in our dataset are located far from each other and individual customers do not visit more than one store.

same scale, and are uncorrelated [5]. As both requirements are violated in our setting, we work with Mahalanobis distance instead, which is scale-invariant and allows for positive correlation between F and M. It is defined between two customers i and j as follows

$$d_M(i,j) = \sqrt{(i-j)^T \Sigma^{-1} (i-j)} \tag{2}$$

where Σ is the within-cluster covariance matrix and all other variables are defined as before. As the composition of the clusters is not known beforehand, we estimate Σ from the initial F and M values of each customer using the methodology of Art *et al.* (1982).

The clustering procedure itself is in fact an optimization problem. The eventual partitioning of the customers is based on the least-squares criterion, i.e. the minimization of the sum of square-error for all customers in the database, with the errors defined as the Mahalanobis distances between each customer and the cluster centers

$$E = \sum_{c=1}^{k} \sum_{i \in C_c} |i - m_c|^2 \tag{3}$$

where k is the number of clusters, i is the point in the F-M plane representing individual customer i, and m_c is the mean of cluster C_c. To minimize (3), the algorithm will assign each customer to the cluster with the closest mean.

We choose to apply the K-means clustering procedure of MacQueen (1967), in which each cluster is represented by the center of the cluster. The number of clusters k needs to be chosen in advance, here we fix it at three. By forming three clusters and discarding the middle one, we can highlight the potential differences in elasticity and curvature between the loyal and non-loyal segment, without worrying about customers that are somewhere in between and could potentially add a lot of noise to the comparison. The k-means clustering procedure with $k = 3$ will produce exactly three clusters of the greatest possible distinction, as compact and as detached as possible (Pauler and Dick, 2006). There are two major steps when performing this method, the assignment step and the reestimation step (Wu *et al.*, 2009). In the first step, the algorithm chooses three customers as a first

[5] The different scale of F and M implies that the variance of the monetary variable is much larger than the variance of the frequency variable, therefore M has more effect on the resulting clusters than F if the distances are not normalized. The positive correlation between the F and M attributes implies that customers i and j are distributed around their cluster center in a non-spherical manner, so that allocation of the customers towards the different clusters should take into account not only the distance to the cluster center, but also the direction.

guess of the initial cluster centers. Then, all other customers are assigned to the cluster that minimizes the Mahalanobis distance between the customer under consideration and the cluster mean over the coordinates F and M. The clusters that we obtain at this stage are only temporary. Once all customers are assigned, the cluster means are recalculated during the second step and the algorithm repeats by examining each customer again and placing it in the cluster with the closest mean. This iterative process continues until there is no longer a reassignment of customers among the different clusters.

We have to take into account that the results of the k-means clustering procedure are sensitive to the presence of outliers in the data (van der Laan *et al.*, 2003). When we look at our customer base, we notice that there are a limited number of heavy buyers. Both the choice of initial cluster centers in the assignment step and the iterative formation of the clusters in the reestimation step will be impacted by these outliers. We will now explain how we adapt the standard k-means clustering procedure to deal with both sources of outlier distortion in the final clusters.

The initialization method of the algorithm is designed to find reasonably good clusters during the assignment step, i.e. even before any reestimation occurs. As such, outliers have a higher probability to be chosen as an initial cluster center. To avoid this inherent pitfall of the procedure, we perform a preliminary cluster analysis with 100 clusters. In the next step, each cluster containing less than 20 customers is deleted, and the centers of the remaining clusters are used as input seeds in an assignment step with $k = 3$. In this way, outliers are excluded as potential cluster centers. The rationale is that outliers will be far away from most other customers with respect to F and M, so that they end up in a low-frequency cluster during the preliminary cluster analysis. Once the cluster centers are set, the excluded outliers are reintroduced into the dataset before the reestimation step starts.

Although the influence of severe outliers on the initial cluster centers is dealt with by the deletion of low frequency clusters in the preliminary analysis, they still threaten to distort the natural formation of the clusters during the multiple iterations of the k-means algorithm by pulling the cluster centers towards them. To avoid that, we resort to the L_p clustering criterion of Späth (1985) with maximum reduction of outlier effects. This method does not minimize the mean square difference between customers and their respective cluster means, as in the standard case of k-means clustering without outlier correction, but the mean absolute difference between customers and their respective cluster medians. Instead of equation (3), the partitioning criterion therefore becomes

$$E = \sum_{c=1}^{k} \sum_{i \in C_c} |i - m_c| \tag{4}$$

with m_c now defined as the median of cluster C_c and all other variables as defined before. This criterion introduces a weighting scheme in the algorithm that favors customers close to the cluster centers when recomputing the latter. In other words, it minimizes the influence of outliers on the reestimation of the cluster centers.

Table 1 contains some descriptive statistics of the three clusters that we obtain from the adapted k-means clustering procedure described above and compares them with those of the joint dataset [6]. As can be seen in the table, we obtain a non-loyal cluster containing approximately 80% and a loyal cluster with less than 4% of the customers [7]. The remaining 16% end up in the middle cluster and will be discarded for the demand analysis of section 4. Although the loyal customers make up only a small part of the customer base, they are in fact responsible for one third of total expenditure at the six stores under consideration, only slightly less than the much larger non-loyal segment. The cluster median of the frequency variable for the non-loyal and loyal customer groups are 5 and 51 times, respectively. For the monetary value of the purchases, the respective cluster medians are 48 and 1564 euro.

Table 1: Descriptive statistics of clusters

	Joint	Loyal	Neutral	Non-loyal
# of customers	998086	35212	161512	801362
Median frequency	5.00	50.83	23.61	4.80
Median monetary value	73.38	1564.47	495.85	47.66

4 Demand analysis

4.1 The model

Now that the customers are segmented, we can test for loyalty-induced differences in their spending behaviour through a comparative demand analysis of the loyal and non-loyal

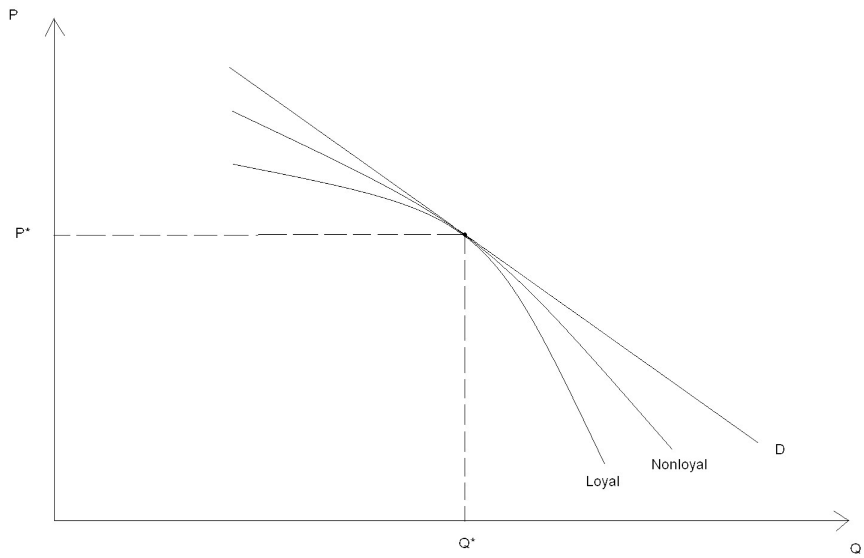
[6]This analysis is based on the limited dataset containing the 20 product categories that we select based on market share and price variation requirements, see section 4.2 for more details.

[7]This outcome is in line with the finding of Allaway *et al.* (2006) that only a small percentage of loyalty card users demonstrate behaviour that can be considered truly loyal.

clusters. Two important aspects of the analysis are the elasticity and the curvature of demand. The elasticity measures the responsiveness of the quantity demanded of a good to a change in its price, whereas the curvature measures the price elasticity of the price elasticity, i.e. the sensitivity of the price elasticity of demand for a good to a change in its relative price (Dossche *et al.*, 2010). The curvature is indicative for the change in the slope of the demand curve at different levels of the relative price.

When the relative price of a good increases, frequent buyers cut back on consumption by more than non-loyal customers. The former are very responsive to price levels that exceed the previously experienced price, whereas the latter only observe the current price level without reference to previous prices. When the relative price of a good decreases, random shoppers will increase their consumption by more than the loyal customers. The former are more likely to be bargain hunters and actively search for a low price, whereas the latter were ready to buy at the previous price and therefore react less to price reductions. Consequently, we expect to find a higher curvature parameter, i.e. a more concave demand curve, in the loyal segment of the customer base. Figure 1 shows a graphical representation of the above argument [8].

Figure 1: Demand curve for loyal and non-loyal customer segments



[8]The graph serves as a mere illustration of the argument. It is not based on any specific elasticity or curvature parameters in the data, nor does it need to be the case that loyal and non-loyal customer segments have the same price elasticity of demand at P^*.

In order to derive the elasticity and curvature parameters for both segments, we resort to the Behavioural Almost Ideal Demand System (B-AIDS) of Dossche *et al.* (2010). This is an extension of the workhorse AIDS model of Deaton and Muellbauer (1980), capturing the potential non-linearity in the demand curve, and allowing for flexible estimation of the required parameters. The standard AIDS model is based on the PIGLOG class of consumer preferences, it permits exact aggregation over consumers, and provides a local first-order approximation to any true demand system (Deaton and Muellbauer, 1980). Although the AIDS model is perfectly suited for an analysis of supermarket scanner data, and is known for its flexibility, transparency and ease of estimation, the standard version of the model does not allow for free estimation of the curvature parameter (Dossche *et al.*, 2010). The behavioural extension of the AIDS model offers a solution to this shortcoming by introducing a quadratic effect of the relative price of a good on top of the usual direct price effects. The basic specification of the B-AIDS model in budget share form is the following,

$$s_i = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln p_j + \beta_i \ln \left(\frac{X}{P}\right) + \sum_{j=1}^{N} \delta_{ij} \left(\ln \left(\frac{p_j}{P}\right)\right)^2 \tag{5}$$

where i=1,...,N is the number of items included in the demand system, $s_i = (p_i q_i)/X$ is the expenditure share of item i in the product category, p_j is the price of item j, X is total category expenditure, and P is the translog price index for this particular product category. It is defined by Deaton and Muellbauer (1980) as

$$\ln P = \alpha_0 + \sum_{j=1}^{N} \alpha_j \ln p_j + \frac{1}{2} \sum_{j=1}^{N} \sum_{i=1}^{N} \gamma_{ij} \ln p_i \ln p_j \tag{6}$$

When we look at equation (5), the added quadratic term in the relative price is immediately obvious [9]. The model hence allows for a nonlinear effect of the relative price level of an item on its expenditure share in the category. The standard AIDS model is nested in equation (5) as a special case when $\delta_{ij}=0$. The extended equation (5) is a valid representation of consumer preferences as long as the standard adding-up ($\sum_{i=1}^{N} \alpha_i = 1, \sum_{i=1}^{N} \gamma_{ij} = 0, \sum_{i=1}^{N} \beta_i = 0, \sum_{i=1}^{N} \delta_{ij} = 0$), homogeneity ($\sum_{j=1}^{N} \gamma_{ij} = 0$), and symmetry ($\gamma_{ij} = \gamma_{ji}$) restrictions hold (Dossche *et al.*, 2010).

For ease of computation, Deaton and Muellbauer (1980) propose an approximation of the nonlinear translog price index given in (6) by the Stone price index, defined as

[9] In section 4.4, we check the robustness of our results to the price index specification in the quadratic term of the expenditure share equation (5).

$$\ln P^* = \sum_{i=1}^{N} s_i \ln p_i \tag{7}$$

where s_i is again the expenditure share of good i in the product category, and p_i is the price of item i. The use of the Stone index as an approximation to the true nonlinear price index makes the demand model linear in the parameters and facilitates its estimation. The linear approximation is highly accurate when the different price series of the demand model are collinear (Alston *et al.*, 1994). We estimate our demand models at the product category level, based on item price series inside relatively narrow product categories. These can be expected to show considerable collinearity, making the linear approximation very accurate in our context.

Based on the coefficients of the linear approximate B-AIDS demand model, Dossche *et al.* (2010) show how to derive the elasticity and curvature parameters of the demand model. The computation of the price elasticity of demand is based on the approximation approach of Alston *et al.* (1994) and Buse (1994), which they show to be superior to many other methods using Monte Carlo simulations. This approach leads to the following expression for the positive uncompensated price elasticity of demand

$$\varepsilon_i = 1 - \frac{\gamma_{ii}}{s_i} + \beta_i - \frac{2\delta_{ii} \ln(p_i/P^*)}{s_i} + 2\sum_{j=1}^{N} \delta_{ij} \ln\left(\frac{p_j}{P^*}\right) \tag{8}$$

This expression for the elasticity of demand in the Behavioural AIDS model clearly incorporates nonlinear effects of the relative price, which were introduced by the quadratic term in the budget share equation (5). If $\delta_{ii} < 0$, the relative price has a positive effect on the elasticity. Given that s_i is typically far below 1, this will likely imply a concave demand curve, i.e. the elasticity of demand is higher when the relative price is high. When $\delta_{ii} > 0$, the demand curve will most likely be convex.

At steady state, all relative prices are equal to 1, and the expression for the price elasticity of demand is identical to the one from the standard AIDS model

$$\varepsilon_i = 1 - \frac{\gamma_{ii}}{s_i} + \beta_i \tag{9}$$

Logarithmic derivation of equation (8) with respect to price gives the following implied curvature parameter at steady state [10]

$$\epsilon_i = \frac{1}{\varepsilon_i}\left[(\varepsilon_i - 1)(\varepsilon_i - 1 - \beta_i) - \frac{2\delta_{ii}(1-s_i)}{s_i} + 2\left(\delta_{ii} - s_i \sum_{j=1}^{N} \delta_{ij}\right)\right] \tag{10}$$

The impact of δ_{ii} on the curvature of demand is negative for reasonable values of s_i, i.e. the lower δ_{ii}, the higher the curvature of demand, ceteris paribus. The implied curvature parameter is still positively correlated with the price elasticity of demand, albeit less restrictively than in the standard AIDS model, in which $\delta_{ii} = \delta_{ij} = 0$.

4.2 Identification and Estimation

We randomly select 75 broad product categories as the starting point of our demand analysis. We follow the methodology of Dossche *et al.* (2010) and include four items per product category plus a fifth composite item, which is constructed as a weighted average of all other items in the category. This fifth 'item' is introduced to fully capture substitution opportunities for the four selected items. We choose to limit the category-level demand analysis to four main items in order to keep estimation manageable, both with respect to the number of parameters to be estimated and the availability of observations. In the B-AIDS model, the expenditure share of a certain item depends on the price of the other items inside the same category. If too many items are included individually, we risk losing observations due to shorter or non-overlapping data availability.

Due to these methodological choices, we limit the scope of the data to 75 product categories containing 5 items each. The selection of the four top products for each category is inspired by data availability and market share requirements. We first select the items which are available for purchase in each of the six stores at least 95% of the time, i.e. the item has to be on the shelf in each store in at least 73 out of 76 bi-weekly periods. This ensures a minimal loss of observations. Among the remaining items, four are selected based on highest market share in the category. All other items are bundled in the fifth, composite item called 'other'. If there are different top products across stores, we select those with the best ranking in most stores.

Once this is done for all 75 product categories, we impose two requirements on the categories for them to be withheld in the comparative elasticity and curvature analysis. First, we require the four selected top products to jointly represent at least a 20% market

[10] See appendix B of Dossche *et al.* (2010) for the mathematical derivation.

share of the product category to which they belong. This should ensure that these items are pivotal and can be viewed as representative for their category. Secondly, we want sufficient price variation for each of the selected items. More specifically, we require at least five price changes for each of the selected items [11]. At least one of these should be a regular price change, i.e. not a temporary markdown. This second requirement should ensure that a demand curve can be estimated accurately, and that the elasticity and curvature parameters that are derived from the coefficients of the demand model are significant. Out of the 75 product categories that we start with, only 20 satisfy both requirements. They are listed in Appendix A, followed by the number of items in each category. The surviving 20 categories contain a total of 961 items. As we mentioned before, slightly less than 1 million different customers have bought at least one of these items over the considered data period (see table 1).

The invoice lines in the loyal and non-loyal daily transactions databases that we created in the segmentation analysis are transformed into datasets with a bi-weekly frequency that contain the price and total quantity sold for all items. We do this in parallel for the loyal and non-loyal datasets. Selecting the appropriate product codes, these datasets in bi-weekly frequency are then both split up in 20 category-specific datasets each, which are then transformed in order to contain price and quantity data for the four top products and the composite good 'other'. This is the category-specific data structure that we use as input for the demand analysis. We therefore choose to estimate separate demand models at the product category level, limiting the risk of aggregation bias (Fisher *et al.*, 2001). Consumer preferences are assumed to be weakly separable, i.e. consumption decisions in one category are independent from price changes in other product categories. Intra-category allocation of expenditure is made without reference to outside prices (Baltas, 2002).

The empirical demand specification that we use is directly derived from the B-AIDS demand equation (5) and resembles the expression used by Dossche *et al.* (2010):

$$\begin{aligned} s_{imt} =& \alpha_{im} + \sum_{j=1}^{5} \gamma_{ij} \ln p_{jt} + \beta_i \ln\left(\frac{X_{mt}}{P^*_{mt}}\right) + \sum_{j=1}^{5} \delta_{ij} \left(\ln\left(\frac{p_{jt}}{P^*_{mt}}\right)\right)^2 \\ &+ \sum_{j=1}^{5} \varphi_{ij} C_{jt} + \tau_t + \lambda_{it} + \nu_{imt} \end{aligned} \tag{11}$$

where i=1, ..., 5 is the item identifier, m=1, ..., 6 is the store identifier and t=1, ..., 76 is

[11] A temporary markdown, which we define here as any episode of one or two price points below the most left and right adjacent price, is counted as one price change.

the time subscript defined in bi-weekly periods. s_{imt} is the expenditure share of item i at store m and time t. p_{jt} is the price of item j at time t, X_{mt} is total category expenditure at store m and time t, and P^*_{mt} is the store-specific Stone price index at time t. The quadratic term in the relative price captures potential non-linearities in the demand curve. The circular dummy C_{jt} is equal to one when item j is advertised and on display in the retailer's circular at time t. There is no subscript m as the circular is common to all stores. The time trend variable τ_t captures long-term shifts in expenditure share of one item relative to the other items in the category. Three separate holiday dummies λ_{it} are included for Easter, Christmas and New Year, which should capture shifts in spending behaviour linked to holiday festivities. The time trend and the dummies will capture broad demand shocks that are common across all stores. The intercept α_{im} captures item- and store-specific fixed effects, and controls for fixed product item characteristics and structural heterogeneity in consumer preferences across stores, for example due to a different regional demographic structure [12].

Studying store level data requires aggregation over individual consumers. Although this could wash out interesting differences between individual shoppers, it tends to average out individual stochastic behaviour, reducing noise in the dependent variable (Hoch *et al.*, 1995). We are only interested in potential differences in spending behaviour between the loyal and non-loyal segment of the customer base, hence the loss of information at the individual level is not problematic in our context.

The estimation methodology that we apply is Seemingly Unrelated Regression (SUR). At first sight, estimating a price-quantity relationship offers the classic example of an endogeneity problem, and resorting to IV estimation techniques would seem to be the most straightforward way of dealing with this problem. Nonetheless, we believe that there are no identification problems for the demand curve in our setting due to two characteristics of the data that prevent prices p_{it} to be correlated with the error term ν_{imt} (Dossche *et al.*, 2010). First of all, prices are set at the beginning of each bi-weekly period and remain unchanged for at least two weeks. Hence, the retailer introduces a source of nominal price rigidity in its price series, and does not continuously change its price to equilibrate supply and demand. Prices p_{it} are then predetermined with respect to equation (11), and should not be correlated with the contemporaneous error term ν_{imt}.

The second data characteristic that avoids correlation between the price and the error term and enhances identification of the demand curve, is the chain-wide price setting policy of the retailer. Every two weeks, all prices are reviewed across all store locations.

[12] To control for item-specific fixed effects, we have also demeaned $ln(p_{jt}/P^*_{mt})$ before introducing it into the quadratic term in the regression (Dossche *et al.*, 2010).

When they decide to change the price of a certain item i, they do so for every store simultaneously. There is no reason to suspect that chain-wide prices p_{it} would be correlated with the store-specific error term ν_{imt}. Specific demand shocks at the store-level that end up in the error term will not have enough weight to incite a price change at the chain-wide level.

One could of course argue that a forward-looking retailer will take into account anticipated demand fluctuations when they set the price of their products in the current period. This could potentially lead to correlation between the price and the contemporaneous error term. However, due to the price setting policy of our retailer, only anticipated demand shocks at the chain-wide level will be incorporated in their pricing decisions. Those should be captured by the circular and holiday dummies in the regressions, and hence not show up in the error term. The same argument applies to time-invariant item-specific characteristics, which will be captured by the fixed effect α_{im}.

Another argument against SUR arises if the retailer reacts to past demand shocks when setting the current price, for example by charging a higher price in the current period in reaction to a stockout in the previous period. However, this only leads to correlation between the price and the error term if demand shocks are correlated over time. Autocorrelation in the error term is very weak in our regressions, so this argument will not bias our results in any significant way. Taking all of these arguments into account, we can safely assume that endogeneity is not a threat to our results, and SUR is an appropriate estimation method. And even when the specific characteristics of our data were to be ignored, Buse (1994) shows that the modest advantage in bias of an IV estimator is more than offset by its larger variance. Dossche *et al.* (2010) re-estimate their B-AIDS model using an IV method as a robustness check and the 3SLS estimates for the elasticities and curvatures that they obtain are very similar to their SUR estimates.

Each category- and store-specific demand model is estimated separately. Homogeneity ($\sum_{j=1}^{N} \gamma_{ij} = 0$), and symmetry ($\gamma_{ij} = \gamma_{ji}$) restrictions are imposed to the model. Symmetry is also imposed on the effects of the circular dummies ($\varphi_{ij} = \varphi_{ji}$). When estimating each system of equations, we have to drop one of the five equations in order to avoid singularity of the contemporaneous variance-covariance matrix of the disturbances (Buse, 1994). We drop the equation for 'other'. Its parameters can be recovered using the adding-up conditions ($\sum_{i=1}^{N} \alpha_i = 1, \sum_{i=1}^{N} \gamma_{ij} = 0, \sum_{i=1}^{N} \beta_i = 0, \sum_{i=1}^{N} \delta_{ij} = 0$).

4.3 Results

Each category-specific demand model is estimated at the store level, and for loyal and non-loyal datasets in parallel, giving us 240 estimated demand models and 960 derived elasticity and curvature parameters, evenly split between the loyal and non-loyal customer segments [13]. These parameters can be compared in the aggregate, and on a category-by-category basis to detect potential loyalty-induced differences in consumption behaviour. Table 2 shows the price elasticity of demand by product category. The median price elasticity across the 20 categories is 1.52 for the loyal customer segment and 1.68 for the non-loyals. The latter therefore react on average slightly more to price changes, although the opposite is true for 8 out of 20 categories, pointing to extensive heterogeneity in the elasticity parameters across product categories. This is not a new result, and it originates in the combination of choice and quantity decisions. Loyal customers appear to be less price sensitive in the choice decision but more price sensitive in the quantity decision (Krishnamurthi and Raj, 1991). They buy certain items in any case, but adapt the quantity according to the current price level. Non-loyal customers on the other hand will only be persuaded to buy at the store when the price is low enough, so they either buy or they don't. The use of aggregate data masks the choice and quantity dimensions, making it hard to predict differences in overall price elasticities. The curvature parameter, which is the main part of our analysis, is positively correlated with the price elasticity of demand, so we have to take it into account when we compare the shape of the demand curve between loyal and non-loyal customers.

Table 2: Price elasticity of demand

Product Category	Loyals	Non-loyals	Product Category	Loyals	Non-loyals
Baking flour	0.94	0.97	Mineral Water	2.08	1.91
Chips	1.53	1.38	Nappies	2.54	3.69
Coke	2.41	1.38	Plasters	0.75	0.04
Detergent	0.18	0.84	Potatoes	0.79	1.17
Emmental	2.21	4.64	Smoked Salmon	3.32	4.46
Floorcloth	4.58	4.42	Sugar	0.92	0.67
Fruit Juice	0.50	0.81	Toilet paper	2.89	2.96
Lemonade	1.35	1.21	Tuna	1.50	1.68
Margarine	1.50	2.28	Whiskey	2.41	2.56
Mayonnaise	1.04	0.14	Wine	2.11	5.81
			MEDIAN	1.52	1.68

Note: The individual elasticity parameters of each product category are computed as the median across the four top products of the category and across the six stores under consideration.

The comparison of the curvature parameter between loyal and non-loyal customers is indicative for a potential discrepancy in the way consumers react to price changes. Com-

[13] The elasticity and curvature parameters of the composite item 'other' are not withheld in the comparative analysis due to its continuously changing composition.

paring both loyalty segments shows us if frequent shoppers indeed value a stable price more than non-loyal customers, which in turn supports the idea of implicit contracts as a source of price stickiness in retailing. Table 3 shows the curvature of demand by product category. The median curvature across the 20 categories is 5.08 for the loyal customer segment and 2.13 for the non-loyals. Hence, we find evidence that the loyal customers have a more concave demand curve. This result not only holds in the aggregate, but also for 16 out of 20 individual product categories.

Table 3: Curvature of demand

Product Category	Loyals	Non-loyals	Product Category	Loyals	Non-loyals
Baking flour	4.78	1.64	Mineral Water	3.22	-0.32
Chips	5.48	1.73	Nappies	8.44	6.83
Coke	5.53	2.04	Plasters	2.91	-2.08
Detergent	-4.62	-3.04	Potatoes	0.33	0.12
Emmental	6.29	4.49	Smoked Salmon	1.41	2.22
Floorcloth	7.64	6.48	Sugar	7.98	1.23
Fruit Juice	0.79	0.33	Toilet paper	3.42	3.77
Lemonade	3.09	-0.40	Tuna	4.29	3.60
Margarine	6.77	4.65	Whiskey	8.47	5.80
Mayonnaise	6.57	4.11	Wine	5.38	6.52
			MEDIAN	5.08	2.13

Note: The individual curvature parameters of each product category are computed as the median across the four top products of the category and across the six stores under consideration.

Taking into account that it is five times cheaper to keep a loyal customer compared to adding a new one, retailers will not want to risk antagonizing their loyal shoppers (Cheng and Chen, 2009). A situation ensues in which both the buyer and the seller have an interest in stable prices. This is the perfect breeding ground for a bilateral commitment to an implicit contract [14]. The power of the result is underscored by the fact that non-loyal customers have a slightly higher elasticity parameter. Due to the positive correlation between elasticity and curvature, this biases the results to finding no effect of loyalty. Although the aggregate curvature parameter is much lower for non-loyal customers, the latter also react more to price increases than decreases.

[14] Nakamura and Steinsson (2011) elaborate on this issue in a context where consumers are subject to internal deep habit formation. Firms then commit to an implicit contract/sticky price to manage customer's expectations about future prices.

4.4 Robustness

In this section, we check the robustness of our results with respect to some alternative model specifications, and provide some additional evidence in support of a loyalty-induced effect on the curvature of demand.

We test two distinct alternative specifications of the expenditure share equation by replacing the Stone price index by a different reference price in the quadratic term of equation (5). First, instead of looking at the effect of the relative price of the items inside its category on the expenditure share s_i of item i, we check the influence of price changes by imposing the price of the item in the previous period as the reference price instead of P^* in the quadratic term of equation (5)

$$s_{it} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln p_{jt} + \beta_i \ln \left(\frac{X_t}{P_t} \right) + \sum_{j=1}^{N} \delta_{ij} \left(\ln \left(\frac{p_{jt}}{p_{j,t-1}} \right) \right)^2 \tag{12}$$

Besides the relative price or the change in price with respect to the previous period, customers can also react to deviations of the price from a certain regular price level. To test this specification, we replace P^* in the quadratic term of equation (5) by the price that is most common in the 12-month period leading up to time t

$$s_i = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln p_j + \beta_i \ln \left(\frac{X}{P} \right) + \sum_{j=1}^{N} \delta_{ij} \left(\ln \left(\frac{p_j}{p_{j,reg}} \right) \right)^2 \tag{13}$$

Based on the coefficients of these alternative expenditure share specifications, the elasticity and curvature parameters can be calculated using expressions (9) and (10). Their median values across our 20 product categories are presented in table 4, together with the baseline results from the main analysis based on equation (5). Although there are some minor changes in the values of the elasticity and curvature parameters at the category-level, the cross-category results in table 4 confirm the key conclusions from section 4.3. The price elasticity of demand is slightly lower for the loyal customers, and more importantly, they have a more concave demand curve than the non-loyal customers. It appears that all specifications pick up the same basic characteristic of consumer behaviour that loyal customers value a stable and fair price. They react more negatively to high or increasing relative price levels and less positively to low or decreasing relative price levels than non-loyals.

Table 4: Elasticity and curvature parameters of alternative demand specifications

	ε_L	ε_{NL}	ϵ_L	ϵ_{NL}
Equation (5)	1.52	1.68	5.08	2.13
Equation (12)	1.34	1.51	4.81	2.20
Equation (13)	1.65	1.77	4.90	2.28

Note: ε_L and ε_{NL} are the elasticity parameters, and ϵ_L and ϵ_{NL} are the curvature parameters for the loyal and non-loyal segments, respectively.

The comparative analysis of the curvature parameter supports a loyalty-induced effect of the relative price level on the elasticity of demand. The B-AIDS model is able to incorporate this behavioural aspect of consumption through the presence of the quadratic term in the expenditure share equation (5). The value of the parameter δ_{ii} from the regression features prominently in the expression for the curvature of demand (10) and therefore directly translates into the value of the reported curvature parameter. Not surprisingly, the mean value of the 80 (20x4) estimates of δ_{ii} in our sample is almost three times larger, in absolute value, for the loyal compared to the non-loyal segment, -0.76 versus -0.27. However, neither the value of δ_{ii} nor the curvature parameters of table 3 imply anything about the significance of δ_{ii} or a potential difference therein between loyal and non-loyal customers. Therefore, we present in table 5 the percentage of significant estimates of δ_{ii} at different significance levels for both loyal and non-loyal customers segments.

Table 5: Significance of δ_{ii}

	Loyal	Non-loyal
10%	61%	33%
5%	55%	29%
1%	39%	23%

Note: The results are computed as the number of significant estimates of δ_{ii} divided by the total number of estimates, i.e. 80.

Irrespective of the significance level, the estimate of δ_{ii} is significant for a lot more products when we consider loyal compared to non-loyal customers. For loyal shoppers, δ_{ii} is significant at the 5% level more often than not, whereas this is the case for less than one out of three products when we consider the non-loyal customer segment. This confirms our main result of a loyalty-induced effect of the relative price level on the elasticity of demand, and the high percentages reported in table 5 lend firm support to the behavioural extension of the AIDS model as defined in equation (5).

5 Conclusion

Using supermarket scanner data, we show analytically that loyal customers have a more concave demand curve than non-loyal customers, where we define loyalty in a behavioural way based on the frequency and monetary value of purchases over an extended period of time. The more pronounced concavity of demand shows up in the aggregate, and for all but some individual product categories. It implies that loyal customers react more negatively to price increases, and less positively to price decreases than non-loyals. The preference for a stable price is increasing with the behavioural loyalty of the customer.

When the relative price level increases, loyal customers cut back on consumption more extensively than non-loyals. Repeat buyers are very responsive to prices that exceed the price level that they experienced in the previous period. Random shoppers only observe the current price and are less able to relate this price level to previous experiences. Their reaction is bound to be less strong. When the relative price level decreases, random shoppers will increase their consumption by more than the loyal customers. The former are more likely to be bargain hunters and search actively for a low price, whereas the latter were ready to buy at the previous price, so their reaction to the price reduction is bound to be low.

If a firm or retailer increases its price when demand is high, it risks to lose its high-value loyal customers. Cutting the price in the wake of depressed demand mainly attracts less interesting bargain hunters, who will shop elsewhere when the price returns to its original level. These findings provide ample incentive to the retailer to commit to an implicit contract. Volatile prices on behalf of the retailer risk to turn off high-value regular customers and hurt long-run profits. Sticky prices are a natural outcome of this process, as retailers will try to keep their prices as stable as possible in order to preserve the trust of their clientele. This empirical result supports the conclusion of survey evidence that implicit contracts are an important source of price stickiness.

Appendix A: Selected product categories

Product Category	# Items	Product Category	# Items
Baking flour	21	Mineral water	70
Chips	138	Nappies	65
Cola	42	Plaster	33
Detergent	43	Potatoes	26
Emmental	58	Smoked salmon	19
Floorcloth	11	Sugar	19
Fruit juice	57	Toilet paper	39
Lemonade	37	Tuna	72
Margarine	67	Whiskey	82
Mayonnaise	45	Wine	17

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