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Private-Label Use and Store Loyalty

The authors develop an econometric model of the relationship between a household's private-label (PL) share and its behavioral store loyalty. The model includes major drivers of these two behaviors and controls for simultaneity and nonlinearity in the relationship between them. The model is estimated with a unique data set that combines complete purchase records of a panel of Dutch households with demographic and psychographic data. The authors estimate the model for two retail chains in the Netherlands—the leading service chain with a well-differentiated high-share PL and the leading value chain with a lower-share PL. They find that PL share significantly affects all three measures of behavioral loyalty in the study: share of wallet, share of items purchased, and share of shopping trips. In addition, behavioral loyalty has a significant effect on PL share. For the service chain, the authors find that both effects are in the form of an inverted U. For the value chain, the effects are positive and nonlinear, but they do not exhibit nonmonotonicity, because PL share has not yet reached high enough levels. The managerial implications of this research are important. Retailers can reap the benefits of a virtuous cycle; greater PL share increases share of wallet, and greater share of wallet increases PL share. However, this virtuous cycle operates only to a point because heavy PL buyers tend to be loyal to price savings and PLs in general, not to the PL of any particular chain.

Keywords: private labels, store brands, store loyalty, share of wallet, simultaneity, nonlinear effects

Private labels (PLs) in the consumer packaged goods industry have experienced a worldwide 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, and the market share in Western Europe is even larger (Kumar and Steenkamp 2007). Planet Retail (2007, p. 1) recently concluded that "[PLs] 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 their PLs are (1) higher retail margins on PL, (2) negotiating leverage with national brand (NB) manufacturers, and (3) 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 article is on the third reason—the purported ability of PLs to improve consumers' loyalty to a particular retailer.

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Conventional wisdom maintains that PL use is associated with higher store loyalty. For example, Richardson, Jain, and Dick (1996, p. 181) state that "store brands help retailers increase store traffic and customer loyalty by offering exclusive lines under labels not found in competing stores." Likewise, the Private Label Manufacturers Association (2007) Web site states that "retailers use store brands to increase business as well as to win the loyalty of their customers." However, empirical evidence on the subject is mixed. On the 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. 119–20). Corstjens and Lal's (2000) analytical model supports PLs' ability to build store loyalty, and Sudhir and Talukdar (2004) report indirect support for PLs' store differentiating ability. On the other hand, there is evidence that consumers may not differentiate between different retailers' PLs; that is, PL users may be loyal to PL products in general, not to the PL of a particular retailer (Richardson 1997). If this is the case, it is difficult to understand 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 question still remains 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 time and money in the chain increases a consumer's familiarity with the chain's PL across multiple categories. Such familiarity with the chain's PL is an important predictor of PL proneness (Richardson, Jain, and Dick 1996). In addition, consumers who consistently shop at the

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chain, rather than 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. Implications for retailers are different depending on which way the causality operates between PL use and store loyalty.

Second, the relationship may be nonlinear, possibly even nonmonotonic. Ailawadi and Harlam (2004) find that medium PL users contribute more than light users or nonusers of PLs to retailer sales and profits, but heavy PL users contribute less than medium users. The ability of PLs to increase store loyalty in Corstjens and Lal's (2000) model is also predicated on a "balance" between consumers who prefer PLs and those who prefer NBs. It is critical to understand the nature of nonlinearity 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 purchase relationship, in general, empirical evidence is 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 have actual 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). Finally, no study models either simultaneity or nonlinearity. 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 quantify this relationship conclusively.

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. We define PL share as the household's PL spending (in dollars or, in our empirical study, in euros) at the chain as a percentage of its total spending (in euros) in that chain on categories in which the chain offers a PL product. We operationalize store loyalty as the household's share of wallet (SOW) in the chain—that is, its spending in the chain (in euros) as a percentage of its total spending on supermarket products—but we validate our findings using two alternative behavioral loyalty measures: share of items purchased and share of shopping trips.

The model allows for reverse causality and nonlinearity 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 data set with complete information on the supermarket purchases of a Dutch household panel across all stores, as well as the households' 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 is positioned on high "service" with high PL share, and the other is positioned as the foremost "value" chain with lower PL share.

Data

Our empirical setting is Dutch grocery retailers. Our data set combines several sources. We use purchase records from GfK's consumer hand-scan panel in the Netherlands for the period between January 1, 2001, and January 1, 2004. The GfK panel consists of more than 4000 panelists, representing a stratified national sample of Dutch consumers. With some attrition and new recruitment of panelists each year, the data set contains three years of data from a little more than 50% of the panelists; the remaining panelists are 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 data set 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 in which it shops can be calculated with actual purchases of PLs versus NBs. As we noted previously, few studies have had access to SOW data, and PL use has often been measured with perceptual data (e.g., Ailawadi, Neslin, and Gedenk 2001), prompting Richardson, Jain, and Dick (1996) to call for behavioral measures based on panel data.

The hand-scan data set 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 the location, area, and number of checkout counters for all the stores in our data set.

In summary, our data set combines behavioral measures of key constructs with survey-based psychographic and demographic data from the same households, thus obviating concerns about 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 in which 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: Albert Heijn (the flagship of Royal Ahold, one of the world's largest grocery retailers) and C1000. Albert Heijn has a market share of approximately 27%, and C1000 has a market share of approximately 15%. We focus on these two large chains so that we have a sufficient sample size to allow for stable parameter estimation and to cover the two main types of positioning in the retail market—namely, service and value. Albert Heijn is the largest chain positioned on "service," and 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 (the median number of stockkeeping units [SKUs] per category is 121.4 versus 100.2 for C1000), and have more counters per unit area, but they also have higher prices. In Albert Heijn, PL plays a larger role—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.

Model

Our primary interest in this research is to estimate the reciprocal and potentially nonlinear 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] Table 2 summarizes the classification.

Some determinants affect both SOW and PL share, others affect only SOW, and still others affect only PL share. Thus, we can 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. Because 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:

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

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

The abbreviations used for the variables in Equations 1 and 2 are self-explanatory, and complete definitions appear in the Appendix. The subscript "it" is for consumer i in year t, and the model is estimated for each chain. We 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,

[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 and three commonly used demographic variables (education, income, and number of children in the household).

TABLE 1
Positioning of the Two Retail Chains

Mean Value of	Albert Heijn	C1000
Weighted price index	1.24	.96
Price rating	5.7	6.2
Product assortment rating	6.5	6.3
SOW	28.1%	28.2%
PL share	42.1%	28.8%
Distance (km)	.84	.97
Area (thousands of square meters)	1.19	.80
Counters per hundred square meters	.82	.71
Number of categories	63	62
Number of categories with PL	46	42
Average number of items per category	121.4	100.2
% of items that are PL	22.7%	16.8%

TABLE 2
Correlates of SOW and PL Share

	Retailer Characteristics	Consumer Characteristics
Product assortment and quality	Store area	Quality consciousness Brand loyalty Propensity for PL
Pricing	Price index[a] NB – PL price differential[a]	Price consciousness
In-store service	Counters per unit area	Shopping enjoyment
Location	Distance	

[a]These variables vary across consumers according to the product categories they buy. They are weighted averages of the values for the main product departments; the weights are the individual consumer's total expenditures in each department, across all chains in which the consumer shops.

such as the logarithmic formulation, capture concavity, the quadratic formulation enables us also to capture potential nonmonotonicity.

Second, the SOW equation is identified by three variables that do not appear in the PL share equation. The distance the consumer travels from home to the closest store belonging to the chain (Distance), the area (Area), and the number of checkout counters per unit area (Counters) of the store are likely to influence the consumer's decision of how much to shop at the chain (i.e., SOW), but there is no reason for the variables to affect the consumer's decision of whether to buy PLs or NBs, given that he or she is 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. Whereas the overall price level in the chain for products relevant to the consumer may affect both SOW and PL share, the price differential between NBs and PL, NBPLdiff, should only influence the consumer's choice between PL and NBs, 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, because our model is nonlinear 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 two-stage least squares (2SLS) estimation (see Kelejian 1971; Wooldridge 2002, pp. 235–37). Furthermore, we conducted a test of our overidentifying restrictions (Wooldridge 2002, pp. 122–23) and examined the robustness of our results by relaxing these exclusion restrictions one at a time, reestimating the model, and making sure that our key model estimates did not change significantly.

Fifth, because 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 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 statistically stronger, are available on request.)

Empirical Analysis

Description of Sample

Our data set 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. We compute panelists' SOW in a chain as their total purchases (in euros) in the chain divided by their total purchases across all 20 chains in the Netherlands that have at least 1% market share. We compute panelists' PL share in a chain as their PL purchases in the chain (in euros) divided by their total purchases in that chain of the categories in which the chain has a PL. This measure reflects the panelist's choice between NBs and the PL, when such a 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 because consumers who buy a lot from a chain are more likely to buy categories in which a PL is not available, and therefore their PL share would be 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 that 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 to be loyal to a chain, both of which are relatively stable behaviors. In addition, 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 period for each household and found substantively similar results.

The chain-level empirical analysis we report subsequently is based on annual observations for 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 are not driven by the purchase behavior of a few consumers who happen to make the odd visit to a chain they would usually not patronize. Of the 1904 panelists in the Albert Heijn analysis, 34% have one year of data, 27% have two years, and 39% have three years, for a total of 3899 observations. Of the 1445 panelists in the C1000 analysis, 38% have one year of data, 28% have two years, and 34% have three years, for a total of 2846 observations.

Because there is fairly little overlap between panelists who shop at Albert Heijn and those who shop at C1000—approximately 30% of the panelists shop at both chains—the simultaneous model for the two chains cannot be estimated jointly. This is not a concern, because 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 whereas others do not 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 chain but not the other.

Bivariate Association Between PL Share and SOW

We first provide some model-free insights into the relationship between PL share and three measures of store loyalty: SOW (our focal measure), share of items, and share of trips. Table 3 shows the average on all three store loyalty measures for different PL share levels in each chain. It reveals an inverted U-shaped 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%.

There are also important differences to note between the two chains. The rate of change in SOW at different levels of

TABLE 3
Bivariate Relationship Between SOW and PL Share

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

PL share is higher at Albert Heijn than at C1000. Furthermore, the distribution of PL share is 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 Albert Heijn having 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.

The bivariate association in Table 3 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 4 displays coefficient estimates of the logistic transformed SOW and PL share equations for Albert Heijn, and Table 5 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 the other determinants of these constructs.[2]

SOW equation. Location- and pricing-related drivers have expected effects on SOW in both chains. Share of wallet decreases with the distance the consumer must travel to the store and with the price index because both represent a disutility to the consumer. In addition, price-conscious consumers have a 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 PLs (in other chains) has a negative effect on SOW, consistent with

TABLE 4
2SLS Model Estimates for Albert Heijn

	Coefficient in Equation for Logit Transformed	
Variable	SOW	PL Share
PL share	17.98**	—
	(2.39)	
(PL share)^2	–23.35***	—
	(–2.85)	
SOW	—	5.66***
		(4.80)
(SOW)^2	—	–6.03***
		(–4.83)
Store area	.10*	—
	(1.67)	
Quality consciousness	—	–.06***
		(–3.21)
Brand loyalty	—	–.03*
		(–1.68)
Propensity for PL	–4.62***	.15
	(–11.87)	(.68)
Weighted price index	–18.18***	–10.86***
	(–4.52)	(–7.71)
Weighted NB – PL differential	—	–.13***
		(–7.94)
Price consciousness	–.20***	.002
	(–5.75)	(.12)
Counters per unit area	58.52***	—
	(4.09)	
Shopping enjoyment	–.05	–.06***
	(–1.30)	(–3.54)
Distance to store	–.16***	—
	(–5.94)	
Education	.10***	.01
	(3.91)	(.97)
Income	–.02	–.01**
	(–1.28)	(–2.02)
Number of children	–.17***	–.06***
	(–4.38)	(–3.61)
2002 dummy	.32***	.00
	(2.99)	(.08)
2003 dummy	–.65***	–2.25***
	(–6.04)	(–8.86)
Overlap dummy	–.52***	–.12***
	(–7.44)	(–3.73)
Adjusted R^2	.174	.080

**p* < .10.
***p* < .05.
****p* < .01.
Notes: t-statistics are in parentheses.

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

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 that is significant for Albert Heijn but 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.

PL share equation. The directional effects of many of the drivers of PL share within a chain are consistent with prior literature. Similar to Ailawadi, Neslin, and Gedenk (2001), we find that quality-conscious and brand-loyal consumers have lower PL share. We also find that the price differential between NBs and PLs has a negative effect on PL share. Although this may appear counterintuitive, it is consistent with prior research (Hoch and Banerji 1993). One explanation is that consumers associate price with quality and perceive the PL as being of poorer quality if the differential in prices is large (Dhar and Hoch 1997). Raju, Sethuraman, and Dhar (1995) offer another reason. They note that in categories in which cross–price sensitivity between NBs and PLs is high, even a small price differential is enough to make consumers switch to PLs. However, retailers recognize this, and in cross–price sensitive categories, they maintain a low price differential and still obtain high PL share. Thus, in equilibrium, there are higher PL shares in categories with smaller price differentials.

TABLE 5
2SLS Model Estimates for C1000

	Coefficient in Equation for Logit Transformed	
Variable	**SOW**	**PL Share**
PL share	–4.59 (–.36)	—
(PL share)^2	31.11 (1.40)	—
SOW	—	1.77* (1.67)
(SOW)^2	—	–1.51 (–1.37)
Store area	.63*** (2.80)	—
Quality consciousness	—	–.05*** (–3.19)
Brand loyalty	—	–.06*** (–3.13)
Propensity for PL	–5.56*** (–7.57)	.16*** (7.49)
Weighted price index	–33.72*** (–4.58)	3.75* (1.90)
Weighted NB – PL differential	—	–.03*** (–3.33)
Price consciousness	.01 (.10)	.01 (.56)
Counters per unit area	37.60 (.87)	—
Shopping enjoyment	.05 (.75)	.01 (.47)
Distance to store	–.18*** (–6.33)	—
Education	–.03 (–.91)	.01 (1.38)
Income	.02 (.74)	–.00 (–.35)
Number of children	–.15** (–2.09)	.07*** (4.81)
2002 dummy	–.21 (–.88)	.16** (2.07)
2003 dummy	–2.06*** (–5.75)	.39*** (4.45)
Overlap dummy	–.39*** (–2.68)	–.09** (–2.47)
Adjusted R^2	.066	.117

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: t-statistics are in parentheses.

Consistent with the notion of PL proneness as a consumer disposition (Richardson, Jain, and Dick 1996), we find that propensity to buy PLs (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 due to 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 focused on price but rather on NBs. 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 4 show, both the main and the 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, as with interactions, should not be interpreted in isolation, as Cohen and colleagues (2003, pp. 193–207) caution. The estimated effect of PL share on SOW and its statistical significance varies with the level of PL share, and vice versa. To understand fully second-order polynomial effects, Cohen and colleagues recommend that researchers calculate the first-order partial derivative—called the "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:

PL Share	Effect on SOW[a]	t-Statistic
.10	13.31*	2.25
.20	8.64*	2.00
.30	3.97	1.44
.40	–.70	–.51
.50	–5.37**	4.27

SOW	Effect on PL Share[a]	t-Statistic
.10	4.45**	4.77
.20	3.25**	4.72
.30	2.04**	4.56
.40	.84**	3.63
.50	–.37**	–2.12

*$p < .05$.
**$p < .01$.
[a]Effect is on logistic transformation.

These calculations indicate an inverted U-shaped 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 approximately 40%, its effect becomes 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. Furthermore, SOW has an inverted U-shaped 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 5 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. However, SOW has a significant effect on PL share, but the quadratic term is not significant. As we noted previously, these effects do not provide the full picture, because the effect and statistical significance of PL share on SOW varies across the PL share continuum, and vice versa. Again, we calculate the simple slopes for different levels of PL share and for different levels of SOW:

PL Share	Effect on SOW[a]	t-Statistic
.10	1.64	.19
.20	7.86*	1.73
.30	14.08***	4.91
.40	20.30***	3.43
.50	26.52***	2.64
.60	32.75**	2.28
SOW	**Effect on PL Share[a]**	**t-Statistic**
.10	1.47*	1.75
.20	1.17*	1.87
.30	.86**	2.11
.40	.56***	2.68
.50	.26**	2.00
.60	–.04	–.15

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]Effect is on logistic transformation.

These calculations provide insight into the complex nonlinear 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 nonmonotonicity. Higher SOW also leads to higher PL share, but again, the effect does not exhibit significant nonmonotonicity. These monotonic effects are confirmed when we estimate a logarithmic formulation for C1000 instead of the quadratic. The logarithmic formulation shows a significant, 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 few consumers who have high PL share at this chain. In our sample, only 67, or 2.4%, of the observations for C1000 have a PL share of 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 insofar as 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

Arguably, SOW is the most widely used store loyalty measure by marketing practitioners. For analytical purposes, though, it suffers from the limitation that it is intrinsically linked to PL share because PLs are typically sold at lower prices than NBs. Thus, if there were no changes in the shopping behavior of consumers other than that they switch some of their purchases in a chain from NBs to PL, we should observe 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 categories that do not appear in the computation of PL share (because there is no PL or distinction between PL and NB): fresh produce, meat, alcohol, and flowers.

We reestimated our 2SLS model for all three alternative measures of store loyalty. Our results, which are available on request, are 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 PL Users and the Inverted U

To understand better the behavior of PL purchasers in the two chains, we conducted an exploratory analysis of the characteristics associated with consumers exhibiting low

[3]In contrast, the logarithmic formulation does not perform well for Albert Heijn, for which the effect is nonmonotonic and therefore is better captured by the quadratic formulation. Complete results based on the logarithmic formulation are available on request.

(<20%), medium (20%–60%), and high (>60%) PL share in a particular chain. Table 6 provides means of several characteristics for these three groups of shoppers at Albert Heijn, for which we found an inverted U-shaped effect of PL share on SOW, and at C1000, for which we did not find evidence for such nonmonotonicity. 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 "NB cherry pickers," with significantly higher brand loyalty and quality consciousness. However, there is a notable 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 NBs wherever they are cheapest. At C1000, however, this segment is less inclined to purchase PLs in general.

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 underscores the notion that high PL buyers may not be the most worthwhile 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, Neslin, and Gedenk 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. Its heavy PL buyers also have a higher SOW at hard discounters that sell almost exclusively PL products at low prices (Kumar and Steenkamp 2007). In general, therefore, the pattern of results across the three PL groups is similar for the two chains.

Discussion

Although PLs are 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, little is known about the interrelationship 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 and nonlinearity and includes other key determinants of the two constructs, and we 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 that SOW significantly affects PL share for both chains. These effects are strong but nonmonotonic for the service chain whose PL is well differentiated and has high penetration. We find that SOW initially increases strongly with PL share, but beyond PL share of approximately 40%, it begins to decrease. Similarly, PL share also increases strongly with SOW but only to a certain point, beyond which PL share begins 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. Furthermore, PL share at this chain has not yet reached high enough levels to exhibit nonmonotonic effects.

The inverted U-shaped effect of PL share on SOW can be explained by the notion that consumers who buy 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

TABLE 6
Exploratory Analysis of Light and Heavy PL Users

Characteristic	Mean Value When PL 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**
PL share at other chains (excluding hard discounters)	.16	.17	.20**
SOW 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**
PL share at other chains (excluding hard discounters)	.18**	.23	.26*
SOW 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 PL share group at $p < .05$.
**Mean is significantly different from mean in medium PL share group at $p < .01$.

but also share of trips and share of items are low among heavy PL users (Table 3) and by the finding that they have higher PL share in other chains than medium PL users (Table 6). It is also consistent with exploratory patterns that Ailawadi and Harlam (2004) report, 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-shaped effect of SOW on PL share can be explained by the previously established finding 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, loyal consumers, who patronize one chain for most or all of their purchases, are more likely to buy not only the categories in which PL is acceptable to them but also the categories in which PL is not acceptable to them in that chain. Their SOW in the chain is high, but because these consumers are not willing to purchase PL in certain categories, they reach a ceiling on their PL purchases. Because 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 nonmonotonic effect for C1000, because there are few heavy PL shoppers at C1000, so the range of data is not enough to reveal the downward portion of the inverted U. Why are there so few heavy PL shoppers at C1000? It is not because they dislike PLs per se, because this group has high PL share at other chains (26%) and high SOW at hard discounters (19%) that 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 3 and Table 6 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-shaped relationship between PL share and SOW shows that even for a high-quality PL program, it can be overdone. This has been the experience of the United Kingdom's J. Sainsbury chain, which has a positioning similar to Albert Heijn and a PL share that exceeded 60%. It needed to scale back its emphasis on PL because SOW began to decline as consumers believed that the dominant presence of the Sainsbury PL constrained their choice. In the United States, 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 needed to retract.

Thus, sophisticated retailers that have a high-quality, well-differentiated PL face a conundrum. Although there may be a rationale for further growing PL, especially from a margin perspective, retailers need to be wary of how far they can push PL at the expense of NBs. 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 PL. Subsequently, they could be migrated to the more differentiated, relatively premium PL, with its loyalty-creating benefit. However, this strategy will have limited effect because the light PL group is typically small for sophisticated chains; it is only 8% at Albert Heijn. There is also the possibility that buyers of the standard PL will 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 example, the United Kingdom's Tesco carries seven Tesco subbrands 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 in which consumers are currently reluctant to buy PL. In the United States, Target has been successful in imbuing its store brand with imagery. If retailers can pull this off, they will be able to combine the high intensity of PL buying with high SOW.

Chains without a well-differentiated PL program face a different challenge—namely, convincing shoppers to increase their PL buying intensity. Their PL share threshold for achieving loyalty benefits is higher than that for their well-differentiated competitors, so they need to increase PL share more among their light PL users and nonusers. Although their current PL share levels are too low to exhibit negative loyalty returns, our analysis suggests that they are likely to face negative returns, similar to their competitors, if their PL share becomes 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, such as C1000, is to develop a strong PL assortment. The first step is to improve actual quality through better sourcing and innovation, but it is equally important to convince consumers of the quality of the PL. Value chains often suffer from an unfavorable gap between actual and perceived PL quality. For example, whereas 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 United States adopted an innovative approach to do just that. For five weeks, the retailer designated three NB products and its corresponding Publix brand items for the promotion. Consumers who purchased the NB received the Publix product free (*Supermarket News* 2007). In summary, building a compelling PL program through real and perceived quality improvements is essential for such chains.

[4]This was confirmed in a recent GfK Benelux 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).

Directions for Further Research

Although this research answers 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.

Further 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 and percentage of categories and SKUs that are PL explain variation in SOW and PL share across chains. Because we estimated our model separately for each chain, these variables, which exhibit little variation within a chain, were not relevant. However, they are likely to be important in a cross-chain model.

Private-label products in some categories may be more effective in engendering SOW than PLs in other categories. For example, increased PL share in hedonic and high-perceived-risk categories, such as 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 would complicate the model, but this is a fruitful area for further research.

Although 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 trade-offs retailers face in their PL objectives: higher product margins on PL, higher leverage in NB manufacturer negotiations, and higher consumer store loyalty. Demonstrating the existence of such trade-offs is an important contribution of this article.

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. This 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.

APPENDIX
Variable Definitions

Variable	Definition
SOW	Percentage of total expenditures (in euros) across 64 categories and 20 retail chains that a household spends at the given chain.
PL share	PL purchases (in euros) of the panelist in the chain divided by total purchases of the panelist in the chain in categories in which the chain has a PL product. Fresh produce and meats are not included in this computation, because there is no distinction between NBs and PLs 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 NBs less average price per equivalent unit of PL as a percentage of average NB 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 checkout counters per square meter in the chain's store nearest to the panelist's home zip code.
General PL propensity	PL purchases (in euros) of the panelist in other chains divided by total purchases of the panelist in those chains.

APPENDIX
Continued

Variable	Definition	Variable	Definition
Price consciousness[a] (Cronbach's α = .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"; and "I generally strive to buy products at the lowest price."	Brand loyalty[a] (Cronbach's α = .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"; and "If my preferred brand is not available in the supermarket, I can easily choose another brand." (reverse coded)
Quality consciousness[a] (Cronbach's α = .69)	Three-item scale: "I always strive for the best quality"; "Quality is decisive for me while buying a product"; and "Sometimes, I save money on groceries by buying products of lower quality." (reverse coded)	Shopping enjoyment[a] (Cronbach's α = .71)	Three-item scale: "I really like to browse in stores"; "I really do not like grocery shopping" (reverse coded); and "I really enjoy doing grocery shopping in the supermarket."

[a]Likert scale ranges from 1 ("strongly disagree") to 5 ("strongly agree").

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