Article

Opening the Umbrella: The Effects of Rebranding Multiple Category-Specific Private-Label Brands to One Umbrella Brand

Kristopher O. Keller, Inge Geyskens, and Marnik G. Dekimpe

Abstract
The authors study the consequences of rebranding multiple category-specific private-label (PL) brands by "opening the umbrella" and unifying them under a common brand name. Retailers expect positive consequences that may manifest themselves in two ways: (1) an increased intrinsic brand strength and (2) an improved marketing-mix effectiveness. The authors analyze three substantially different retailers that rebranded one of their PL tiers. Consistent with the national-brand literature on umbrella rebranding, all three retailers realized an increase in the rebranded PL tier's intrinsic brand strength, along with a reduced price elasticity. However, and in contrast to the national-brand literature, the effectiveness of both price-promoting and assortment size dropped for all three retailers after they unified their category-specific PLs under a common umbrella name.

Private labels (PLs) already account for over 22% of the grocery sales in the United States (Stern 2019), and in several European countries (e.g., Spain, the United Kingdom), market shares are approaching the 50% mark. With PLs no longer having to justify their quality, some are making the transition to consumer packaged goods brands in their own right (Seenivasan, Sudhir, and Talukdar 2016). Many retailers, however, still offer PLs with brand names that are restricted to a narrow set of closely related product categories that individually may lack the muscle to become strong brands of their own. To overcome this impediment, retailers are ever more consolidating their category-specific PL brands by "opening the umbrella," and unifying them under a common brand name. U.S.-based Save-A-Lot, for example, has announced that it will rebrand its standard PLs under a single brand name to replace its multiple individual brand names (Store Brands Decisions 2016). European examples include the Belgian market leader Colruyt, which replaced its more than 50 category-specific standard PL brands, such as "Cribbits," "Davinia," and "Galaxi," with one umbrella brand name ("Boni Selection"). Similarly, the retail chain SPAR unified its 50+ economy PL brands in the Netherlands (among which "Casa Italiana," "Landhof," and "Koningssuper") under the umbrella brand name "OK€."

Are such rebranding strategies successful? Industry experts believe they are (Pierce 2011; Planet Retail 2014), and also

retailers are optimistic about their PL rebranding efforts (Store Brands Decisions 2012a). SuperValu, for example, expected its PL sales to grow by about $70 million per year because of the rebranding (York 2011). These hopes can be attributed to two factors: practitioners feel that "it is easier to build equity in a single brand" (Kolm 2016), and that umbrella branding will "help create efficiencies in . . . marketing" (Store Brands Decisions 2012b). However, do changes in intrinsic brand strength and marketing-mix effectiveness actually materialize? And are they necessarily positive? Indeed, the rebranding could also backfire if consumers had developed favorable associations with the abandoned category-specific brand names, making them reluctant to embrace the new umbrella positioning. Relatedly, it is unclear whether the presence of the same PL name across all categories throughout the store will affect the sensitivity to additional PL stockkeeping units (SKUs) under that name or to promotional activities for the umbrella-branded PL.

Kristopher O. Keller is Assistant Professor of Marketing, Kenan-Flagler Business School, University of North Carolina at Chapel Hill, USA (email: kristopher_keller@kenan-flagler.unc.edu). Inge Geyskens is Professor of Marketing, Tilburg University, the Netherlands (email: i.geyskens@tilburguniversity.edu). Marnik G. Dekimpe is Research Professor of Marketing, Tilburg University, the Netherlands, and Professor of Marketing at KU Leuven, Belgium (email: m.g.dekimpe@tilburguniversity.edu).

Even though numerous studies have considered conditions under which brand extensions may be more or less appropriate (see, e.g., Völckner and Sattler 2006), few studies have empirically analyzed the reputational effects of umbrella branding (Bronnenberg, Dubé, and Moorthy 2019, p. 338). Moreover, the few studies that did so focused on national brands (NBs; e.g., Aaker and Joachimsthaler 2000; Erdem and Sun 2002). While these studies indeed found that umbrella branding across a few closely related categories increases both the NB's intrinsic strength and the effectiveness of several marketing-mix instruments, it is not clear that this will also be the case when umbrella branding a retailer's PL offering. Unlike NB manufacturers, retailers moving to umbrella branding do not have a flagship category with a well-established parent brand to capitalize on. They need to do so for a much larger and broader set of categories that involve not only complementary but also substitute and unrelated categories (Sayman and Raju 2004). Moreover, NBs typically have a greater stake in individual categories. They can invest considerably more resources in developing category-specific associations for their brands than retailers can for each of their many categories (Lamey et al. 2012).

The higher prevalence of umbrella branding in the PL domain (Richards, Yonezawa, and Winter 2015) and the aforementioned intricacies in evaluating its impact (Sayman and Raju 2004) stand in sharp contrast with the scant literature on the issue. We intend to fill this void and thereby address repeated calls for more research on the applicability of NB-based branding principles to the PL domain in general (Grewal, Levy, and Lehmann 2004), and umbrella-branded PLs more specifically (Dekimpe et al. 2011, p. S22; Keller, Dekimpe, and Geyskens 2016, p. 16; Lourenço and Gijsbrechts 2013, p. 381). We aim to address the following research questions:

RQ1: To what extent does a PL's intrinsic brand strength change when shifting from category-specific branding to umbrella branding?

RQ2: To what extent does a PL's marketing effectiveness change when shifting from category-specific branding to umbrella branding? If it changes, for which marketing instruments and how (much)?

We empirically study these questions in the context of the Dutch retail banners SPAR and Attent, which rebranded 50+ category-specific economy PL brands to a unified umbrella brand.[1] To better isolate the rebranding effects, we identified seven retail banners that carried the same category-specific PL brands as SPAR and Attent (because they belonged to the same buying group) but that did not change to umbrella branding. For each retail banner, we obtained weekly sales data for a large number of product categories both before and after the rebranding. This data set will enable us to perform before-and-after-

with-control-group analyses. Moreover, to rule out that our findings are idiosyncratic to the specific retailers under investigation, we subsequently extend our analysis to a retailer from another country (Colruyt in Belgium), which differs substantially in terms of size, format, positioning, and PL success before the rebranding, and which rebranded its standard rather than its economy PL tier.

Our results provide retailers that still offer category-specific PL brands with insight into the various implications of a shift to umbrella branding. Although PL umbrella branding has become a frequently observed practice in the current retailscape, looking at the market leader (if reported by Euromonitor) in the largest five countries in each of six continents, close to 30% of the banners still use category-specific branding. Importantly, our results speak to both the retailers' top-level management and the category managers who have to implement the strategy. Specifically, our findings allow category managers to make better-informed decisions, given the potentially changed effectiveness of the various marketing-mix instruments. Moreover, we provide a nuanced way for top-level management to evaluate the overall effectiveness of this strategic initiative.

Theoretical Background

Umbrella or family branding is often motivated on the assumption that the common brand name leads to a "connection in consumers' minds," which generalizes consumers' preferences to the different product categories using the name (Fry 1967, p. 237). The underlying idea for such a halo or spillover effect is that one can not only take advantage of increased brand recognition and recall because of the added exposure potential but also leverage the reputation of the brand across categories (Sebri and Zaccour 2017).

Proponents argue that the use of an umbrella brand name facilitates consumers' mental categorization and evaluation of these products, as only one recurring brand name is used (Aaker 2012). Categorization theory suggests that consumers organize objects into different cognitive clusters to increase processing efficiency (Cohen and Basu 1987). When consumers can categorize a new object as a member of an earlier defined cluster, they can retrieve their evaluations associated with that cluster and apply them to the new object, resulting in a better understanding and reduced uncertainty (Liu et al. 2017). In a retail setting, consumers frequently rely on external cues, such as brand names or logos (Keller, Dekimpe, and Geyskens 2016), to categorize products.

Using a common brand name (as opposed to multiple different brand names) can also be a way to credibly signal positive quality correlations (Miklós-Thal 2012; Wernerfelt 1988). The ensuing reduction in uncertainty may affect product utility positively and, ultimately, increase the brand's intrinsic strength (Erdem 1998). Both Erdem (1998) and Erdem and Winer (1998) document that consumers' preferences for a brand name can indeed be correlated across categories (see also Singh, Hansen, and Gupta [2005]). However, other studies point out that cross-category signaling and learning effects for

---

[1] Retailers make umbrella rebranding decisions at the PL tier level (e.g., economy, standard, or premium PL tier).

umbrella-branded products are by no means automatic (Erdem and Chang 2012), nor always positive. When the same name is used across too many or too different categories, the approach may backfire, and result in a reduced identity and intrinsic brand strength (Völckner and Sattler 2006).

In spite of the high incidence of umbrella branding, and even though many game-theoretic studies have studied the potential underlying economics (e.g., Cabral 2009; Miklós-Thal 2012; Wernerfelt 1988), Bronnenberg, Dubé, and Moorthy (2019) concluded that the empirical evidence of spillovers in consumer quality beliefs remains limited and inconclusive. Moreover, most of that limited empirical evidence pertains to brand extensions for *NBs*. Even though PL branding can, to some degree, be considered an extreme case of a brand extension (Sayman and Raju 2004), there are several key differences. First, umbrella-branded NBs typically evolve gradually from a flagship category (often referred to as the parent category). At the same time, the extensions (where the same name is subsequently applied) usually involve a limited number of closely related complementary categories. Umbrella-branded PLs, in contrast, appear throughout the store and include a much larger number of complementary, substitute, and unrelated categories. Because of that, the danger of brand dilution may, at first sight, be more imminent, as consumers may doubt that the retailer can provide consistent quality across so many different categories (Ailawadi and Keller 2004).

Furthermore, the disappearance of all category-specific brands (within a short period) with a familiar and possibly unique positioning may create confusion among consumers. Category-specific brands typically use a positioning that is congruent with the category (Inman, Shankar, and Ferraro 2004) and/or that adheres to the prevalent trade dress (Van Horen and Pieters 2012), as they do not need to compromise their positioning relative to brands in other product categories (Aaker and Joachimsthaler 2000; Rao, Agarwal, and Dahlhoff 2004). As umbrella PL brands must adapt to a common design grid across categories (De Jong 2019), positive category-specific associations and trade dress advantages can get lost with the rebranding. This could lower consumers' appreciation of a product, and result in a reduced intrinsic brand strength.

Morrin (1999) and Sayman and Raju (2004), in contrast, argue that because it is difficult to link the PL's umbrella name to a specific category, consumers may become primed through more abstract (or higher-order) associations (Dacin and Smith 1994), such as value for money or acceptable quality. This would make the large number of rebranded categories a benefit rather than a liability. Using scanner data for up to 13 product categories, Sayman and Raju (2004) found in a cross-sectional (across-retailer) design that a higher number of PLs in other categories indeed corresponds to a higher PL share in a retailer's target category. Still, this number (while larger than the five categories used in Erdem and Chang [2012] or the three categories studied in Richards, Yonezawa, and Winter [2015]) remains far below the typical number of categories in a retailer's PL portfolio.

More importantly, none of these prior studies has considered the implications for the PL's marketing-mix effectiveness. As NBs become stronger, their price elasticity has been found (see, e.g., Datta, Ailawadi, and Van Heerde 2017; Sivakumar and Raj 1997) to become smaller (less negative), while they receive a stronger response to promotional discounts (e.g., Datta, Ailawadi, and Van Heerde 2017). The latter finding has been attributed to the larger pool of customers that stronger brands can attract through their price discounts (Sethuraman 1996, 2009). However, given that PL brands (and especially the economy tier) are already sold at the lowest prices in the market, it is unclear to what extent this will also be the case when the intrinsic strength of the PL brand increases with the rebranding. Similarly, given that the same name is used throughout the store, an unchanged promotional frequency in a given category may still be perceived as higher and thereby result in a lower promotional elasticity (Foekens, Leeflang, and Wittink 1998), even when the PL has become stronger after the rebranding. In terms of assortment size, even though product-line length has been found to be one of the strongest drivers of NB success (Ataman, Van Heerde, and Mela 2010), shoppers may become overwhelmed by the many PL SKUs that now carry the same name, and perceive less variety in the store (Briesch, Chintagunta, and Fox 2009; Rooderkerk, Van Heerde, and Bijmolt 2013), resulting in a much smaller, or even negative, assortment elasticity after the PL rebranding.

In summary, it is not clear to what extent the limited empirical evidence on the positive intrinsic brand strength and marketing-mix effects observed with NBs will automatically extend to a PL setting when retailers decide to change their established category-specific PL names to one common umbrella brand name. Given the widespread and increasing prevalence of such rebrandings, we empirically assess the performance implications of a number of recent PL rebrandings.

Data and Research Setting

We study a PL umbrella rebranding at two banners, SPAR and Attent, of the leading Dutch convenience-store retailer SPAR Holding. The Netherlands has a highly developed retailing landscape, which has been used repeatedly to study retailing in general and PLs in particular (e.g., Ailawadi, Pauwels, and Steenkamp 2008; Sotgiu and Gielens 2015). SPAR uses a hi–lo price positioning and a high service level. It operated 227 outlets at the end of 2015. In the Netherlands, grocery retailers set prices centrally, implying that no price-zoning practices are used (Sotgiu and Gielens 2015). SPAR carries an economy and a standard PL tier. From March 2013 to November 2014, SPAR rebranded all its category-specific economy PL brands to one umbrella brand, "OK€." Figure 1 shows four example SKUs before and after the rebranding.

Attent is active in the same market as SPAR, also carries an economy and standard PL tier, and rebranded the same (economy) PL tier. However, compared with SPAR, Attent operates smaller neighborhood stores and provides somewhat less service. It sets its own marketing-mix strategy: it offers fewer
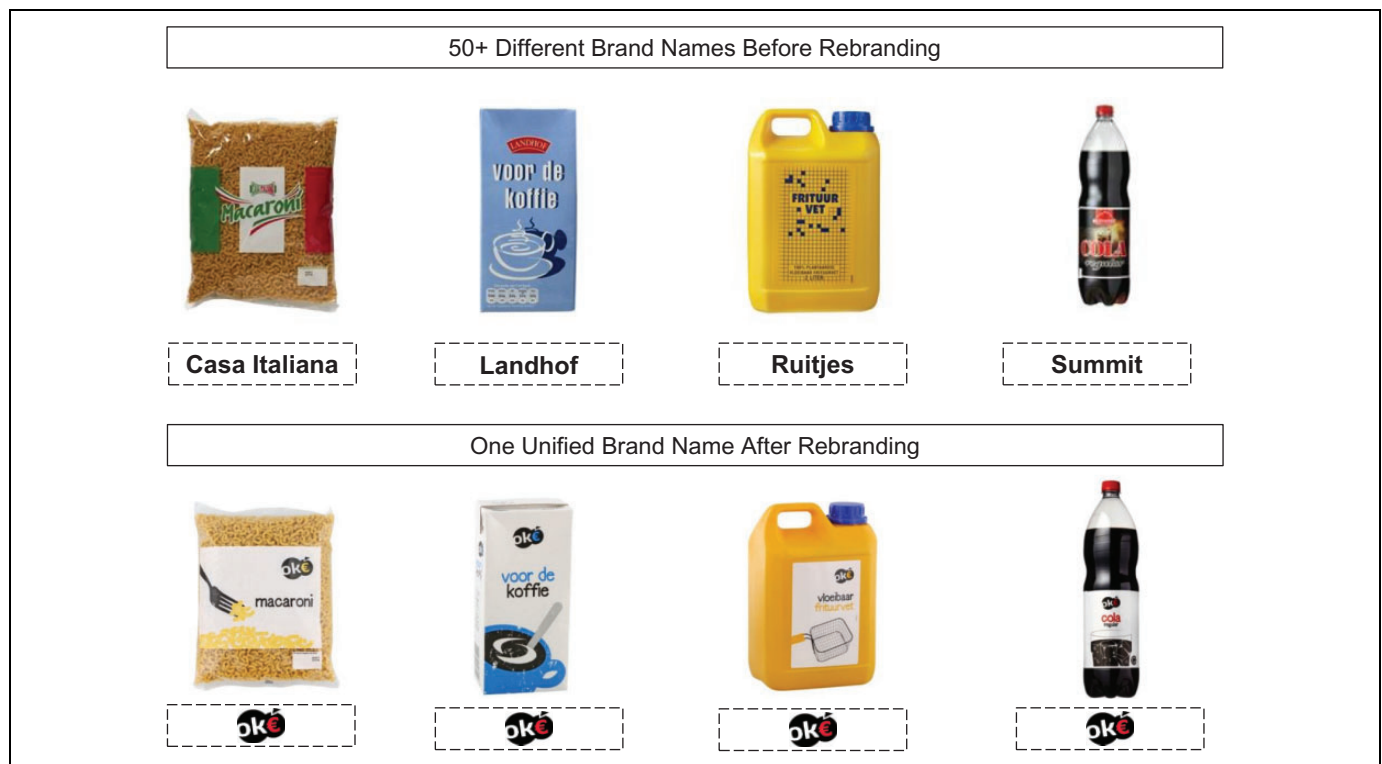
Figure 1. PL-tier rebranding in four example categories to the umbrella brand "OK€."

price promotions than SPAR and uses no advertising. Attent operated 72 outlets at the end of 2015.

SPAR and Attent's PL rebranding provides a clean setting that allows us to study the effect of the rebranding in isolation. During the rebranding, SPAR and Attent changed neither the physical specifications (e.g., ingredients, package type) of their PL products nor their PL suppliers. Moreover, the rebranding took place on a category-by-category basis such that they rebranded all SKUs within a category within the same week. For the rebranded PL tier, they used only one supplier per category. The order in which they rebranded the categories was determined by the ending date of the current contract with the PL supplier of that category. Typically, PL suppliers procure very short (12 to 24 months long) contracts (De Jong 2019; Ter Braak, Dekimpe, and Geyskens 2013). Whenever a contract was to be renewed, the category was rebranded.

The retailers communicated the name change clearly as a rebranding to their consumers to ensure that consumers would learn in a timely way about the rebranding and not be taken by surprise. For every (to be) rebranded SKU, SPAR and Attent provided a shelf label that announced the old SKU would get a new design and brand name. In the weeks of the rebranding, the new, rebranded SKUs were placed at the back of the shelves and would appear as the old SKUs (with the category-specific brand names) were sold out. In addition, SPAR and Attent created flyers that they prominently displayed at the cash registers. The flyer announced the upcoming/ongoing rebranding of the category-specific brands to the new umbrella brand. The flyer also served to inform those

consumers that may not have bought the focal PL yet and may have missed the shelf labels.

Critical to our investigation is that no major changes occurred for SPAR and Attent during our observation period. We used LexisNexis and SDC Platinum to check the business press for potential concurrent events (e.g., store remodelings, startups of online operations, mergers and acquisitions) to rule out that the rebranding coincides with potentially confounding changes at either banner. We also searched SPAR and Attent's news portals for any press releases or news reports that might suggest changes in the retailer's strategies around the time of the rebranding. Neither SPAR nor Attent made announcements about events that could have interfered with the rebranding.

We obtained weekly store-scanner data from SPAR and Attent from 2011 to 2015 on *all* product categories in their rebranded PL tier, ranging from dairy and nondairy food to beverages, household care, and personal care. We analyze 53 (47) categories for SPAR (Attent), all of which (1) have at least 52 weeks of nonzero sales data for the rebranded PL tier both before and after the rebranding, (2) also feature NBs and another PL tier (to control for potential interdependencies between the tiers), and (3) are not fresh goods categories (where products are mostly unbranded). Across these categories, we observe, on average, 129 (130) weeks before and 111 (112) weeks after the rebranding for SPAR (Attent).

In addition to the data described previously, we created a control group to allow us to perform a before-and-after-with-control-group analysis. We identified seven retail banners (e.g., Deen, Deka-Markt, Hoogvliet) that carried the same category-

Table 1. Variable Operationalizations.

Construct	Definition	Reference
Sales	Quantity sold (in equivalent units, such as grams, milliliters or pieces) of category i in week t.	Lourenço and Gijsbrechts (2013)
Price	Market-share-weighted price per unit volume in category i in week t.	Pauwels and Srinivasan (2004)
Price promotions	Market-share-weighted share of products with a price promotion in category i and week t according to the algorithm by Gedenk and Neslin (2000), using 5% as a discount threshold value. This algorithm allows for price promotions of up to six weeks.	Gedenk and Neslin (2000)
Assortment size	Outlet-weighted number of SKUs offered in category i in week t.	Sotgiu and Gielens (2015)
Trend	Variable running from $t = 1$ up to (maximally) $t = 261$ for each category i.	Godfrey, Seiders, and Voss (2011)
Banner advertising	To allow for carryover effects, an adstock variable is defined as $X_{1, t} = c \, adv_t + (1 - c) \, X_{1, t-1}$, where adv_t is retailer advertising spending in thousand euros in week t, obtained from Nielsen Media Research. The decay parameter c is determined using a grid search over the [.05, .95] interval in .10 increments.	Gielens (2012)
Outlets	The number of outlets operated in week t.	Gielens and Dekimpe (2007)
Consumer confidence	Monthly composite indicator, capturing households' expectations of their financial situation, the general economic situation, unemployment, and savings over the next 12 months.	Geyskens, Gielens, and Gijsbrechts (2010)
Seasonal and holiday effects	Twelve four-weekly period dummy variables, along with eight pulse dummy variables, each capturing a national public holiday (New Year's Eve, Good Friday, Easter, Queen's/King's Day, Liberation Day, Ascension Day, Pentecost, and Christmas). The latter take on the value of 1 in the week of the public holiday and 0 otherwise.	Ataman, Van Heerde, and Mela (2010)

Notes: For price and price promotions, we aggregate from the SKU level to the PL-tier level using (time-invariant) full-period market shares as weights (for a similar practice, see, e.g., Pauwels and Srinivasan [2004]).

specific PL brands (with the same brand names) as SPAR and Attent (as they were members of the same buying group, a situation described in more detail in Geyskens, Gielens, and Wuyts 2015), but that did not change to an umbrella brand name. For each of these retail banners, we have weekly data for the same categories and time as for SPAR and Attent.

Using data from Spotzi (www.spotzi.com) covering the geo-location of all grocery retail outlets in the Netherlands in the years of our study, we calculated the share of outlets of the treatment retailers that overlapped with *any* of the control retailers' outlets within their trading zone. Because the control retailers were mostly active in different regions of the country than the treatment retailers, only 9% (7%) of SPAR (Attent) outlets were within a two-kilometer driving radius, which is the average distance consumers drive to their primary supermarket in the Netherlands (Deloitte 2018). We dropped these outlets before aggregating the outlet level data to the retailer level to rule out direct competition between treatment and control retailers and satisfy the stable unit treatment value assumption (SUTVA) (to which we return subsequently).

The data come at the category-SKU-week level. To reduce the impact of extreme values, we winsorize SKU sales and prices at the 1% and 99% levels (see, e.g., Rego, Morgan, and Fornell 2013). We aggregate the data across SKUs to the PL-tier level, using the procedure outlined in Pauwels and Srinivasan (2004).[2] Similar to Sotgiu and Gielens (2015), we use volume sales as our performance metric. Volume sales is an important performance indicator for managers that is particularly well suited "if [we] want to … assess the impact of changes in the marketing mix" (Hanssens, Parsons, and Schultz 2003, p. 52). We study three of the most prominent category-level marketing-mix tools—price, price promotions,[3] and assortment size—while controlling for the retailer's marketing-mix instruments that are chain-wide (including advertising and the retailer's number of outlets), the level of consumer confidence, and national holidays. We deflated the pricing and advertising variables with the consumer price index. Table 1 shows the operationalizations.

Estimation Strategy

Our objective is to identify the effect of a PL umbrella rebranding on the rebranded PL tier's sales. In doing so, we face two challenges. First, our data generation process lacks a random assignment of rebranded categories into treatment and control conditions. Therefore, we estimate a difference-in-differences (DiD) model and use a quasiexperimental procedure in which we match categories for the two retailers that rebranded with the same category from one of the retailers that carried the same PL brands but opted not to engage in a PL rebranding exercise. Second, we need to ensure that our findings are not driven by self-selection and endogeneity. We now explain in detail each step of our identification strategy (for an overview, see Table 2).

---

[2] In line with Gielens (2012), we do not include SKUs with an average market share below .1% across the data span.

[3] More specifically, we study the share of products that is being price-promoted. For brevity, we refer to "price promotions" throughout the article.

Table 2. Overview of Analyses.

Analysis	Objective
Control group construction	Selecting and validating
(a) Mahalanobis distance matching	the controls
(b) Compare treated and resulting controls	
DiD analysis	Identifying category-
(a) Validation of assumptions	specific rebranding
• Parallel-trend assumption	effects through a
(b) Estimation, accounting for	quasiexperimental
• Intercept and slope endogeneity	approach, absent a
• Category heterogeneity	randomized control design
Robustness checks	Testing the sensitivity of
(a) Aggregation bias	the results and ruling
(b) Alternative operationalization	out alternative
(c) Post-promotion dip	explanations
(d) Cross-tier effects	
(e) Alternative trading zone	
(f) Different PL tier and retailer	

Creating a Matched Control Group

We conduct a distance-matching analysis (Guo and Fraser 2015, p. 177) in which we pair each rebranded category of SPAR and Attent with the same category of one of the seven control retailers that did not engage in the rebranding.[4] Using a 52-week pretreatment observation window, we compute for each category the Mahalanobis distance between the treated category and the potential control candidates using the variables in Table 3. We then select the match with the smallest distance. After matching, the rebranded categories and the control categories have become indistinguishable in terms of the pretreatment characteristics, except for the focal PL-NB price differential ($ps < .01$). This difference is not unexpected, however, given the more service-oriented positioning of SPAR and Attent (we elaborate on this when motivating the constant-bias assumption of the conditioning variable). Table 3, Panel A, reports pretreatment summary statistics for the matched control group.

Difference-in-Differences

We use a DiD approach to estimate the effect of the PL rebranding on focal PL sales and compare the PL sales before and after the rebranding with those of the matched category. We estimate a log-log model (that relates the log of volume sales to the log of the continuous covariates) because it offers direct estimates of the marketing-mix elasticities. Formally,

$$
\begin{aligned}
\ln(S_{i,t}) = {} & \beta_{1,i} + \beta_{2,i}\, T_{i,t} + \beta_{3,i}\, T_{i,t}^2 \\
& + \sum_{j=4}^{6} \beta_{j,i} \ln(MKT_{j,i,t}) + \eta_{0,i}\, X_t' \\
& + \sum_{k=1}^{22} \eta_k X_{k,t} + TREAT_i \Bigg[\beta_{1,i}^{treat} + \beta_{2,i}^{treat}\, T_{i,t} \\
& + \beta_{3,i}^{treat}\, T_{i,t}^2 + \sum_{j=4}^{6} \beta_{j,i}^{treat} \ln(MKT_{j,i,t}) \\
& + \eta_{0,i}^{treat}\, X_t' + \sum_{k=1}^{22} \eta_k^{treat} X_{k,t} \Bigg] \\
& + POST_{i,t} \Bigg[\beta_{1,i}^{post} + \beta_{2,i}^{post}\, T_{i,t} + \beta_{3,i}^{post}\, T_{i,t}^2 \\
& + \sum_{j=4}^{6} \beta_{j,i}^{post} \ln(MKT_{j,i,t}) + \eta_{0,i}^{post}\, X_t' \Bigg] \\
& + TREAT_i \times POST_{i,t} \Bigg[\beta_{1,i}^{rebr} + \beta_{2,i}^{rebr}\, T_{i,t} \\
& + \beta_{3,i}^{rebr}\, T_{i,t}^2 + \sum_{j=4}^{6} \beta_{j,i}^{rebr} \ln(MKT_{j,i,t}) \\
& + \eta_{0,i}^{rebr}\, X_t' \Bigg] + \varepsilon_{i,t},
\end{aligned}
$$

(1)

where $S_{i,t}$ represents a PL tier's volume sales (capturing the sales of all focal PL SKUs in product category i that were rebranded, and expressed in equivalent units to adjust for different package sizes) in category i at SPAR in week t. In line with Godfrey, Seiders, and Voss (2011), we allow for a flexible evolution of the PL tier's sales by including both $T_{i,t}$, with $T_{i,t}$ a trend variable running from t = 1 up to (maximally) t = 261 for each category i, and its square, $T_{i,t}^2$.[5] $MKT_{j,i,t}$ represents three marketing-mix tools: price (j = 4), price promotions (j = 5), and assortment size (j = 6). $TREAT_i$ is the treatment group dummy variable that equals one for all product categories i of SPAR (i.e., the treatment group), and zero otherwise. $POST_{i,t}$ is a step dummy variable that takes on the value of one after SPAR rebrands its PL tier in category i and zero before. Of focal interest are the $\beta_{1-6,i}^{rebr}$ parameters, as they measure the

---

[4] Matching was performed at the retailer level after excluding the treatment retailers' outlets that overlapped with any of control retailers' outlets within their trading zone.

[5] Because we allow the intercept and parameters of the trend and squared trend to change with the rebranding, we have six parameters per retailer to represent the evolution in base sales. This enables us to capture a large variety of trajectories in a parsimonious way. To better isolate the effects of interest, we do not use the immediate four weeks before and after each category's rebranding in the estimation (Ma, Ailawadi, and Grewal 2013; Vroegrijk 2012). Also in the aforementioned matching procedure, the four weeks prior to the rebranding were not used. The time trend and time trend squared variables are highly correlated. We therefore orthogonalize these variables by regressing the squared term on the corresponding linear one and using the residuals in our analyses (for a similar "partialing-out" procedure, see Batra and Sinha [2000] or Ter Braak, Dekimpe, and Geyskens [2013]).

Table 3. Summary Statistics by Group before the Rebranding.

	SPAR			Attent		
	Treatment	Control	t-Stat.	Treatment	Control	t-Stat.
A: 52 Weeks Before						
Category sales growth	−.100	−.111	−.122	−.175	−.089	.754
Focal PL sales growth	−.082	−.094	−.076	.020	−.017	−.241
NB share	.532	.541	.254	.492	.540	1.272
Focal PL share	.163	.171	.357	.147	.168	.879
Focal PL-NB price differential	.333	.554	5.935***	.348	.565	5.513***
Focal PL-NB price-promotions differential	.421	.700	1.293	.825	.611	−.625
Focal PL-NB assortment-size differential	.206	.190	−.453	.221	.198	−.504
B: 52 Weeks After						
Category sales growth	−.031	−.122	−.857	.128	−.106	−2.182**
Focal PL sales growth	.423	−.095	−2.604**	.840	−.292	−4.858***
NB share	.524	.538	.403	.472	.537	1.805*
Focal PL share	.157	.166	.392	.163	.162	−.021
Focal PL-NB price differential	.342	.604	6.722***	.356	.618	6.305***
Focal PL-NB price-promotions differential	.485	.489	.021	1.141	.421	−1.452
Focal PL-NB assortment-size differential	.211	.201	−.243	.254	.209	−.844

*$p < .10$.
**$p < .05$.
***$p < .01$.

Notes: Two-sided tests of significance. As described in footnote 5, we do not include the immediate four weeks before and after each category's rebranding in the calculation. Variables are operationalized as follows: Category (focal PL) sales growth is measured as the average of the first difference of log-transformed category (focal PL) sales. NB (focal PL) share is the average market share of NBs (focal PLs) in a category. The marketing-mix related variables are operationalized as the average of the ratio of focal PL price (price promotions or assortment size) to NB price (price promotions or assortment size). All averages are taken over the 52 weeks leading up to (Panel A) or following (Panel B) the rebranding and all variables without negative values are log-transformed. The considered variables were selected based on data availability and support for their potential relevance in the extant PL literature (e.g., Dhar and Hoch 1997; Sethuraman and Gielens 2014).

effects of the rebranding. All β parameters can vary over categories. We estimate a similar equation for Attent.

Control variables. As control variables (X'_t and $X_{k,t}$, with k running from 1 to 22), we include the retailer's log-transformed advertising (at the banner level), X'_t, as well as its interaction with the $TREAT_i$ and $POST_{i,t}$ dummy variables. In addition, we include the logarithm of the number of retailer outlets open in a given week. We further add the logarithm of the consumer confidence index to control for consumers' tendency to purchase more PLs in economic downturns (Lamey et al. 2012). The latter two control variables are mean-centered to allow us to evaluate the intrinsic brand strength at their mean levels. For the advertising variable, we apply a similar minimum-centering procedure as with the assortment variable. Finally, we include eight dummy variables, reflecting public holidays during which consumers may purchase more or less PLs, along with four-weekly dummy variables to further control for seasonality. The η parameters represent the control variables' effects on category i's sales. $\epsilon_{i,t}$ is a random error term.

Accounting for NBs and the other PL tier. We use Equation 1 to estimate the effects of the rebranding on the PL tier's sales and to calculate changes in the rebranded PL tier's intrinsic brand strength and marketing effectiveness. However, retailers also offer NBs and often have more than one PL tier, and these may be interdependent. To control for this, we state similar equations for the retailer's NBs and its other PL tier. Moreover, by also considering these other brand types, we will be able to assess the total revenue implications of the rebranding. To increase efficiency, we estimate these equations jointly with the corresponding equation for the rebranded PL tier using SUR. Thus, the error terms $\epsilon_{i,t}$ can be correlated across NB and PL tiers and are assumed to be distributed MVN(0, Σ).

Identifying assumptions. The DiD approach relies on the assumption of parallel post-treatment counterfactual trends. Because these are unobservable, this assumption is intrinsically untestable. As a proxy, we assess whether the pretreatment trends are parallel, under the assumption that the pretreatment trends would have continued after the treatment in its absence. We follow Angrist and Krueger (1999) (for a recent application in marketing, see, e.g., Gallino and Moreno 2014) by estimating Equation 2 on the prerebranding data:

$$\ln(S_{i,t}) = \delta_{1,i} + \delta_2 T_{i,t} + \delta_3 T_{i,t}^2 + \sum_{k=1}^{22} \eta_k X_{k,t}$$
$$+ TREAT_i \left[\delta_{1,i}^{treat} + \delta_2^{treat} T_{i,t} + \delta_3^{treat} T_{i,t}^2 \right.$$
$$\left. + \sum_{k=1}^{22} \eta_k^{treat} X_{k,t} \right] + \mu_{i,t}, \qquad (2)$$

where $T_{i,t}$, $X_{k,t}$, and $TREAT_i$ are defined as in Equation 1. Several of the common-trend parameters are significant (δ_2 and
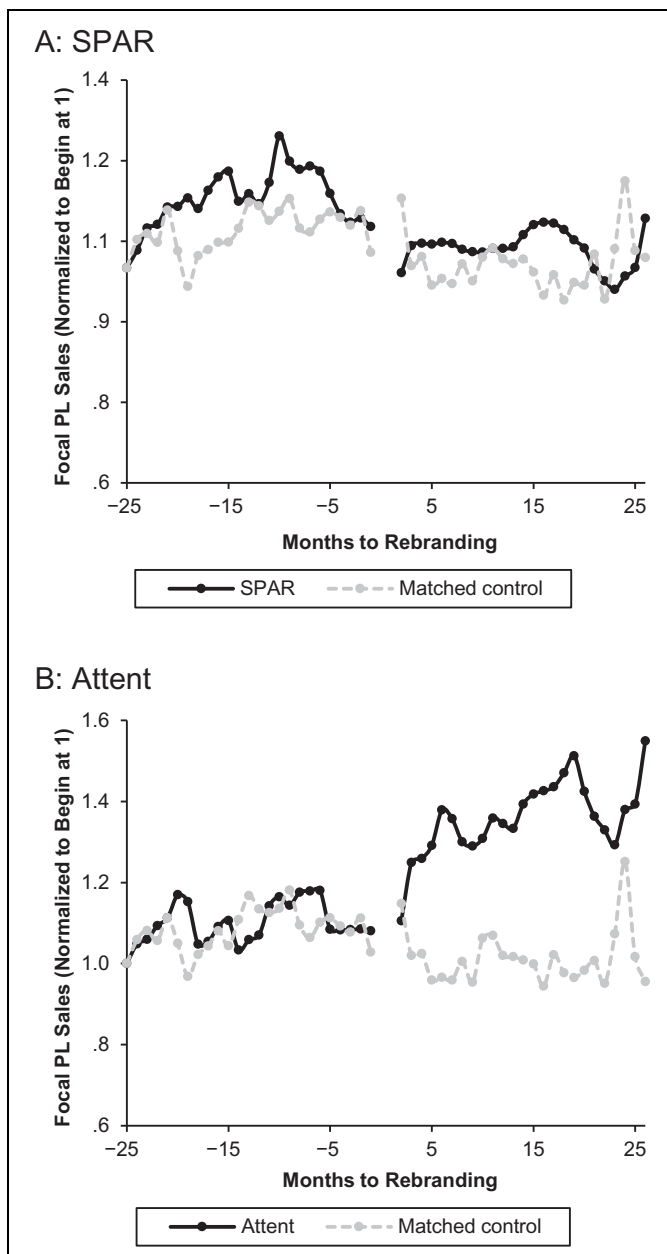
Figure 2. The focal PL tier's sales evolution before and after the rebranding.

Notes: As we describe in footnote 5, we do not include the immediate four weeks before and after each category's rebranding in the calculation.

δ_3 for SPAR and δ_3 for Attent, $ps < .01$). More importantly, the trend deviations for both SPAR (δ_2^{treat}, $p > .10$; δ_3^{treat}, $p > .10$) and Attent (δ_2^{treat}, $p > .10$; δ_3^{treat}, $p > .10$) are not significant. Thus, we find support for the idea that the pretreatment trends are statistically equivalent. Figure 2 provides a visual verification.[6]

Second, while both the treatment and control retailers belonged to the same buying group (and therefore carried the same category-specific PL brands before SPAR's and Attent's rebranding), it is important to note that the choice to rebrand (or not) was *not* made based on considerations that are themselves influenced by the treatment. Instead, this was determined by the retailers' time-invariant strategic positioning, in that the more service-oriented banners, SPAR and Attent, opted to rebrand, while the more value-oriented control banners opted not to do so. As discussed in Lechner (2010, p. 178), variables that cannot change over time are exogenous by construction when one considers a time-varying treatment. As such, also the constant-bias or exogeneity assumption of the conditioning variable is satisfied. Finally, as we explained previously, because we dropped the 9% of SPAR outlets and 7% of Attent outlets that were geographically close to one of the control retailers' outlets, and thus likely to compete directly, violation of the SUTVA assumption is unlikely.

Endogenous Sample Selection

We are confronted with several potential endogeneity problems due to sample selection. In particular, (1) the decision of *which tier* to rebrand (the economy PL tier or the standard PL tier), (2) the decision of *when to start* rebranding that tier, (3) the decision of *which product categories* and SKUs to rebrand within the selected tier, and (4) the decision of in *which order* to rebrand those categories might all be chosen strategically and thus be endogenous.

One could argue that retailers can choose which PL tier to rebrand. However, SPAR and Attent umbrella-branded their standard PL tier since the brands' inception (which was more than two decades ago) and no longer had that choice at the time of our study. Moreover, retailers typically make umbrella-rebranding decisions at the PL-tier level. That is, if they decide to rebrand a PL tier, often *all* product categories of that PL tier are rebranded, as well as *all* SKUs within those product categories. This was also the case for SPAR and Attent. Thus, we do not face endogeneity issues (1) and (3) in our setting. As for the decision of when to start the rebranding exercise, the decision to make the OK€ umbrella brand available to interested retail members was made at the buying-group level. Therefore, this decision is not likely to be directly related to the outcomes of one specific retailer in the buying group (Sande and Ghosh 2018, p. 198), making issue (2) less of a concern. Moreover, both SPAR and Attent decided right away to make use of the rebranding possibility, rather than strategically postpone to a later point of time.

The sequence in which SPAR and Attent rebranded the various categories within the PL tier was (as indicated previously) exogenously determined by the time existing supplier contracts ended. As such, the order of the rebranding was not

---

[6] The observed divergence between SPAR/Attent and the matched-control sales series can be due to (1) a change in intrinsic brand strength following the rebranding, (2) a change in marketing-mix effectiveness, and (3) different

levels of one or more marketing-mix series. In this study, we focus on the first two of these potential drivers.

strategically chosen to maximize performance. To validate this managerial assertion, we estimated a Cox hazard model with the week of the rebranding as the dependent variable, and the same set of independent variables that we used for the matching (see also Table 3), plus the focal PL's profitability. We report the results in Web Appendix A. None of the covariates are significant, indicating that they did not drive the order in which the categories were rebranded.[7] This finding increases our confidence in SPAR and Attent's information that the order in which they rebranded the categories was solely driven by contract expiry dates and not by strategic considerations (e.g., the PL tier's low/high profitability in the category). Thus, we also do not face an endogeneity issue as to the order in which the categories were rebranded (issue 4).

Endogeneity of Levels of the Marketing-Mix Variables

The marketing-mix variables $MKT_{j,i,t}$ in Equation 1 can be correlated with the error term, as they may depend on unobserved demand shocks, rendering them endogenous. In a panel data setting like ours, this correlation can come from three sources (Papies, Ebbes, and Van Heerde 2017, p. 602): (1) unobserved factors that vary over cross-sections (i.e., product categories), but not over time (e.g., PL quality); (2) unobserved factors that vary over time but not over cross-sections (e.g., uncontrolled seasonality); and (3) unobserved factors that vary over both time and cross-sections. We correct for endogeneity source (1) by using fixed-effects estimation, where we specify a dummy variable per cross-section. We cover (2) by including four-weekly dummy variables. To account for (3), we employ an augmented control-function approach (Luan and Sudhir 2010). Specifically, we regress each potential endogenous variable on all exogenous variables and a set of instrumental variables (IVs) to derive the control-function correction (i.e., the residuals from this first stage; Sridhar et al. 2016).

In line with Luan and Sudhir (2010) and Chakravarty, Kumar, and Grewal (2014), we account for both intercept and slope endogeneity. Intercept endogeneity has a long tradition in the marketing literature and refers to managers being strategic about setting the marketing mix in response to unobserved (to the researcher) demand shifters (e.g., employee and top-management commitment) (Luan and Sudhir 2010). Slope endogeneity, in contrast, deals with the fact that (marketing-mix) choices are often affected by managers' private information about the likely differential effectiveness of the marketing mix (e.g., after the rebranding, a retailer may alter its prices to account for a higher expected price effectiveness).

We derive our IVs from two conceptually different sources. As advocated by Nevo (2001), we include the retailer's wholesale price as a first IV. The underlying idea is that retailers are likely to adjust their marketing mix in response to shocks in the wholesale price (i.e., cost shocks), but given that the wholesale price is unobserved by consumers, these may be unrelated to the unobserved demand shocks (see, e.g., Chintagunta 2002). The second group of IVs consists of the marketing variables (price, assortment size, and banner advertising) from a retailer from a neighboring country (Papies, Ebbes, and Van Heerde 2017, p. 601). The logic is that both countries are driven by common supply shocks (e.g., ingredient costs drive price variation in the two countries in the same way). In addition, no common demand shocks should occur across the two markets, nor should marketing-mix actions be coordinated (Sotgiu and Gielens 2015, p. 791). This is more likely to be the case when a different set of retailers is active in the two markets. In our setting, this overlap was limited, given that the leading Dutch retailers (Albert Heijn, Jumbo, and C1000) were not active in Belgium during our observation window, while the leading Belgian retailers (Colruyt, Delhaize, and Carrefour) were not active in the Netherlands.[8,9] Finally, because of the anticipated potential changes in the endogenous variables by the rebranding, we also include as IVs the interactions of the instruments with $POST_{i,t}$ (Wooldridge 2002; for a similar practice, see Van Heerde et al. [2013]).

Changes in Intrinsic Brand Strength and Marketing Effectiveness

We can directly derive the changes in intrinsic brand strength and marketing effectiveness from the DiD model in Equation 1. Following Leeflang et al. (2009) and Sriram, Balachander, and Kalwani (2007), we use a brand's baseline sales (i.e., net of marketing-mix and other effects) as our measure of intrinsic brand strength, which we define (consistent with prior literature) as the sales corresponding to the bare minimum of marketing support. Hanssens, Wang, and Zhang (2016) and Slotegraaf, Moorman, and Inman (2003), for example, have set this minimum at zero, which makes sense for price promotions and banner advertising, but less so for price and assortment size. For the latter, a nonzero base support is required, as an assortment size of zero implies no sales by definition (Ataman, Van Heerde, and Mela 2010). We set assortment size to the minimum level observed in our time span for, respectively, the focal PL tier, the NBs, and the other PL tier, in a given category. To evaluate intrinsic brand strength at these levels, we "minimum-center" (similar to the use of mean-centering) assortment size in our estimation by subtracting the category-

---

[7] We find very similar results when replacing variables based on NB values with those of the other PL tier.

[8] Specifically, we use for each marketing-mix instrument of the Dutch retailers the corresponding marketing-mix value from Colruyt, the Belgian retailer that is part of one of our robustness checks. The Netherlands and Belgium are very similar in terms of macroeconomics, consumer spending (spend per capita, price inflation), and grocery retail (retail sales per capita, number of outlets per capita).

[9] Following Sande and Ghosh (2018), we used the Durbin–Wu–Hausman test, which revealed no evidence of endogeneity for price promotions. For the control variable "banner advertising," we used two additional instruments obtained from the Dutch Central Bureau of Statistics, capturing advertising costs and marketing research costs, respectively, in addition to advertising from Colruyt.

specific minimum value from the variable's values for a given retailer (the minimum support level for the price-promotions variable is zero).

For the price variable, we use the logical counterpart; that is, we "maximum center" by subtracting the maximum level observed per category. Our model accounts for the fact that the intrinsic strength of a brand is not necessarily constant, but can (even in the absence of a rebranding) vary over time (Ho-Dac, Carson, and Moore 2013), by allowing for a flexible, yet parsimonious, evolution through a trend variable and its square. Thus, at any point in time T_i, the change in intrinsic brand strength in category i attributable to the rebranding is

$$\Delta BS_i(T_i) = (e^{\beta_{1,i}^{rebr} + \beta_{2,i}^{rebr} T_{i,t} + \beta_{3,i}^{rebr} T_{i,t}^2}) - 1. \qquad (3)$$

The extent to which the effectiveness of the various marketing-mix instruments j (j = 4, 5, 6) in category i changes after the rebranding is captured directly as $\Delta ME_{j,i} = \beta_{j,i}^{rebr}$.

Results

Model-Free Evidence

Table 3, Panel B, compares the sales of the rebranded PL tiers of SPAR and Attent with those of the control group 52 weeks after the rebranding, and the corresponding values for price, price promotions, and assortment size. As Table 3 shows, on average, SPAR's negative PL growth in the year before the rebranding was turned around after the rebranding, while Attent's PL growth increased. No such patterns were observed for the control groups. As a result, for both retailers, the non-significant difference in PL growth between treatment and control groups before the rebranding became highly significant afterward. This supports the generally positive sentiment about PL umbrella branding. It is, however, unclear whether these effects are due to an increase in the PL's intrinsic brand strength and/or marketing effectiveness after the rebranding, or to other developments in the Dutch consumer packaged goods market.

Results

Table 4 presents the parameter estimates of the DiD specification in Equation 1, averaged across 53 categories for SPAR and 47 categories for Attent, respectively. Multicollinearity does not seem to be an issue, with all correlations well under the .8 cutoff value suggested by Judge et al. (1998), as shown in Web Appendix B (maximum correlation = .226 for SPAR and .346 for Attent). We account for first-order autocorrelation by applying the Prais–Winsten correction (Datta, Ailawadi, and Van Heerde 2017). Our instruments are strong, as evidenced by an average correlation between first-stage predictions and endogenous variables of, respectively, .83 (SPAR) and .86 (Attent) and significant Sanderson and Windmeijer (2016) multivariate F-tests ($ps < .01$). The Hansen-J test supports that our instruments are uncorrelated with the error term ($p > .10$), which attests to their validity (Wooldridge 2002, p. 123).

Because the endogeneity correction terms are estimated quantities, we follow Papies et al. (2017) and report bootstrapped standard errors.

Change in intrinsic brand strength following the PL rebranding. One year after the rebranding, SPAR and Attent's rebranded PL tiers had increased with 36.5% and 20.2% in intrinsic brand strength, respectively (SPAR: $\Delta BS = .365, p < .01$; Attent: $\Delta BS = .202, p < .01$).[10] Because our model accounts for the fact that the strength of a brand is not necessarily constant, but can vary over time, we calculate intrinsic brand strength at different points in time, according to Equation 3. We set $T_{i,t}$ (1) at one year after the rebranding in line with the PL (Keller, Dekimpe, and Geyskens 2016) and product-introduction (Lamey et al. 2018) literature, (2) at 26 and 39 weeks as two shorter time horizons (using the same number of product categories as the 52-week analysis), and (3) at 65 and 78 weeks as two longer time horizons (which reduces the number of available categories in the estimation from 53 to 50 [48] for SPAR, and from 47 to 43 [42] for Attent). In all time windows, intrinsic brand strength is found to be consistently higher than before the rebranding.

Change in marketing-mix effectiveness following the PL rebranding. For the marketing mix, all rebranding effects are significant, indicating a statistically significant impact of the rebranding. The price sensitivity dropped for both SPAR ($\beta^{rebr} = .537, p < .01$) and Attent ($\beta^{rebr} = .644, p < .01$). The price-promotions effectiveness of SPAR ($\beta^{rebr} = -.027, p < .01$) and Attent also decreased following the rebranding ($\beta^{rebr} = -.006, p < .01$), as did their assortment-size effectiveness (SPAR: $\beta^{rebr} = -.423, p < .01$; Attent: $\beta^{rebr} = -.291, p < .01$). As to assortment size, consumers may get overwhelmed by the many SKUs that now carry the same brand name, and perceive less variety in the store (Rooderkerk, Van Heerde, and Bijmolt 2013). Similarly, the increased exposure to promotions for the same brand across many categories leads to a reduced price-promotion elasticity (in line with the findings of Foekens, Lee-flang, and Wittink [1998] on the negative relationship between promotional frequency and promotional effectiveness). The lower price elasticity, in turn, is consistent with the increased intrinsic strength of the PL after the rebranding, and in line with the (NB-based) findings of Datta, Ailawadi, and Van Heerde (2017).

Heterogeneity across categories. One may wonder to what extent the changes in intrinsic brand strength and marketing-mix effectiveness are consistent across categories. As a first probe

---

[10] The brand-strength effect differs between SPAR and Attent, even though the reported values in Table 4 for the underlying parameters ($\beta_{1,i}^{rebr}$, $\beta_{2,i}^{rebr}$, and $\beta_{3,i}^{rebr}$) are similar. These reported parameters represent weighted (by the inverse of their standard error) cross-category averages. Similarly, the intrinsic brand-strength change, along with its standard error, is first computed (per Equation 3) at the category level using category-specific parameters, after which the weighted average across categories is derived.

Table 4. Parameter Estimates of the Difference-in-Differences Model.

DV: Sales ($lnS_{i,t}$)	Parameters Involved	Parameter Estimates			
		N = 26,415		N = 23,490	
		SPAR		Attent	
Variable		Control Group	Deviation from Control Group	Control Group	Deviation from Control Group
Intercept	$\beta_{1,i}$	7.970***		7.615***	
Trend	$\beta_{2,i}$	.002***		.002***	
Trend²	$\beta_{3,i}$	.000		.000*	
Price	$\beta_{4,i}$	−.152**		−.056	
Price promotions	$\beta_{5,i}$	.004***		.004***	
Assortment size	$\beta_{6,i}$	.027		.037	
Treat	$\beta_{1,i}^{treat}$		−10.035***		−11.608***
Treat × Trend	$\beta_{2,i}^{treat}$		−.002**		−.003***
Treat × Trend²	$\beta_{3,i}^{treat}$		−.000		−.000***
Treat × Price	$\beta_{4,i}^{treat}$		−.039		−.051
Treat × Price promotions	$\beta_{5,i}^{treat}$		−.004***		.002*
Treat × Assortment size	$\beta_{6,i}^{treat}$		.727***		.598***
Post	$\beta_{1,i}^{post}$	−.294***		−.315***	
Post × Trend	$\beta_{2,i}^{post}$	−.003***		−.004***	
Post × Trend²	$\beta_{3,i}^{post}$	−.000		−.000	
Post × Price	$\beta_{4,i}^{post}$	−.192***		−.198***	
Post × Price promotions	$\beta_{5,i}^{post}$	−.010***		−.010***	
Post × Assortment size	$\beta_{6,i}^{post}$	.065**		.098***	
Treat × Post	$\beta_{1,i}^{rebr}$		.431***		.425***
Treat × Post × Trend	$\beta_{2,i}^{rebr}$		.003		.008***
Treat × Post × Trend²	$\beta_{3,i}^{rebr}$		−.000**		−.000
Treat × Post × Price	$\beta_{4,i}^{rebr}$		.537***		.644***
Treat × Post × Price promotions	$\beta_{5,i}^{rebr}$		−.027***		−.006***
Treat × Post × Assortment size	$\beta_{6,i}^{rebr}$		−.423***		−.291***
Endogeneity correction terms	✓				
Control variables	✓				

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Two-sided tests of significance. We only report parameter estimates for the focal PL tier. The reported values refer to the weighted average across product categories. The weight for β is, following Van Heerde et al. (2013), the inverse of its standard error.

into this issue, we regressed category-specific changes in intrinsic brand strength and marketing-mix effectiveness on the prior NB concentration in the category (low vs. high; defined using a median split) and the prior PL share in the category (low vs. high; again based on a median split), while controlling for the focal PL revenues in the category before the rebranding. For both SPAR and Attent, we find neither the change in intrinsic brand strength nor any of the changes in marketing-mix effectiveness to differ systematically between high versus low levels of either prior NB concentration or PL share (all $ps >$ .10). All in all, it seems reasonable to conclude that our key insights generalize across categories that differ widely in competitive structure.

Robustness checks. We assess the robustness of our findings to (1) a potential aggregation bias (by comparing our logarithmic model with a linear model; Christen et al. 1997), (2) alternative operationalizations of the base marketing-support level (viz., the 5th and 10th percentiles for assortment size, rather than the minimum observed value, and the 95th and 90th percentiles for price, rather than the maximum observed value), (3) an additional postpromotion dip variable, (4) the inclusion of the other tiers' marketing-mix variables as additional control variables (e.g., to account for the cross-price effects from NBs and the other PL tier on the rebranded PL tier), and (5) selecting a wider trading-zone radius to drop treated stores and satisfy the SUTVA assumption. In all instances, our focal insights are not

Table 5. Summary Comparison of the Three Retailers Studied.

	SPAR	**Attent**	**Colruyt**
Country studied	The Netherlands	The Netherlands	Belgium
Store format	Convenience	Neighborhood	Supermarket
Service level	High	Average	Average
Price positioning	Hi–lo	Hi–lo	EDLP
Value sales (in million USD)	506.6	145.1	6,340.7
Number of outlets	227	72	233
Selling space (in sqm)	99,500	22,100	350,700
Total PL share	44.9%	48.5%	47.2%
Rebranded PL tier	Economy PL	Economy PL	Standard PL
Rebranded PL tier's share	15.4%	13.2%	22.6%

Notes: Based on GfK (2016), the Euromonitor Global Market Information Database, retailer store-scanner data (SPAR and Attent), and GfK household-panel data (Colruyt). Except for total PL share and the rebranded PL tier's share, where across-category averages are provided based on the data span before the rebranding, data are for 2015.

affected. The Appendix contains a detailed description of these robustness checks.

In addition, we assess the replicability for a different PL tier at a substantially different retailer, Colruyt. Colruyt is the market leader in Belgium, operates a low-price supermarket format with an average service level (GfK 2016), and is substantially larger in terms of total revenue than either SPAR or Attent. Most importantly, Colruyt differs from SPAR and Attent in that it rebranded its standard PL—which, with a 22.6% share, was already very successful before the rebranding—to the umbrella brand "Boni Selection." It offers a second PL tier that is positioned as an economy PL. Colruyt operated 233 outlets at the end of 2015. For Colruyt, we have access to GfK household panel data, including a variety of marketing-mix tools, but no wholesale prices. Moreover, we did not find press releases or news reports that might suggest important changes in Colruyt's strategy during our observation period. Although this is somewhat less clean, we use the same potential control group and matching procedure for Colruyt as for SPAR and Attent. A comparison of Colruyt to SPAR and Attent appears in Table 5.

We present the parameter estimates of the DiD model for Colruyt in Web Appendix C. The results are very consistent across the three cases, despite the retailers' very different prior success of the rebranded PL tier. As for SPAR and Attent, Colruyt's rebranded PL tier's intrinsic brand strength increases after the rebranding (Δ BS $= .322$, $p < .01$), while the effectiveness of price ($\beta_4^{\text{rebr}} = .272$, $p < .01$), price promotions ($\beta_5^{\text{rebr}} = -.018$, $p < .01$), and assortment size ($\beta_6^{\text{rebr}} = -.154$, $p < .05$) drop.

Discussion

Retailers have been growing their PL portfolios for decades by introducing PLs into new product categories, often with new brand names. At the same time, PLs have become stronger and by now are a "widely accepted brand class of their own" (Seenivasan, Sudhir, and Talukdar 2016, p. 802) that "should be treated as a true consumer brand to succeed in today's retail environment" (Daymon 2020, p. 6). In light of these

developments, retailers often consider rebranding multiple category-specific PL brands within a tier to one umbrella brand. The reasons for this are manifold and range from providing an easier PL categorization for consumers through a unified appearance to expected marketing-effectiveness gains. So far, little research has examined the performance implications of such a PL rebranding strategy, nor whether NB insights automatically generalize to this setting (Ailawadi and Keller 2004). This is surprising, given the high (and increasing) prevalence of umbrella branding among PLs (Richards, Yonezawa, and Winter 2015) and some fundamental differences between both settings (Grewal, Levy, and Lehmann 2004; Sayman and Raju 2004), making the issue both managerially and theoretically relevant.

To address this gap, we identified three substantially different retailers who rebranded one of their PL tiers and derived empirically to what extent the rebranding indeed resulted in the hoped-for intrinsic-brand strength and marketing effectiveness improvements. Importantly, the evidence consistently shows that the rebranded PL tier's intrinsic brand strength increases considerably after the rebranding. Using the same brand name across an entire PL tier seems to reduce consumers' uncertainty and increase the sales of the PL brand. The common design grid that umbrella-branded PLs use across categories apparently does not lead to a comparatively larger sales loss due to missed category-specific associations and/or trade dress advantages, resulting in a positive net effect. Thus, even though the common brand name is not restricted (as repeatedly advised in the NB-focused brand extension literature) to a limited set of closely related complementary categories, positive higher-order associations seem to be facilitated through the common PL name across many unrelated and substitute categories. This higher intrinsic brand strength translates (consistent with previous NB findings) into a reduced price elasticity, making the PL less dependent on rock-bottom prices to appeal to potential customers.

However, a very different picture emerges in terms of price promotions and assortment-size effectiveness. While Erdem and Sun (2002) found a higher effectiveness of price

Table 6. Overview of Findings and Implications.

	Finding	Rationale	Implications
Intrinsic brand strength	Increases	Umbrella branding a PL across a broad set of categories allows for cross-category reputational effects through abstract, higher-order associations (Morrin 1999).	Retailers are justified in their optimistic assessment of umbrella branding's brand-building potential.
Marketing effectiveness			
Price	Less negative	Stronger brands are characterized by a lower (less negative) price elasticity (Datta et al. 2017).	PLs are turning into true consumer brands, making them less dependent on rock-bottom prices.
Price promotions	Less positive	The price discount effect is a negative function of a brand's promotional frequency (Foekens, Leeflang, and Wittink 1998).	Avoid silo (own-category only) thinking in setting the umbrella brand's promotional intensity.
Assortment size	Less positive	Too many SKUs carrying the same name lead to a lower perceived variety in the store (Rooderkerk, Van Heerde, and Bijmolt 2013).	Be aware of SKU proliferation for the umbrella-branded PL line.

promotions for umbrella-branded than for category-specific NBs, this no longer holds when rebranding an entire PL tier, while the effectiveness of SKU additions is found to decrease. The cumulative exposure to the common brand name across a large and diverse set of categories throughout the store seems to lead to a reduced variety perception. Similarly, the negative relationship between promotional frequency and discount effectiveness—that was already documented at the brand (Krishna 1994) and category (Krishna 1994; Raju 1992) level—also appears to hold when the higher perceived intensity of discounts emerges from same-name promotional exposures in other categories. The very different number of categories involved in PL and NB umbrella branding may well explain these diverging findings.

Our study has not only addressed repeated academic calls for more research on key retail-branding decisions (Dekimpe et al. 2011; Grewal, Levy, and Lehmann 2004; Lourenço and Gijsbrechts 2013) but also has clear managerial implications, which we summarize in Table 6. While umbrella branding has become a frequently observed practice in the retailscape, numerous leading retailers across both developed and emerging economies still use category-branded PLs. For example, in the United States (Albertson's), Australia (Aldi), Canada (Safeway), Colombia (Almacenes Éxito), India (Big Bazaar), Italy (Eurospin), and Mexico (OXXO), one out of the top five retailers—defined in terms of market share—used category-specific branding by the end of 2019. In Croatia (Lidl, Tommy), Germany (Aldi, Lidl), Poland (Biedronka, Lidl), Russia (Magnit, Auchan), and Saudi Arabia (Al Othaim, Al Raya), two out of five, and in Turkey (Bim, A101, Sok), even three out of the top five retailers still use category-specific branding (all information obtained through Planet Retail). Interestingly, Amazon is also currently handling multiple category-specific PL brands, such as "Happy Belly" coffee, "Presto" laundry detergent, and "Wickedly Prime" snack items, with industry observers indicating that they will likely consolidate these various brands under an umbrella brand at a later point in time (Planet Retail 2017). Our findings may help

these retailers in understanding the implications of a potential shift to umbrella branding.

Interestingly, the retailers in our study did not adjust their marketing mix in line with the altered effectiveness of the marketing-mix instruments after the PL rebranding. To compare the retailers' marketing mix before and after the rebranding, we calculate for each category the average value of each marketing-mix tool 52 weeks after the rebranding and divide it by the average value of that tool 52 weeks before the rebranding. We then compare, using a t-test, this ratio for each of the three retailers with a similar ratio calculated for the respective control groups. We find that none of the retailers changed their price levels relative to the control retailers ($ps > .10$). However, despite the decreased effectiveness, both SPAR and Attent increased their price promotions (SPAR: t = 2.77, $p < .01$; Attent: t = 2.10, $p < .05$), while Attent and Colruyt increased their assortment size (Attent: t = 2.81, $p < .01$; Colruyt: t = 3.40, $p < .01$). These findings are in line with research on embedded exchange theory, which has shown that managers are prone to facilitate the outcome of their expectations through their behavior to make sure they are right (Sorenson and Waguespack 2006). In case of a rebranding, this "self-confirming conduct"—which may not always be optimal from a profit-maximizing point of view—may manifest itself through increased marketing support for the rebranded PL line (e.g., by offering more price promotions or introducing additional SKUs), even if the effectiveness of these instruments decreases.

Finally, to provide top-level managers with information about the rebranding's *overall* success, we assess the effect on the retailers' *total* sales in each category (i.e., their PL [rebranded and other PL tier] as well as NB [value] sales). We do so by first calculating for each retailer the change in category-specific volume sales following the rebranding, based on our DiD analyses. To get to overall chain-wide effects, we consider the revenue implications (given the different units in which the various categories are measured) and multiply the absolute change in a category's volume sales by the average price in the prerebranding period (this price was not increased

relative to the control retailers following the rebranding). In a similar vein, we calculate for every retailer its change in revenues for its other PL tier and the NBs sold in their stores. Subsequently, we sum within categories. For all three retailers, we find that their total revenues across product categories increased after the rebranding, and significantly so for SPAR and Attent (ps < .01).

Limitations and Future Research

First, an advantage of our study is that we had in-depth institutional knowledge, which enabled us to rule out a variety of endogeneity concerns. Still, our study design did not involve a random assignment of retailers and/or categories into the treatment or control conditions, making any causal inference conditional on the validity of our selected control retailers as counterfactual (Goldfarb and Tucker 2014). In addition, it would have been desirable to analyze equally deep data for a broader cross-section of retailers to increase the generalizability of our findings further. Still, even though the three retailers we investigated are very different from each other along multiple dimensions, our empirical results are very similar. Relatedly, while our results generalized across the rebranding of the economy and standard PL tier, it would be interesting to see whether this also holds for the later added premium PL tier (Ter Braak, Geyskens, and Dekimpe 2014). Furthermore, it would be interesting to explore whether our results also hold, and maybe even become stronger, when retailers rebrand their category-specific PLs with an umbrella brand that explicitly includes the banner's name (Keller, Dekimpe, and Geyskens 2016).

Second, we were unable to investigate whether the effectiveness of PL advertising changes after an umbrella rebranding, because "advertising data providers are still limited to collecting advertising data at the retailer level" (Dekimpe and Geyskens 2019, p. 7). Instead, we controlled for advertising at the retail banner level. We found that the retailer's focal PL tier becomes less dependent on the retailer's banner advertising. Future research could investigate whether these results still hold once more granular advertising data, at the PL-tier and product-category level, become available.

Third, one reason for retailers to move to umbrella branding may be cost savings. Because retailers can invest considerably fewer resources in their PLs than brand manufacturers can for their NBs (Lamey et al. 2012), the affordability of umbrella branding may be particularly important for retailers. Future research could investigate the effects of umbrella branding on retailer profitability.

Finally, we are not aware of any empirical studies on the addition of category-specific brands to an existing umbrella brand, either for NBs or for PLs. Future research could explore the flipside of our setting (i.e., instances in which retailers first feature an umbrella brand and then add category-specific brands). Would such a shift entail a positive change in marketing effectiveness (as a symmetric effect would predict), or will the new category-specific brands "get lost in the NB crowd" and experience even lower marketing effectiveness?

Appendix

Robustness Checks

Aggregation Bias. To estimate Equation 1, we use sales data that were aggregated across stores within categories and weeks. This could give rise to an aggregation bias unless the marketing-mix variables are homogeneous across stores in each week (Christen et al. 1997). SPAR and Attent use a unified pricing strategy across their stores where the headquarters set prices and promotions. Although aggregation bias is, therefore, not an issue for these two marketing tools, the assortment size may well differ between stores. Christen et al. (1997) showed that logarithmic models are more prone to aggregation bias than linear models. If the model results are robust between our log-log specification and the alternative linear specification, the aggregation issue, if at all present, is not likely to be serious (for a similar reasoning, see Nijs et al. [2001] and Steenkamp and Geyskens [2014]). To make the parameter estimates comparable across both instances, we first indexed the sales and marketing-mix variables by dividing their weekly values by their over-time category-specific average (Van Heerde, Gijsbrechts, and Pauwels 2008). For the assortment variable, we then computed (across the different categories i) the correlation between the parameter estimates of our focal specification and the ones obtained from the linear model. This correlation was a high .88 for SPAR and .92 for Attent, which confirms that aggregation bias is not likely to be a problem for that marketing instrument either. When indexing relative to the prerebranding averages, we obtained comparable correlations of .91 for SPAR and .92 for Attent.

Alternative Operationalization of Base Marketing-Support Level. When estimating Equation 1, we set, in line with prior academic literature (Hanssens, Wang, and Zhang 2016; Slotegraaf, Moorman, and Inman 2003), the level of the price-promotions variable to zero, as we are interested in an intrinsic-brand-strength evaluation at the bare minimum of marketing support. For assortment size, we used the minimum observed value and for price the corresponding counterpart, the maximum observed value. To assess whether these choices drive our results, we reestimate our model using two alternative values for the base marketing support (the 95th and 90th percentiles for price and the 5th and 10th percentiles for assortment size). The effects are comparable to those in the focal analysis. Web Appendix D provides detailed results.

Additional Postpromotion Dip. While our price promotions variable may appear to only capture the instantaneous effect of price promotions, its operationalization kept track of price promotions of up to six weeks. As such, it captured not only the immediate effect but also allowed for a potential dip after the start of the promotion (Gedenk and Neslin 2000). Still, to test whether our model sufficiently reflects postpromotion dips, we compute an explicit postpromotions variable and add it both as main and interaction effects to

Equation 1. The corresponding DiD estimates are not significant (ps $> .10$) and do not affect the focal parameter estimates in terms of magnitude, sign, or significance. Web Appendix D presents detailed results.

Cross-Tier Marketing Effects. Equation 1 focuses on the own-tier effects of the marketing instruments. Yet the marketing-mix actions of one PL tier may affect the other PL tier as well as the NBs. We therefore respecify Equation 1 and add the marketing-mix variables of NBs and the other PL tier as additional control variables (e.g., cross-price effects from the other PL tier on the rebranded PL tier). Except for the cross-effect of the other PL tier's and NB's price on the rebranded PL tier's sales, none of these effects are significant (ps $> .10$). Most importantly, all own-effects remain robust in this alternative model. Web Appendix D reports detailed results.

Alternative Trading Zone. To satisfy the SUTVA assumption, we dropped treated stores that operated nearby control stores to rule out potential competition. We used a two-kilometer driving radius because this is the average distance Dutch consumers drive to their primary supermarket (Deloitte 2018); it is also already somewhat more than twice the distance to the nearest supermarket in the Netherlands (which is about .9 km; Baydar, Melser, and Zuurmond 2010). As a robustness check, we redid the matching and all analyses with a 50% larger driving distance (i.e., 3 km), because (1) this is close to the 2 miles considered in both Holmes (2011) and Pope and Pope (2015) to identify households "within a Walmart's neighborhood," and (2) a typical SPAR or Attent store is considerably smaller than a typical Walmart store (and thus is unlikely to have a larger catchment area than a Walmart store). The results are very robust, with a consistently positive and significant change in intrinsic brand strength and comparable changes in marketing-mix effectiveness. Web Appendix D provides detailed results.

Acknowledgments

Associate Editor

Venkatesh Shankar

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

References

Aaker, David A. (2012), *Building Strong Brands*. New York: Simon and Schuster.

Aaker, David A. and Erich Joachimsthaler (2000), "The Brand Relationship Spectrum: The Key to the Brand Architecture Challenge," *California Management Review*, 42 (4), 8–23.

Ailawadi, Kusum L. and Kevin L. Keller (2004), "Understanding Retail Branding: Conceptual Insights and Research Priorities," *Journal of Retailing*, 80 (4), 331–42.

Ailawadi, Kusum L., Koen Pauwels, and Jan-Benedict E.M. Steenkamp (2008), "Private-Label Use and Store Loyalty," *Journal of Marketing*, 72 (4), 19–30.

Angrist, Joshua D. and Alan B. Krueger (1999), "Empirical Strategies in Labor Economics," in *Part A of Handbook of Labor Economics*, Osrley Ashenfelter and David Card, eds. New York: Elsevier, 1277–1366.

Ataman, M. Berk, Harald J. van Heerde, and Carl F. Mela (2010), "The Long-Term Effect of Marketing Strategy on Brand Sales," *Journal of Marketing Research*, 47 (5), 866–82.

Batra, Rajeev and Indrajit Sinha (2000), "Consumer-Level Factors Moderating the Success of Private Label Brands," *Journal of Retailing*, 76 (2), 175–91.

Baydar, Osman, Chantal Melser, and Marijn Zuurmond (2010), "Supermarket Within Walking Distance for Most Dutch People," CBS.nl (September 7), https://www.cbs.nl/en-gb/news/2010/36/supermarket-within-walking-distance-for-most-dutch-people.

Briesch, Richard A., Pradeep K. Chintagunta, and Edward J. Fox (2009), "How Does Assortment Affect Grocery Store Choice?" *Journal of Marketing Research*, 46 (2), 176–89.

Bronnenberg, Bart J., Jean-Pierre Dubé, and Sridhar Moorthy (2019), "The Economics of Brands and Branding," in *Handbook of the Economics of Marketing*, Jean-Pierre Dubé and Peter E. Rossi, eds. North-Holland: Elsevier, 291–358.

Cabral, Luís M. B. (2009), "Umbrella Branding with Imperfect Observability and Moral Hazard," *International Journal of Industrial Organization*, 27 (2), 206–13.

Chakravarty, Anindita, Alok Kumar, and Rajdeep Grewal (2014), "Customer Orientation Structure for Internet-Based Business-to-Business Platform Firms," *Journal of Marketing*, 78 (5), 1–23.

Chintagunta, Pradeep K. (2002), "Investigating Category Pricing Behavior at a Retail Chain," *Journal of Marketing Research*, 39 (2), 141–54.

Christen, Markus, Sachin Gupta, John C. Porter, Richard Staelin, and Dick R. Wittink (1997), "Using Market-Level Data to Understand Promotion Effects in a Nonlinear Model," *Journal of Marketing Research*, 34 (3), 322–34.

Cohen, Joel B. and Kunal Basu (1987), "Alternative Models of Categorization: Toward a Contingent Processing Framework," *Journal of Consumer Research*, 13 (4), 455–72.

Dacin, Peter A. and Daniel C. Smith (1994), "The Effect of Brand Portfolio Characteristics on Consumer Evaluations of Brand Extensions," *Journal of Marketing Research*, 31 (2), 229–42.

Datta, Hannes, Kusum L. Ailawadi, and Harald J. van Heerde (2017), "Does Consumer-Based Brand Equity Manifest Itself in Sales-Based Brand Equity and in Marketing Mix Effectiveness?" *Journal of Marketing*, 81 (3), 1–20.

Daymon (2020), *Winning in Center Store: How U.S. Retailers Should Prioritize for Success*. Stamford, CT: Daymon.

DeJong, Koen A.M. (2019), *The Private Label Revolution: Sharing Knowledge from Research and Practice*. Vught, The Netherlands: International Private Label Consult BV.

Dekimpe, Marnik G. and Inge Geyskens (2019), "Retailing Research in Rapidly Changing Times: On the Danger of Being Leapfrogged by Practice," *Journal of Retailing*, 95 (1), 6–9.

Dekimpe, Marnik G., Katrijn Gielens, Jagmohan S. Raju, and Jacquelyn S. Thomas (2011), "Strategic Assortment Decisions in Information-Intensive and Turbulent Environments," *Journal of Retailing*, 87 (1), S17–S28.

Deloitte (2018), "Consumentenonderzoek 2018 (Consumer Research)," Maastricht, the Netherlands.

Dhar, Sanjay K. and Stephen J. Hoch (1997), "Why Store Brand Penetration Varies by Retailer," *Marketing Science*, 16 (3), 208–27.

Erdem, Tülin (1998), "An Empirical Analysis of Umbrella Branding," *Journal of Marketing Research*, 35 (3), 339–51.

Erdem, Tülin and Sue Ryung Chang (2012), "A Cross-Category and Cross-Country Analysis of Umbrella Branding for National and Store Brands," *Journal of the Academy of Marketing Science*, 40 (1), 86–101.

Erdem, Tülin and Baohong Sun (2002), "An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding," *Journal of Marketing Research*, 39 (4), 408–20.

Erdem, Tülin and Russell S. Winer (1998), "Econometric Modeling of Competition: A Multi-Category Choice-Based Mapping Approach," *Journal of Econometrics*, 89 (1/2), 159–75.

Foekens, Eijte W., Peter S.H. Leeflang, and Dick R. Wittink (1998), "Varying Parameter Models to Accommodate Dynamic Promotion Effects," *Journal of Econometrics*, 89 (1/2), 249–68.

Fry, Joseph N. (1967), "Family Branding and Consumer Brand Choice," *Journal of Marketing Research*, 4 (3), 237–47.

Gallino, Santiago and Antonio Moreno (2014), "Integration of Online and Offline Channels in Retail: The Impact of Sharing Reliable Inventory Availability Information," *Management Science*, 60 (6), 1434–51.

Gedenk, Karen and Scott A. Neslin (2000), "The Role of Retail Promotion in Determining Future Brand Loyalty: Its Effect on Purchase Event Feedback," *Journal of Retailing*, 75 (4), 433–59.

Geyskens, Inge, Katrijn Gielens, and Els Gijsbrechts (2010), "Proliferating Private-Label Portfolios: How Introducing Economy and Premium Private Labels Influences Brand Choice," *Journal of Marketing Research*, 47 (5), 791–807.

Geyskens, Inge, Katrijn Gielens, and Stefan Wuyts (2015), "United We Stand: The Impact of Buying Groups on Retailer Performance," *Journal of Marketing*, 79 (4), 16–33.

GfK (2016), GFK *Zomerrapport: Prestatie En Waardering Van Supermarktformules*. Dongen, the Netherlands: GfK.

Gielens, Katrijn (2012), "New Products: The Antidote to Private Label Growth?" *Journal of Marketing Research*, 49 (3), 408–23.

Gielens, Katrijn and Marnik G. Dekimpe (2007), "The Entry Strategy of Retail Firms into Transition Economies," *Journal of Marketing*, 71 (2), 196–212.

Godfrey, Andrea, Kathleen Seiders, and Glenn B. Voss (2011), "Enough Is Enough! The Fine Line in Executing Multichannel Relational Communication," *Journal of Marketing*, 75 (4), 94–109.

Goldfarb, Avi and Catherine E. Tucker (2014), "Conducting Research with Quasi-Experiments: A Guide for Marketers," working paper, Rotman School of Management.

Grewal, Dhruv, Michael Levy, and Donald R. Lehmann (2004), "Retail Branding and Customer Loyalty: An Overview," *Journal of Retailing*, 4 (80), ix–xii.

Guo, Shenyang and Mark W. Fraser (2015), *Propensity Score Analysis: Statistical Methods and Applications*. Thousand Oaks, CA: SAGE Publications.

Hanssens, Dominique M., Leonard J. Parsons, and Randall L. Schultz (2003), *Market Response Models: Econometric and Time Series Analysis*. Boston: Kluwer Academic Publishers.

Hanssens, Dominique M., Fang Wang, and Xiao-Ping Zhang (2016), "Performance Growth and Opportunistic Marketing Spending," *International Journal of Research in Marketing*, 33 (4), 711–24.

Ho-Dac, Nga N., Stephen J. Carson, and William L. Moore (2013), "The Effects of Positive and Negative Online Customer Reviews: Do Brand Strength and Category Maturity Matter?" *Journal of Marketing*, 77 (6), 37–53.

Holmes, Thomas J. (2011), "The Diffusion of Wal-Mart and Economies of Density," *Econometrica*, 79 (1), 253–302.

Inman, J. Jeffrey, Venkatesh Shankar, and Rosellina Ferraro (2004), "The Roles of Channel-Category Associations and Geodemographics in Channel Patronage," *Journal of Marketing*, 68 (2), 51–71.

Judge, George G., Carter R. Hill, William E. Griffiths, Helmut Lütkephol, and Tsoung-Chao Lee (1998), *Introduction to the Theory and Practice of Econometrics*. Hoboken, NJ: John Wiley & Sons.

Keller, Kristopher O., Marnik G. Dekimpe, and Inge Geyskens (2016), "Let Your Banner Wave? Antecedents and Performance Implications of Retailers' Private-Label Branding Strategies," *Journal of Marketing*, 80 (4), 1–19.

Kolm, Josh (2016), "Brands of the Year 2016: Leader of the Pack," *Strategy* (September 27), http://strategyonline.ca/2016/09/27/brands-of-the-year-2016-leader-of-the-pack/.

Krishna, Aradhna (1994), "The Impact of Dealing Patterns on Purchase Behavior," *Marketing Science*, 13 (4), 351–73.

Lamey, Lien, Barbara Deleersnyder, Jan-Benedict E.M. Steenkamp, and Marnik G. Dekimpe (2012), "The Effect of Business-Cycle Fluctuations on Private-Label Share: What Has Marketing Conduct Got to Do with It?" *Journal of Marketing*, 76 (1), 1–19.

Lamey, Lien, Barbara Deleersnyder, Jan-Benedict E.M. Steenkamp, and Marnik G. Dekimpe (2018), "New Product Success in the Consumer Packaged Goods Industry: A Shopper Marketing

Approach," *International Journal of Research in Marketing*, 35 (3), 432–52.

Lechner, Michael (2010), "The Estimation of Causal Effects by Difference-in-Difference Methods," *Foundations and Trends in Econometrics*, 4 (3), 165–224.

Leeflang, Peter S.H., Tammo H.A. Bijmolt, Jenny van Doorn, Dominique M. Hanssens, Harald J. van Heerde, Peter C. Verhoef, et al. (2009), "Creating Lift Versus Building the Base: Current Trends in Marketing Dynamics," *International Journal of Research in Marketing*, 26 (1), 13–20.

Liu, Yan, Krista J. Li, Haipeng Chen, and Subramanian Balachander (2017), "The Effects of Products' Aesthetic Design on Demand and Marketing-Mix Effectiveness: The Role of Segment Prototypicality and Brand Consistency," *Journal of Marketing*, 81 (1), 83–102.

Lourenço, Carlos J.S. and Els Gijsbrechts (2013), "The Impact of National Brand Introductions on Hard-Discounter Image and Share-of-Wallet," *International Journal of Research in Marketing*, 30 (4), 368–82.

Luan, Y. Jackie and K. Sudhir (2010), "Forecasting Marketing-Mix Responsiveness for New Products," *Journal of Marketing Research*, 47 (3), 444–57.

Ma, Yu, Kusum L. Ailawadi, and Dhruv Grewal (2013), "Soda Versus Cereal and Sugar Versus Fat: Drivers of Healthful Food Intake and the Impact of Diabetes Diagnosis," *Journal of Marketing*, 77 (3), 101–20.

Miklós-Thal, Jeanine (2012), "Linking Reputations Through Umbrella Branding," *Quantitative Marketing and Economics*, 10 (3), 335–74.

Morrin, Maureen (1999), "The Impact of Brand Extensions on Parent Brand Memory Structures and Retrieval Processes," *Journal of Marketing Research*, 36 (4), 517–25.

Nevo, Aviv (2001), "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica*, 69 (2), 307–42.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and Dominique M. Hanssens (2001), "The Category-Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1–22.

Papies, Dominik, Peter Ebbes, and Harald J. van Heerde (2017), "Addressing Endogeneity in Marketing Models," in *Advanced Methods for Modeling Markets*, Peter S.H. Leeflang, Jaap E. Wieringa, Tammo H.A. Bijmolt, and Koen H. Pauwels, eds. New York: Springer, 581–627.

Pauwels, Koen and Shuba Srinivasan (2004), "Who Benefits from Store Brand Entry?" *Marketing Science*, 23 (3), 364–90.

Pierce, Lisa McTigue (2011), "Supervalu Replacing Jewel Store Brands with Single Identity Uniform Packaging," *Packaging Digest* (June 15), http://www.packagingdigest.com/packaging-design/supervalu-replacing-jewel-store-brands-single-identity-and-uniform-packaging.

Planet Retail (2014), *Dansk Supermarked Merges Private Labels*. London: Planet Retail.

Planet Retail (2017), *Growing with Private Label in a New Retail Era*. London: Planet Retail.

Pope, Devin G. and Jaren C. Pope (2015), "When Walmart Comes to Town: Always Low Housing Prices? Always?" *Journal of Urban Economics*, 87, 1–13.

Raju, Jagmohan S. (1992), "The Effect of Price Promotions on Variability in Product Category Sales," *Marketing Science*, 11 (3), 207–20.

Rao, Vithala R., Manoj K. Agarwal, and Denise Dahlhoff (2004), "How Is Manifest Branding Strategy Related to the Intangible Value of a Corporation?" *Journal of Marketing*, 68 (4), 126–41.

Rego, Lopo L., Neil A. Morgan, and Claes Fornell (2013), "Reexamining the Market Share–Customer Satisfaction Relationship," *Journal of Marketing*, 77 (5), 1–20.

Richards, Timothy, Koichi Yonezawa, and Sophie Winter (2015), "Cross-Category Effects and Private Labels," *European Review of Agricultural Economics*, 42 (2), 187–216.

Rooderkerk, Robert P., Harald J. van Heerde, and Tammo H.A. Bijmolt (2013), "Optimizing Retail Assortments," *Marketing Science*, 32 (5), 699–715.

Sande, Jon Bingen and Mrinal Ghosh (2018), "Endogeneity in Survey Research," *International Journal of Research in Marketing*, 35 (2), 185–204.

Sanderson, Eleanor and Frank Windmeijer (2016), "A Weak Instrument F-Test in Linear IV Models with Multiple Endogenous Variables," *Journal of Econometrics*, 190 (2), 212–21.

Sayman, Serdar and Jagmohan S. Raju (2004), "Investigating the Cross-Category Effects of Store Brands," *Review of Industrial Organization*, 24 (2), 129–41.

Sebri, Mouna and Georges Zaccour (2017), "Estimating Umbrella-Branding Spillovers: A Retailer Perspective," *European Journal of Marketing*, 51 (9/10), 1695–712.

Seenivasan, Satheesh, K. Sudhir, and Debabrata Talukdar (2016), "Do Store Brands Aid Store Loyalty?" *Management Science*, 62 (3), 802–16.

Sethuraman, Raj (1996), "A Model of How Discounting High-Priced Brands Affects the Sales of Low-Priced Brands," *Journal of Marketing Research*, 33 (4), 399–409.

Sethuraman, Raj (2009), "Assessing the External Validity of Analytical Results from National Brand and Store Brand Competition Models," *Marketing Science*, 28 (4), 759–81.

Sethuraman, Raj and Katrijn Gielens (2014), "Empirical Generalizations on the Determinants of Store Brand Share," *Journal of Retailing*, 90 (2), 141–53.

Singh, Vishal P., Karsten T. Hansen, and Sachin Gupta (2005), "Modeling Preferences for Common Attributes in Multicategory Brand Choice," *Journal of Marketing Research*, 42 (2), 195–209.

Sivakumar, K. and S.P. Raj (1997), "Quality Tier Competition: How Price Change Influences Brand Choice and Category Choice," *Journal of Marketing*, 71 (3), 71–84.

Slotegraaf, Rebecca J., Christine Moorman, and J.Jeffrey Inman (2003), "The Role of Firm Resources in Returns to Market Deployment," *Journal of Marketing Research*, 40 (3), 295–309.

Sorenson, Olav and David M. Waguespack (2006), "Social Structure and Exchange: Self-Confirming Dynamics in Hollywood," *Administrative Science Quarterly*, 51 (4), 560–89.

Sotgiu, Francesca and Katrijn Gielens (2015), "Suppliers Caught in Supermarket Price Wars: Victims or Victors? Insights from a Dutch Price War," *Journal of Marketing Research*, 52 (6), 784–800.

Sridhar, Shrihari, Frank Germann, Charles Kang, and Rajdeep Grewal (2016), "Relating Online, Regional, and National Advertising to Firm Value," *Journal of Marketing*, 80 (4), 39–55.

Sriram, Srinivasaraghavan, Subramanian Balachander, and Manohar U. Kalwani (2007), "Monitoring the Dynamics of Brand Equity Using Store-Level Data," *Journal of Marketing*, 71 (2), 61–78.

Steenkamp, Jan-Benedict E.M. and Inge Geyskens (2014), "Manufacturer and Retailer Strategies to Impact Store Brand Share: Global Integration, Local Adaptation, and Worldwide Learning," *Marketing Science*, 33 (1), 6–26.

Stern, Neil (2019), "Private Label Powers Ahead . . . But Not Equally," *Forbes* (April 25), https://www.forbes.com/sites/neilstern/2019/04/25/private-label-powers-ahead-but-not-equally/#4624fbce34d5.

Store Brands Decisions (2012a), "Supervalu Thrilled with Private Label Performance," (April 17), https://storebrands.com/supervalu-thrilled-private-label-performance.

Store Brands Decisions (2012b), "Supervalu Transitions Store Brands to Essential Everyday Line," (February 14), http://www.storebrands.info/supervalu-transitions-store-brands-essential-everyday-line.

Store Brands Decisions (2016), "Save-a-Lot to Revamp Its Private Brand Strategy," (April 27), http://www.storebrands.info/store-brand-insights/store-brand-news/save-lot-revamp-its-private-brand-strategy.

Ter Braak, Anne, Marnik G. Dekimpe, and Inge Geyskens (2013), "Retailer Private-Label Margins: The Role of Supplier and Quality-Tier Differentiation," *Journal of Marketing*, 77 (4), 86–103.

Ter Braak, Anne, Inge Geyskens, and Marnik G. Dekimpe (2014), "Why Premium Private Label Presence Varies by Category," *Journal of Retailing*, 90 (2), 125–40.

Van Heerde, Harald J., Els Gijsbrechts, and Koen Pauwels (2008), "Winners and Losers in a Major Price War," *Journal of Marketing Research*, 45 (5), 499–518.

Van Heerde, Harald J., Maarten J. Gijsenberg, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2013), "Price and Advertising Effectiveness over the Business Cycle," *Journal of Marketing Research*, 50 (2), 177–93.

Van Horen, Femke and Rik Pieters (2012), "When High-Similarity Copycats Lose and Moderate-Similarity Copycats Gain: The Impact of Comparative Evaluation," *Journal of Marketing Research*, 49 (1), 83–91.

Völckner, Franziska and Henrik Sattler (2006), "Drivers of Brand Extension Success," *Journal of Marketing*, 70 (2), 18–34.

Vroegrijk, Mark J.J. (2012), "'Smart Shopping': Implications of Hard-Discounters and Multiple-Store Patronage," *doctor dissertation*, CentER, Tilburg University.

Wernerfelt, Birger (1988), "Umbrella Branding as a Signal of New Product Quality: An Example of Signalling by Posting a Bond," *RAND Journal of Economics*, 19 (3), 458–66.

Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

York, Emily Bryson (2011), "Supervalu Replacing Jewel Store Brands," *Chicago Tribune* (June 15), http://articles.chicagotribune.com/2011-06-15/business/ct-biz-0615-bf-private-labels-20110615_1_supervalu-private-brands-house-brands.