PRIVATE LABEL USE AND STORE LOYALTY

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ABSTRACT

Does private label use drive store loyalty? This question is important to retailers, as they decide how much to push private labels over national brands, and to national brand manufacturers, as they look for effective ways to both cooperate with and compete with retailers. Yet, empirical evidence of the association between private label use and store loyalty is both limited and mixed. In this study, we develop an econometric model of the relationship between a household's private label share and behavioral store loyalty. The model includes major drivers of these two behaviors and controls for simultaneity and non-linearity in the relationship between them. It is estimated using a unique dataset that combines complete purchase records of a panel of Dutch households with demographic and psychographic data. We estimate the model for two retail chains in the Netherlands -- the leading service chain with a well-defined private label strategy and higher private label share and the leading value chain with lower private label share.

We find that private label share significantly affects all three measures of behavioral loyalty in our study, share of wallet, share of items purchased, and share of shopping trips. And, behavioral loyalty also has a significant effect on private label share. For the service chain, we find that both effects are strongly non-monotonic in the form of an inverted U. For the value chain, the effects are positive and non-linear but do not exhibit non-monotonicity because private label share has not yet reached high enough levels. The managerial implications of this research are very important. Retailers can reap the benefits of a virtuous cycle – greater private label share increases share of wallet and greater share of wallet increases private label share. But, this virtuous cycle only operates to a point, as heavy private label buyers tend to be loyal to price savings and private labels in general, rather than to the private label of any particular chain.

Keywords: private labels, store brands, store loyalty, share of wallet, simultaneity, non-linear effects.

Private labels in the consumer packaged goods industry have seen a world-wide surge in availability and market share in recent years. Private labels now account for one of every five items sold every day in U.S. supermarkets, drug chains, and mass merchandisers, while the market share in Western Europe is even larger (Kumar and Steenkamp 2007). Planet Retail (2007, p. 1) recently concluded that "Private labels are set for accelerated growth, with the majority of the world's leading grocers increasing their own label penetration."

The main reasons for retailers' desire to grow private label (hereafter denoted PL) are (a) higher retail margins on PL; (b) negotiating leverage with national brand manufacturers; and (c) higher consumer store loyalty. Significant evidence in support of the first two reasons now exists in the literature (e.g., Ailawadi and Harlam 2004; Hoch and Banerji 1993; Narasimhan and Wilcox 1998; Pauwels and Srinivasan 2004). The focus of this paper is on the third reason – the purported ability of PL to improve consumers' loyalty to a particular retailer.

Conventional wisdom has it that PL use is associated with higher store loyalty. For instance, Richardson, Jain and Dick (1996) state that "store brands help retailers increase store traffic and customer loyalty by offering exclusive lines under labels not found in competing stores". Likewise, PLMA (2007) states that "retailers use store brands to increase business as well as to win the loyalty of their customers." Empirical evidence on the subject, however, is mixed. On one hand, a positive correlation between PL use and store loyalty has been observed in some studies (e.g., Ailawadi, Neslin, and Gedenk 2001; Kumar and Steenkamp 2007, pp. 119-120). Corstjens and Lal's (2000) analytical model supports PL's ability to build store loyalty and Sudhir and Talukdar (2004) also report indirect support for PL's store differentiating ability.

But, on the other hand, there is some evidence that consumers may not differentiate between the PLs of different retailers – PL users may be loyal to PL products in general, not to the PL of a particular retailer (Richardson 1997). If that is the case, it is hard to see how PL use would increase store loyalty. Indeed, Singh, Hansen, and Blattberg (2006) show that, among a retailer's customers, heavy PL users are more likely to switch to Wal-Mart when it enters the area. Thus, the jury is still out on whether PL use is associated with greater store loyalty.

Adding complexity to the question are two other issues. First, even if there is a positive correlation between PL use and store loyalty, the causality may be reversed – consumers who are loyal to a store may be more likely to buy its PLs, not the other way around. The process of spending a large portion of their time and money in the chain increases the consumer's familiarity with the chain's PL across multiple categories. Such familiarity with the chain's PL is an important predictor of private label proneness (Richardson, Jain and Dick 1996). Also, consumers who consistently shop at the chain instead of at its competitors, are more likely to attribute this shopping behavior to the chain's quality and may be more positively disposed to its PL. Consistent with this reasoning, Bonfrer and Chintagunta (2004) find that store loyal consumers are more likely to buy PLs. Clearly, implications for retailers are very different depending on which way the causality operates between PL use and store loyalty.

Second, the relationship may be non-linear, possibly even non-monotonic. Ailawadi and Harlam (2004) find that medium PL users do contribute more than light/non-users of PLs to retailer sales and profit, but heavy PL users contribute *less* than medium users. The ability of PL to increase store loyalty in Corstjens and Lal's (2000) model is also predicated on a "balance" between consumers who prefer PL versus national brands. It is critical to understand the nature of non-linearity in the effect of PL use on store loyalty and vice versa if retailers are to make smart decisions about whether and how much to push PL.

Despite the importance of the story loyalty – PL buying relationship, empirical evidence is generally limited to perceptual measures and bivariate correlational patterns. Only a handful of studies examine consumer purchase behavior across multiple product categories (e.g., Ailawadi and Harlam 2004; Corstjens and Lal 2000; Sudhir and Talukdar 2004). Among them, few actually have data on the consumer's loyalty to one or more retailers in the market (Corstjens and Lal 2000), and even fewer control for other drivers of PL share and store loyalty (Sudhir and Talukdar 2004). And, finally, not a single study models either simultaneity or non-linearity. Indeed, Ailawadi and Harlam (2004, p. 163) conclude that research combining demographic and psychographic variables with panel purchase data from multiple retailers in a market is needed to conclusively quantify this relationship.

Our objective is to fill this gap in the literature. We build a simultaneous model of the relationship between a household's PL share at a chain and its loyalty to that chain. PL share is defined as the household's PL spending (in dollars, or in our empirical study, euros) at the chain as a % of its total spending (in euros) in that chain on categories where the chain offers a PL product. Store loyalty is operationalized as the household's share of wallet (hereafter denoted SOW) in the chain, i.e., its spending in the chain (in euros) as a % of its total spending on supermarket products, but we validate our findings using two alternative behavioral loyalty measures, namely share of items purchased and share of shopping trips.

The model allows for reverse causality as well as non-linearity in the relationship between PL share and SOW, includes key determinants of both constructs, and is econometrically identified through several determinants that influence one construct but not the other. We use a unique dataset with complete information on the supermarket purchases of a Dutch household panel across all stores, as well as their demographic and psychographic data obtained through a survey. We estimate the simultaneous model for the two largest Dutch supermarket chains with clearly different positioning, one positioned on high “service” with high PL share and the other as the foremost “value” chain with lower PL share.

DATA

Our empirical setting is Dutch grocery retailing. Our dataset combines several sources. First, we use purchase records from GfK’s consumer hand-scan panel in The Netherlands for the period between January 1st 2001 and January 1st 2004. The GfK panel consists of over 4,000 panelists, representing a stratified national sample of Dutch consumers. With some attrition and new recruitment of panelists each year, the dataset contains three years of data from a little over 50% of the panelists, the remaining panelists being approximately evenly split between one and two years of data. Panel members use a home scanner to scan all their household purchases from all Dutch grocery retailers, and the data are sent electronically to GfK.

For the purposes of our study, the hand-scan dataset yields excellent measures of both key variables: SOW can be calculated with reference to all purchases by the household in all chains, and PL share of the household in each chain where they shop, can be calculated using actual purchases of PLs versus national brands. As noted before, few previous studies have SOW data, while PL use is often measured using perceptual data (e.g., Ailawadi et al. 2001), prompting Richardson et al. (1996) to call for behavioral measures based on panel data.

The hand-scan dataset includes panelist demographic information. In addition, GfK periodically administers panelist surveys that measure psychographic variables. Most of the scales used in the survey are adapted from existing literature. We use data from the survey administered in 2002. Finally, Reed Business provided us with the location, area, and number of checkout counters for all the stores in our data set.

In sum, our dataset combines behavioral measures of key constructs with survey-based psychographic and demographic data from the same households, thus obviating concerns with common method bias that plague analyses using only survey measures (Baumgartner and Steenkamp 2006). The combination also provides access to a broad set of determinants of panelists' SOW and PL share in the chains where they shop. The result is a richer analysis than either type of data alone would permit.

We study the relationship between PL Share and SOW for two leading chains in the Netherlands, namely Albert Heijn (the flagship of Royal Ahold, one of the worlds' largest grocery retailers), and C1000. Albert Heijn has a market share of approximately 27% while C1000 has a market share of about 15%. We focus on these two large chains to have sufficient sample size to allow for stable parameter estimation and to cover the two main types of positioning in the retail market, viz., service and value. Albert Heijn is the largest chain positioned on "service," while C1000 is the largest chain positioned on "value."

Table 1 provides summary information on several variables for Albert Heijn and C1000, and highlights the difference in their positioning. In general, Albert Heijn stores are larger, reflecting their deeper assortments (median number of SKUs per category is 121.4 versus 100.2 for C1000), have more counters per unit area, but also higher prices. PLs play a larger role in Albert Heijn, where, on average, 22.7% of the SKUs in a category are PL versus 16.8% at C1000. And, PL averages 42.1% of total purchases at Albert Heijn versus 28.8% at C1000.

< Insert Table 1 about here >

MODEL

Our primary interest in this research is to estimate the reciprocal and potentially non-linear relationship between consumers' PL Share and SOW in a given chain. This necessitates the specification of a simultaneous equation model between the two constructs. To identify the model, we include several other drivers of PL Share and SOW suggested in the literature.

It is widely accepted in consumer research that behavior is a function of characteristics of the stimulus (i.e., the retail store) and the subject (i.e., the shopper) (Assael 1998). Previous research has identified four groups of drivers that play an important role in consumer shopping behavior in retail contexts: product assortment and quality, pricing, store service and atmosphere, and location (e.g., Ailawadi and Keller 2004; Steenkamp and Wedel 1991). We use this framework of store and consumer characteristics on the one hand and the four dimensions on the other hand, to classify the key determinants of SOW and/or PL share on which we have data. [1] The classification is summarized in Table 2.

< *Insert Table 2 about here* >

Some of these determinants affect both SOW and PL Share, others affect only SOW, and still others affect only PL Share. This allows us to identify our simultaneous system. The rich literature on retail shopping behavior suggests directional hypotheses for the effects of these determinants. In the interest of brevity, however, we do not develop *a priori* hypotheses, choosing, instead, to link their estimated effects to prior literature when we report our empirical results. Since our focus is on obtaining valid estimates of the reciprocal relationship between PL Share and SOW, we present our simultaneous model and highlight its identifying restrictions:

$$\begin{aligned}\text{Log}\left(\frac{\text{SOW}_{it}}{1-\text{SOW}_{it}}\right) = {} & \alpha_0 + \beta_1 \text{PL Share}_{it} + \beta_2 \text{PL Share}_{it}^2 + \alpha_1 \text{Area}_i + \alpha_2 \text{PL Propensity}_i + \\ & \alpha_3 \text{Priceindex}_{it} + \alpha_4 \text{Pricecon}_i + \alpha_5 \text{Counters}_i + \alpha_6 \text{Shopenjoy}_i + \\ & \alpha_7 \text{Distance}_i + \alpha_8 \text{Educ}_i + \alpha_9 \text{Income}_i + \alpha_{10} \text{Numkids}_i + \alpha_{11} \text{Dum2002}_t + \\ & \alpha_{12} \text{Dum2003}_t + \varepsilon_{1it}\end{aligned} \tag{1}$$

[1] In addition to these determinants, we include as covariates two annual dummies (DUM2002 and DUM2003) to control for any time-specific effects or trend during the three year period covered by our analysis as well as three commonly used demographic variables (education, income, and number of children in the household).

$$\text{Log}\left(\frac{\text{PL Share}_{it}}{1-\text{PL Share}_{it}}\right) = \gamma_0 + \beta_3 \text{SOW}_{it} + \beta_4 \text{SOW}_{it}^2 + \gamma_1 \text{Qualcon}_i + \gamma_2 \text{Brandloy}_i + \gamma_3 \text{PL Propensity}_i + \gamma_4 \text{Priceindex}_{it} + \gamma_5 \text{Pricecon}_i + \gamma_6 \text{NBPLdiff}_{it} + \gamma_7 \text{Shopenjoy}_i + \gamma_8 \text{Educ}_i + \gamma_9 \text{Income}_i + \gamma_{10} \text{Numkids}_i + \gamma_{11} \text{Dum2002}_t + \gamma_{12} \text{Dum2003}_t + \varepsilon_{2it} \quad (2)$$

The abbreviations used for the variables in equations (1) and (2) are self-explanatory and complete definitions are provided in Table 3. The subscript *it* is for consumer *i* in year *t*, and the model is estimated for each chain. We wish to make five important points regarding the model. First, we include not only linear but also quadratic effects of our two key constructs, PL Share and SOW. Although other specifications such as the logarithmic formulation capture concavity, the quadratic formulation allows us also to capture potential non-monotonicity.

< *Insert Table 3 about here* >

Second, the SOW equation is identified by three variables that do not appear in the PL share equation. The distance that the consumer travels from home to the closest store belonging to the chain (DIST), the area (AREA) and the number of checkout counters per unit area (COUNTERS) of the store can be expected to influence the consumer's decision of how much to shop at the chain, i.e., SOW. But there is no reason for them to affect the consumer's decision of whether to buy PLs or national brands given that they are shopping in the store, i.e., PL Share.

Third, the PL share equation is identified by three variables that do not appear in the SOW equation. While the overall price level in the chain for products relevant to the consumer may affect both SOW and PL Share, the price differential between national brands and PL, NBPLDIFF, should only influence the consumer's choice between PL and national brands, not the overall decision of how much to shop in the chain. The same applies to the disposition of a consumer to be brand loyal (BRANDLOY) and quality conscious (QUALCON).

Fourth, appropriate identification of the simultaneous model is critical for obtaining valid estimates of the PL Share – SOW relationship, so we paid careful attention to this issue. In particular, since our model is non-linear in the endogenous variables, we ensured that it meets Fisher's (1965) "sufficient condition" for model identification and we included the squares of the exogenous variables as additional instrumental variables in the first stage of our 2SLS estimation, as prescribed by Kelejian (1971) and Wooldridge (2002, p. 235-237). Further, we conducted a test of our over-identifying restrictions (Wooldridge 2002, p. 122-123) and also examined the robustness of our results by relaxing these exclusion restrictions one at a time, re-estimating the model, and making sure that our key model estimates did not change significantly.

Finally, since both SOW and PL share are bound between 0 and 1, it is useful to transform the two dependent variables so that model predictions are within the [0,1] range. The results we report below are based on the logistic transformation because it has the advantage of logical consistency. The untransformed model results, which are substantively similar but tend to be statistical stronger, are available from the authors upon request.

EMPIRICAL ANALYSIS

Description of Sample

Our dataset includes all purchases by panelists of 64 different product categories that cover the full range of grocery shopping, from fresh and dry grocery, to household products, to health and beauty products. A panelist's SOW in a chain is computed as their total purchases (in euros) in the chain divided by their total purchases across all twenty chains in the Netherlands that have at least 1% market share. A panelist's PL share in the chain is computed as the panelist's PL purchases in the chain (in euros) divided by his/her total purchases in that chain of those categories where the chain has a PL. This measure reflects the panelist's choice between national brands versus the private label, when such choice exists. Using the panelist's total purchases in the chain would be inappropriate as a base for computing PL share. Such calculation could create an artificial negative relationship between SOW and PL share as consumers who buy a lot from a chain are more likely to buy categories where a PL is not available and therefore their PL share would appear small.

Our unit of analysis is the individual panelist in a given year. Although we could have expanded the degrees of freedom in our model by using more disaggregate monthly data, we believe annual data are more appropriate. Month-to-month variations in PL purchasing or shopping expenditures are not likely to reflect changes in propensity to buy PL and be loyal to a chain, both of which are relatively stable behaviors. Also, many of the drivers of these two behaviors do not vary from month-to-month. However, to ensure that our results are robust to temporal aggregation, we repeated all our analyses by aggregating over the entire time period for each household and found substantively similar results.

The chain-level empirical analysis reported below is based on annual observations for those panelists who have at least 2% SOW in the chain and for whom data are available on all model variables. This ensures that the results for a chain are based on probable shoppers in that chain, and not driven by the purchase behavior of a few consumers who happen to make the odd visit to a chain that they would not patronize at all. Of the 1904 panelists in the Albert Heijn analysis, 34% have one year of data, 27% have 2 years, and 39% have three years, for a total of 3,899 observations. Of the 1,445 panelists in the C1000 analysis, 38% have one year of data, 28% have two years, and 34% have three years, for a total of 2,846 observations.

Since there is fairly little overlap between panelists who shop at Albert Heijn and C1000 – only about 30% of the panelists shop at both chains – the simultaneous model for the two chains cannot be estimated jointly. This is not a concern since joint estimation does not affect the consistency of the estimates, it only improves efficiency. Still, we control for the fact that some panelists shop at both chains while others don't by including an "OVERLAP" dummy variable in both equations of the model, which is 1 for panelists who shop at both chains and 0 for those who shop at one but not the other.

Bivariate Association between Private Label Share and Share of Wallet

We first provide some model-free insights into the relationship between PL share and three measures of store loyalty, namely SOW – our focal measure – as well as share of items and share of trips. Table 4 shows the average on all three store loyalty measures for different PL share levels in each chain. It reveals an inverted-U pattern in both chains. All three measures of behavioral loyalty are smallest for households with low or high PL share, and largest for households with PL share between 40% and 60%.

< Insert Table 4 About Here >

There are also some important differences to note between the two chains. The rate of change in SOW at different levels of PL share is higher at Albert Heijn compared to C1000. Further, the distribution of PL share is quite different, covering the full range from 0% to 100% in Albert Heijn, with the largest proportion of observations at the 40%-60% PL share level. In contrast, less than 3% of the observations at C1000 have PL Share greater than 60%, and most of them have PL Shares between 20% and 40%. This is consistent with the fact that Albert Heijn has a better developed and differentiated PL program than C1000, and suggests that it may be difficult to estimate the effect on SOW at high levels of PL share for C1000. These differences also highlight the importance of estimating the relationship separately for each chain.

Of course, the bivariate association in Table 4 may be inconsistent because it does not control for other drivers of SOW and PL Share and it gives no insights into the direction of causality. The 2SLS estimates of our model, which we examine next, address both these issues.

Model Estimates: Determinants of SOW and PL Share

Table 5 displays coefficient estimates of the logistic transformed SOW and PL share equations for Albert Heijn, and Table 6 provides corresponding estimates for C1000. Before examining in-depth the effects of central interest in this research, i.e., the relationship between PL Share and SOW, we summarize the impact of other determinants of these constructs.[2]

< Insert Tables 5 and 6 About Here >

Share of Wallet Equation. Location and pricing related drivers have expected effects on SOW in both chains. SOW decreases with the distance the consumer has to travel to the store and with the price index since both represent a disutility to the consumer. Also, price-conscious consumers have lower SOW at Albert Heijn, which is the higher-priced "service" chain. Store area, our surrogate for assortment, has a positive effect in both chains, as would be expected. Consumers' general propensity to buy private label (in other chains) has a negative effect on SOW, consistent with the view that such consumers consider themselves smart shoppers, and are more likely to shop in multiple stores for the best prices. In-store service, as measured by checkout counters per unit area has a positive effect, being significant for Albert Heijn, though not for C1000. It is understandable that in-store service would be more relevant for a chain positioned on service than for a chain positioned on value.

Private Label Share Equation: The directional effects of many of the drivers of PL share within a chain are consistent with prior literature. Like Ailawadi et al. (2001), we find that

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[2] For simplicity of exposition, we refer to effects on SOW and PL Share throughout the empirical section. We remind the reader, however, that the dependent variables in our model are logistic transformations of these two variables, so the effects are technically on those logistic transformations.

quality-conscious and brand-loyal consumers have lower PL share. We also find that the price differential between national brands and private label has a negative effect on PL share. While this may appear counterintuitive, it is actually consistent with prior research (Hoch and Banerji 1993). One explanation is that consumers associate price with quality and perceive that the private label is of poorer quality if the differential in prices gets large (Dhar and Hoch 1997). Raju, Sethuraman, and Dhar (1995) offer another reason. They note that in categories where cross-price sensitivity between national brands and PL is high, even a small price differential is enough to make consumers switch to PL. But retailers recognize this and, in cross-price sensitive categories, they maintain a low price differential and still get high PL share. Thus, in equilibrium, one sees higher PL shares in categories with smaller price differentials.

Consistent with the notion of PL proneness as a consumer disposition (Richardson et al. 1996), we find that propensity to buy PL (in other chains) is positively associated with PL share in the focal chain, though the effect is not significant for Albert Heijn. We also find that the price index (of the consumer's shopping requirements) is negatively associated with PL share at Albert Heijn but positively associated with PL share at C1000. This may be because of the different positioning of the two chains and the consumers who choose to shop there. Consumers whose shopping requirements are more expensive at Albert Heijn, shop less there (as indicated by the negative effect on SOW), but, if they do, they are not very focused on price, but rather on national brands. In contrast, shopping motivations are more predominantly price based at the value chain C1000. Finally, shopping enjoyment is negatively related to PL share, at least at Albert Heijn, which is consistent with the notion that PLs continue to be bought primarily for functional reasons (Kumar and Steenkamp 2007).

Model Estimates: PL Share – SOW Relationship

Albert Heijn. As the first few rows of Table 5 show, both the main and quadratic effects of PL share on SOW are significant, and the same is true of the main and quadratic effects of SOW on PL share. However, polynomial coefficients, like interactions, should not be interpreted in isolation, as cautioned by Cohen at al. (2003, pp. 193-207). The estimated effect of PL share on SOW and its statistical significance varies with the *level* of PL share, and vice versa. To fully understand second-order polynomial effects, Cohen et al. (2003) recommend that researchers calculate the first-order partial derivative – called "simple slope" – and its standard error -- at different values of the predictor. Aiken and West (1991) provide the formula for computing the standard error and therefore the statistical significance of the simple slopes. We provide these calculations below:

PL Share	Effect on SOW#	t-stat	SOW	Effect on PL Share#	t-stat
0.10	13.31**	2.25	0.10	4.45***	4.77
0.20	8.64**	2.00	0.20	3.25***	4.72
0.30	3.97	1.44	0.30	2.04***	4.56
0.40	-0.70	-0.51	0.40	0.84***	3.63
0.50	-5.37***	4.27	0.50	-0.37***	-2.12

Effect is on logistic transformation
*** p<0.01; ** p<0.05; ** p<0.10

These calculations clearly indicate an inverted U effect of PL share on SOW. In other words, an increase in PL share results in higher SOW, but only up to a certain point. At levels of PL share exceeding about 40%, its effect turns negative, i.e., further increases in PL Share decrease SOW. Importantly, mean PL Share at Albert Heijn is 42.1%, which is close to the inversion point. The reverse effect is also strong. SOW has an inverted-U effect on PL share at

Albert Heijn, with inversion between 40% and 50% SOW. This inversion point is well above Albert Heijn's current mean SOW of 28.1%.

C1000. The first few rows of Table 6 show the estimated relationship between PL Share and SOW for C1000, the "value" chain with a less established PL program. Here, the main and quadratic effects of PL share on SOW are not significant. SOW does have a significant effect on PL share but the quadratic term is not significant. However, as noted previously, these effects do not provide the full picture as the effect and statistical significance of PL share on SOW varies across the PL share continuum (and vice versa). We again calculate the simple slopes for different levels of PL share and for different levels of SOW:

PL Share	Effect on SOW[#]	t-stat	SOW	Effect on PL Share[#]	t-stat
0.10	1.64	0.19	0.10	1.47[*]	1.75
0.20	7.86[*]	1.73	0.20	1.17[*]	1.87
0.30	14.08[***]	4.91	0.30	0.86[**]	2.11
0.40	20.30[***]	3.43	0.40	0.56[***]	2.68
0.50	26.52[***]	2.64	0.50	0.26[**]	2.00
0.60	32.75[**]	2.28	0.60	-0.04	-0.15

[#] Effect is on logistic transformation
[***] $p<0.01$; [**] $p<0.05$; [**] $p<0.10$

These calculations provide insight into the complex non-linear relationship between PL share and SOW, which is not directly evident from the overall coefficients. Higher PL share at C1000 leads to significantly higher SOW - but not at very low levels of PL share (below 20%) – and the effect does not exhibit non-monotonicity. Higher SOW also leads to higher PL Share, but again, the effect does not exhibit significant non-monotonicity. These monotonic effects are confirmed when we estimate a logarithmic formulation for C1000 instead of the quadratic. The logarithmic formulation shows a significantly positive effect of Log(PL share) on SOW and a smaller but significant effect of Log(SOW) on PL share.[3]

Why does the estimated relationship for C1000 not follow an inverted U? As we noted previously, C1000 has a less-differentiated and lower penetration PL program. As a result, there are very few consumers who have high PL share at this chain. In our sample, only 67 or 2.4% of the observations for C1000 have PL Share more than 60%, whereas the corresponding number for Albert Heijn is 572 or 14.6% of the observations. From a statistical point of view, there are simply too few observations to reliably uncover the downward portion of the inverted-U for C1000. This imprecision is also evident in the fact that, despite the higher magnitude of the PL Share effect at high levels of PL Share, the associated t-statistic is smaller because the standard error of the estimated effect increases substantially.

Validation Analyses Using Alternative Measures of Store Loyalty

SOW is arguably the store loyalty measure that is the most widely used by marketing practitioners. For analytical purposes though, it suffers from the limitation that it is intrinsically linked to PL share through the fact that PLs are typically sold at lower prices than national brands. Thus, if there were no other change in the shopping behavior of consumers except that they switch some of their purchases in a chain from national brands to PL, we should expect to see a negative relationship between SOW and PL share. To ensure that our results are not driven by this intrinsic definitional effect, we validate the effect of PL Share with two other panel-based measures of store loyalty, share of total items purchased, and share of shopping trips. In addition, we consider an alternative measure of SOW, based only on those categories that do not appear in

[3] In contrast, the logarithmic formulation does not perform well for Albert Heijn where the effect is clearly non-monotonic and therefore is better captured by the quadratic formulation. Complete results based on the logarithmic formulation are available from the authors upon request.

the computation of PL Share (because there is no PL or no distinction between PL and NB) – fresh produce, meat, alcohol, flowers.

We re-estimated our 2SLS model for all three alternative measures of store loyalty. Our results, which are available upon request, are very robust and replicated across all three alternative measures of behavioral loyalty. Thus, our substantive findings on the reciprocal relationship between PL share and store loyalty are supported across multiple measures of store loyalty. They are not because SOW includes price information or because its numerator shares a common element with the denominator of PL Share.

Heavy and Light Private Label Users and the Inverted U

To better understand the behavior of PL purchasers in the two chains, we conducted an exploratory analysis of the characteristics associated with consumers exhibiting low (<20%), medium (20% to 60%), and high (>60%) PL share in a particular chain. Table 7 provides means of some interesting characteristics for these three groups of shoppers at Albert Heijn, for which we found an inverted-U effect of PL share on SOW, and at C1000, for which we did not find evidence for such non-monotonicity. It also flags characteristics whose means are significantly different for the low versus medium and the high versus medium group.

Comparing the low and medium PL share groups is insightful. In both chains, low PL share is associated with lower grocery spending. These consumers seem to be "national brand cherry pickers", with significantly higher brand loyalty and quality consciousness. However, there is an interesting difference between the light PL buyers at the two chains. At Albert Heijn, this group shops at hard discounters for really inexpensive PLs in certain categories, and at various other chains to buy national brands wherever they are cheapest. At C1000, however, this segment is less inclined to purchase PLs in general.

< Insert Table 7 About Here >

A comparison of medium and heavy PL segments shows that, in both chains, the heavy PL segment has the lowest grocery expenditure of all three segments. This underlines the notion that high PL buyers may not be the most interesting segment to target, at least from a revenue point of view. In both chains, the heavy PL segment is associated with greater PL share at other chains, consistent with the notion that heavy PL shoppers are more focused on savings (Ailawadi et al. 2001). Heavy PL buyers appear to be less likely to differentiate between PLs of different chains and more likely to focus on saving money. The savings profile is particularly pronounced for C1000. Their heavy PL buyers also have a higher SOW at hard discounters who sell almost exclusively PL products at very low prices (Kumar and Steenkamp 2007). In general, therefore the pattern of results across the three PL groups is quite similar for the two chains.

DISCUSSION

Despite the fact that PL is at the center of much of the action in the packaged goods industry around the world, and notwithstanding the increasing push that retailers are giving to their PL offering, we still did not know much about the interrelation between consumers' PL purchase behavior and their loyalty to a retailer. To address this void, we specified a model of SOW and PL share that accounts for simultaneity as well as non-linearity and includes other key determinants of the two constructs, and estimated it for two leading chains with different market positions. We combined data on all purchases of a national sample of Dutch households across a broad spectrum of grocery products with rich psychographic variables to conduct our analysis.

We find that PL share significantly affects SOW and SOW significantly affects PL share for both chains. These effects are strong but non-monotonic for the service chain whose PL is well-differentiated and has high penetration. SOW initially increases strongly with PL share, but beyond PL share of about 40%, it starts to decrease. Similarly, PL share also increases strongly with SOW, but only to a certain point beyond which PL share starts to decrease. For the value chain with a less differentiated PL program, PL share has a positive effect on SOW but not at low levels of PL Share. The reverse effect of SOW on PL share is positive, but small. Further, PL Share at this chain has not yet reached high enough levels to exhibit non-monotonic effects.

The inverted-U effect of PL share on SOW can be explained by the notion that consumers who buy some PL from a chain are likely to build some chain loyalty, those who buy no PL at all have no such loyalty, and those who buy a lot of PL are drawn more to savings than to a particular PL, and therefore shop for the best prices in several chains. This is supported by the finding that not only SOW but also share of trips and share of items is low among heavy PL users (Table 4), and by the fact that they have higher PL Share in other chains than medium PL users (Table 7). It is also consistent with exploratory patterns reported by Ailawadi and Harlam (2004), with Singh, Hansen, and Blattberg's (2005) finding that heavy PL buyers are more likely to defect to Wal-Mart, and with Szymanowski and Gijsbrechts (2007) argument that consumers transfer attitudes about one chain's PL to the PLs of other chains.

The inverted-U effect of SOW on PL Share can be explained by the well-established fact that consumers' willingness to purchase PL products varies substantially across product categories (Sethuraman 1992; Steenkamp and Dekimpe 1997). The process of spending a large portion of their time and money in the chain increases consumers' exposure, familiarity, and willingness to buy the chain's PL. However, very loyal consumers, who patronize one chain for most or all of their purchases, are more likely to buy not only the categories where PL is acceptable to them, but also the categories where PL is not acceptable to them, in that chain. Their SOW in the chain is high, but, because they are simply not willing to purchase PL in certain categories, they reach a ceiling on their PL purchases. As the denominator (total expenditure) continues to increase but the numerator (expenditure on PL products) does not, PL share must decrease.

As discussed previously, we did not find a non-monotonic effect for C1000 because there are very few heavy PL shoppers at C1000, so the range of data is not enough to reveal the downward portion of the inverted-U. But why are there so few heavy PL shoppers at C1000? It is not because they dislike PLs *per se* since this group has high PL share at other chains (26%) and high SOW at hard discounters (19%) who only sell PL. Rather, C1000's PL is not sufficiently sophisticated and differentiated to attract large groups of customers. Our analysis of Albert Heijn may represent the likely future scenario for C1000, which is currently trying to ramp up its PL program. The patterns in Table 4 and Table 7 suggest that the chain's push for higher PL share will ultimately hit negative returns.

Implications for Managers

Retailers are making a concerted effort to grow their PL (Kumar and Steenkamp 2007), but the inverted-U relationship between PL share and SOW shows that even for a high-quality PL program, one can overdo it. Interestingly, this has been the experience of U.K.'s J. Sainsbury chain whose positioning is quite similar to Albert Heijn and whose PL Share exceeded 60%. It had to scale back its emphasis on PL because SOW started to decline as consumers felt that the dominant presence of the Sainsbury PL constrained their choice. In the U.S., Sears and A&P are examples of retailers that pushed PL too far in the past, found that store traffic, revenue, and profitability suffered, and had to retract.

So, sophisticated retailers that have a high quality, well-differentiated PL face a conundrum. While there may be a rationale for further growing PL, especially from a margin perspective, retailers have to be wary of how far they can push PL at the expense of national brands. What can they do to grow PL while avoiding the downside? One strategy is to focus on light PL users who currently buy basic, no-frills PL from hard discounters. To attract these shoppers, retailers might develop/expand their budget private label. Subsequently, they could be migrated to the more differentiated, relatively premium private label, with its loyalty-creating benefit. However, this strategy will have limited effect as the light PL group is typically quite small for sophisticated chains – it is only 8% at Albert Heijn. There is also the possibility that buyers of the standard PL may migrate downward, rather than the other way around.

Two other strategies focus on medium-high PL buyers. Sophisticated retailers can develop specialty PLs to increase the perception of choice. For instance, U.K.'s Tesco carries seven Tesco sub-brands focused on distinct need segments (e.g., Tesco Fair Trade). These retailers can also try to imbue their PLs with emotion and imagery to encourage use in categories where consumers are currently reluctant to buy PL. In the U.S., Target has been successful in imbuing its store brand with imagery. If retailers are able to pull this off, they will be able to combine high intensity of PL buying with high SOW.

Chains without a well-differentiated private label program face a different challenge, namely, convincing shoppers to increase their PL buying intensity. Their PL share threshold for seeing loyalty benefits is higher than for their well-differentiated competitors, so they need to increase PL share more among their non- and light PL users. And, even though their current PL share levels are too low to exhibit negative loyalty returns, our analysis suggests that they are likely to face negative returns like their competitors if their PL share does get high enough. Their ability to build a virtuous cycle is also limited by the small reverse effect of SOW on PL.

The challenge for value retailers like C1000 is to develop a strong PL assortment. The obvious first step is to improve actual quality through better sourcing and innovation. But it is equally important to convince consumers of the quality of its PL. Value chains often suffer from an unfavorable gap between actual and perceived PL quality. For example, while C1000's PL regularly performs well in product tests, its perceived quality and credibility are still significantly below Albert Heijn's PL (Steenkamp and Dekimpe 1997).[4] An effective way to turn quality perceptions around is to induce shoppers to try the product. Publix Super Markets in the U.S. adopted an innovative approach to do just that. For five weeks the retailer designated three national brand products and their corresponding Publix-brand items for the promotion. Consumers who purchased the national brand got the Publix product free (Supermarket News 2007). In sum, building a compelling PL program through real and perceived quality improvements is essential for such chains.

Directions for Future Research

Although this research has answered some important questions in what we believe is a convincing way, it also highlights several avenues for further research. Our analysis focuses on two leading chains from one country. It validates the exploratory analysis of two U.S. chains by Ailawadi and Harlam (2004), and is consistent with Singh, Hansen, and Blattberg's (2006) finding that heavy PL users are more likely to defect when Wal-Mart enters the area. However, further research should examine whether our findings generalize to other countries and formats.

Future research could also expand the assortment, quality, pricing, and service determinants of SOW and PL share to improve the overall explanatory power of the model. Variables such as average number of brands and SKUs per category, percentage of categories

[4] This was confirmed in a recent GfKBenelux survey of Dutch consumers. In this survey, the C1000 PL rated only slightly above Albert Heijn's budget PL, called Euroshopper on perceived quality and below Euroshopper on credibility (Jan Havermans, marketing manager GfK Benelux, private communication, November 12, 2007).

and SKUs that are PL, etc. explain variation in SOW and PL share across chains. Since we estimated our model separately for each chain, these variables, which exhibit very little variation within a chain, were not relevant. But, they are likely to be important in a cross-chain model.

PL products in some categories may be more effective in engendering SOW than PLs in other categories. For instance, increased PL share in hedonic and high perceived risk categories like desserts and beauty products may be more effective than higher PL share in dry groceries or household paper products. Similarly, there may be consumer heterogeneity in the relationship between PL share and SOW. Modeling these differences across categories and consumers will complicate the model but this is a fruitful area for future research.

While our results show the limits of PL in generating chain loyalty, this does not mean that retailers will or should stop pushing their PLs. Indeed, further research is needed to examine the tradeoffs retailers face in their PL objectives: higher product margins on PL, higher leverage in national brand manufacturer negotiations, and higher consumer store loyalty. Demonstrating the existence of such tradeoffs is an important contribution of this paper.

In conclusion, increasing loyalty is an important goal for retailers in today's competitive markets, and PL programs have long been regarded as a promising means of doing so. Our research reveals limits to this approach. Indeed, PLs are no silver bullet; they are but one weapon in the retailer's arsenal of positioning strategies.

TABLE 1
POSITIONING OF THE TWO RETAIL CHAINS

Mean value of	Albert Heijn	C1000
Weighted price index	1.24	0.96
Price rating	5.7	6.2
Product assortment rating	6.5	6.3
Share of Wallet	28.1%	28.2%
Private Label Share	42.1%	28.8%
Distance (km)	0.84	0.97
Area (thousands of square meters)	1.19	0.80
Counters per hundred sq meters	0.82	0.71
No. of categories	63	62
No. of categories with PL	46	42
Avg. no. of items per category	121.4	100.2
% of items which are PL	22.7%	16.8%

TABLE 2
CORRELATES OF SHARE OF WALLET AND PRIVATE LABEL SHARE

	RETAILER CHARACTERISTICS	CONSUMER CHARACTERISTICS
PRODUCT ASSORTMENT & QUALITY	Store Area	Quality Consciousness Brand Loyalty Propensity for Private Label
PRICING	Price Index* NB-PL Price Differential*	Price Consciousness
IN-STORE SERVICE	Counters per Unit Area	Shopping Enjoyment
LOCATION	Distance	

* These variables vary across consumers based on the product categories they buy. They are weighted averages of the values for the main product departments where the weights are the individual consumer's total expenditures in each department, across all chains where the consumer shops.

TABLE 3
VARIABLE DEFINITIONS

Variable	Definition
Share of Wallet	Percentage of total expenditures (in euros) across 64 categories and 20 retail chains that a household spends at the given chain
Private label share	Private label purchases (in euros) of the panelist in the chain divided by total purchases of the panelist in the chain in categories where the chain has a private label product. Fresh produce and meats are not included in this computation because there is no distinction between national and private label brands in these products.
Weighted Price Index	Average price in the chain of a market basket containing average purchase amounts of each product category relative to the average across chains. The price index is computed within each of five departments – fresh produce and meats, dry grocery, fresh grocery, general household merchandise, and health and beauty products. The weighted price index for each panelist is the weighted average across the five departments, with weights being the panelist's total *annual* purchases in that department, across chains.
Weighted NB-PL price differential	Average price per equivalent unit of national brands minus average price per equivalent unit of private label as a percentage of average national brand price. The price differential is computed within each of five departments. The weighted price differential for each panelist is the weighted average across departments with weights being the panelist's total annual purchases in that department, across chains.
Store distance	Euclidean distance between the center of the panelist's home zip-code and the nearest store of the chain
Store area	Area of the chain's store nearest to the panelist's home zip-code in thousands of square meters.
Counters per unit area	Number of check-out counters per square meter in the chain's store nearest to the panelist's home zipcode
General private label propensity	Private label purchases (in euros) of the panelist in other chains divided by total purchases of the panelist in those chains
Price consciousness[a] (Cronbach's alpha = 0.79)	Three-item scale: For me, price is decisive when I am buying a product; Price is important to me when I choose a product; I generally strive to buy products at the lowest price.
Quality consciousness[a] (Cronbach's alpha = 0.69)	Three-item scale: I always strive for the best quality; Quality is decisive for me while buying a product; Sometimes I save money on groceries by buying products of lower quality (reverse coded)
Brand loyalty[a] (Cronbach's alpha = 0.79)	Four-item scale: Once I choose a brand I don't like to switch; I prefer the brand I always buy instead of trying another one that I am not sure about; I see myself as a brand loyal person; If my preferred brand in not available in the supermarket, I can easily choose another brand (reverse coded)
Shopping enjoyment[a] (Cronbach's alpha = 0.71)	Three-item scale: I really like to browse in stores; I really do not like grocery shopping (reverse coded); I really enjoy doing grocery shopping in the supermarket

[a] Likert scale from 1 to 5 (Strongly disagree to Strongly agree)

TABLE 4
BIVARIATE RELATIONSHIP BETWEEN SHARE OF WALLET AND PRIVATE LABEL SHARE

Range of Private Label Share	Mean Value at Albert Heijn of				Mean Value at C1000 of			
	N	Share of Wallet	Share of Items	Share of Trips	N	Share of Wallet	Share of Items	Share of Trips
0% to 20%	324	14.3%	12.1%	15.6%	751	28.3%	28.5%	29.6%
20% to 40%	1402	35.7%	33.1%	36.2%	1482	40.9%	41.8%	41.6%
40% to 60%	1601	42.6%	40.4%	43.2%	546	44.1%	45.0%	45.0%
60% to 80%	472	30.8%	28.3%	31.5%	58	20.7%	20.8%	24.7%
80% to 100%	100	20.9%	16.6%	19.6%	9	19.0%	20.0%	22.1%

TABLE 5
2SLS MODEL ESTIMATES FOR ALBERT HEIJN

Variable	**Coefficient in Equation for Logit Transformed**	
	Share of Wallet	**Private Label Share**
Private label share	17.98** (2.39)	--
[Private label share]^2	-23.35*** (-2.85)	--
Share of wallet	--	5.66*** (4.80)
[Share of wallet]^2	--	-6.03*** (-4.83)
Store area	0.10* (1.67)	--
Quality consciousness	--	-0.06*** (-3.21)
Brand loyalty	--	-0.03* (-1.68)
Propensity for private label	-4.62*** (-11.87)	0.15 (0.68)
Weighted price index	-18.18*** (-4.52)	-10.86*** (-7.71)
Weighted NB – PL Differential	--	-0.13*** (-7.94)
Price consciousness	-0.20*** (-5.75)	0.002 (0.12)
Counters per unit area	58.52*** (4.09)	--
Shopping enjoyment	-0.05 (-1.30)	-0.06*** (-3.54)
Distance to store	-0.16*** (-5.94)	--
Education	0.10*** (3.91)	0.01 (0.97)
Income	-0.02 (-1.28)	-0.01** (-2.02)
Number of kids	-0.17*** (-4.38)	-0.06*** (-3.61)
2002 dummy	0.32*** (2.99)	0.00 (0.08)
2003 dummy	-0.65*** (-6.04)	-2.25*** (-8.86)
Overlap dummy	-0.52*** (-7.44)	-0.12*** (-3.73)
Adjusted R^2	0.174	0.080

Note: t-statistics are in parentheses
***$p<0.01$; **$p<0.05$; *$p<0.10$

TABLE 6
2SLS MODEL ESTIMATES FOR C1000

Variable	**Coefficient in Equation for Logit Transformed**	
	Share of Wallet	**Private Label Share**
Private label share	-4.59 (-0.36)	--
[Private label share]^2	31.11 (1.40)	--
Share of wallet	--	1.77* (1.67)
[Share of wallet]^2	--	-1.51 (-1.37)
Store area	0.63*** (2.80)	--
Quality consciousness	--	-0.05*** (-3.19)
Brand loyalty	--	-0.06*** (-3.13)
Propensity for private label	-5.56*** (-7.57)	0.16*** (7.49)
Weighted price index	-33.72*** (-4.58)	3.75* (1.90)
Weighted NB – PL Differential	--	-0.03*** (-3.33)
Price consciousness	0.01 (0.10)	0.01 (0.56)
Counters per unit area	37.60 (0.87)	--
Shopping enjoyment	0.05 (0.75)	0.01 (0.47)
Distance to store	-0.18*** (-6.33)	--
Education	-0.03 (-0.91)	0.01 (1.38)
Income	0.02 (0.74)	-0.00 (-0.35)
Number of kids	-0.15** (-2.09)	0.07*** (4.81)
2002 dummy	-0.21 (-0.88)	0.16** (2.07)
2003 dummy	-2.06*** (-5.75)	0.39*** (4.45)
Overlap dummy	-0.39*** (-2.68)	-0.09** (-2.47)
Adjusted R^2	0.066	0.117

Note: t-statistics are in parentheses
***$p<0.01$; **$p<0.05$; *$p<0.10$

TABLE 7
EXPLORATORY ANALYSIS OF LIGHT AND HEAVY PRIVATE LABEL USERS

Characteristic	**Mean Value when Private Label Share is**		
	Low (Less than 20%)	**Medium (20% to 60%)**	**High (More than 60%)**
Albert Heijn:			
Number of observations	324	3003	572
Yearly Spending (euros)	1540***	1774	1401***
Private label share at other chains (excluding hard discounters)	.16	.17	.20***
Share of wallet at hard discounters (Aldi and Lidl)	.15***	.08	.09
Quality consciousness	.08	.10	-.00***
Brand loyalty	.10	.05	-.07**
C1000:			
Number of observations	751	2028	67
Yearly Spending (euros)	1563***	1722	1342***
Private label share at other chains (excluding hard discounters)	.18***	.23	.26**
Share of wallet at hard discounters (Aldi and Lidl)	.13	.12	.19***
Quality consciousness	.06**	-.05	-.06
Brand loyalty	.16***	-.10	-.05

*** Mean is significantly different from mean in medium private label share group at $p<0.01$
** Mean is significantly different from mean in medium private label share group at $p<0.05$
* Mean is significantly different from mean in medium private label share group at $p<0.10$

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