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Innovation Success: The Overlooked Role of the Retailer

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Report Summary

Despite the billions of dollars spent on new product development and related marketing activities by national-brand manufacturers, it is the retailer who is the gatekeeper to consumers. Not only do they selectively grant access to their shelf space, their shopper-marketing activities in terms of price, promotions, and assortment composition together with their retail context are key drivers for an innovation's subsequent performance at their outlets.

In this report, Lien Lamey, Barbara Deleersnyder, Jan-Benedict Steenkamp, and Marnik Dekimpe examine the role of retailer-controlled drivers in the success of new-product introductions by consumer packaged goods (CPG) manufacturers. They consider their effects on both the retailer's decision to adopt the new product —a necessary but not sufficient condition for innovation success—as well as the subsequent market share the new product acquires at the adopting retailer, one year after its introduction.

Using a selection model, they simultaneously model the retailer's decision regarding which innovations to adopt (out of 100+ innovations launched by leading CPG manufacturers in the U.K. grocery market between June 2005 and June 2008), and trace these innovations' first-year performance across 13 major retail banners.

They find that innovation success is systematically affected by the complex interplay between a set of retailer-controlled factors, pertaining to shopper-marketing instruments used in conjunction with the retailer-category characteristics and the retailer umbrella brand. Importantly, the effectiveness of retailer support for an innovation is highly contingent on the retail banner's brand equity (RBBE). Moreover, the effectiveness of the shopper-marketing variables (price premium, promotion intensity, and innovation uniqueness within a retailer's assortment) varies systematically with certain category variables (like proliferation and private-label strength within the category) which can differ significantly both across the different categories within a given retailer and across the different retail banners for a given category.

Implications for retailers
In general, high-RBBE retailers can set a higher price premium for their innovations, a strategy that is especially effective in categories where the retailer's private label is less successful. High-RBBE retailers are also encouraged to include innovations that are more unique and stand out in their assortment, especially within high-proliferated categories.

In contrast, low-RBBE retailers can boost innovation sales by setting competitive prices and/or by offering more frequent promotions. Their shoppers are found to be more responsive to prices, especially in categories where their private labels compete strongly with the national brands.

Finally, retailers should act quickly and not postpone the adoption of an innovation, as performance at their outlets will decrease as more competing retailers adopt the innovation.

Implications for national-brand manufacturers
These results may help manufacturers understand which retailers are more prone to accept their innovations. In general, manufacturers will have more easy access with their innovations in

categories with more established offerings, at higher-RBBE retailers, when they are more powerful, and when the innovation is launched under a strong brand name. In addition, more expensive innovations are more readily accepted by high-RBBE retailers, who may also require less promotional support for these innovations.

Finally, to the extent possible, manufacturers are recommended to shift their promotional support for the innovation to lower-RBBE retailers (and encourage these retailers to pass on these promotions to their consumers), and to retailers with a stronger private-label presence in the category in which the new product is introduced.

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For Consumer Packaged Goods (CPG) manufacturers as well as retailers, the introduction of new products is recognized as one of the most important marketing activities. The financial rewards from widespread consumer acceptance of an innovation can substantially improve a manufacturer's competitive position and performance (Sorescu and Spanjol 2008), while innovations are also able to protect companies during harsh economic conditions when people cut back on their overall expenses (Lamey et al. 2012). Accordingly, brand manufacturers spend significant resources on the development and launch of new products. But high expenditures in combination with significant failure rates (Völckner and Sattler 2006) make it essential to understand what drives innovation success. Likewise, new products can benefit retailers through increased store traffic, their ability to differentiate a retailer from its competitors, and by signaling store quality, among others (Lin and Chang 2012). However, limited shelf space combined with a high failure rate results in high risks for the retailer as well (Kaufman, Jayachandran, and Rose 2006). Thus, understanding the drivers of national-brand innovation success is crucial for manufacturers and retailers alike.

Prior research has focused on the role of the *manufacturer* (the supply side) in driving national brands' innovation success (e.g., Gielens and Steenkamp 2007; Sorescu and Spanjol 2008), and on characteristics of the *consumer* (the demand side) that determine his/her likelihood to buy innovations (e.g., Arts, Frambach, and Bijmolt 2011; Steenkamp and Gielens 2003). However, the success of an innovation in the CPG industry has become increasingly dependent on the *retailer*. In the past, retailers were merely distributors or 'conveyors' of merchandise. In recent years, their role has changed dramatically, and retailers now play a crucial dual role in new-product success. First, retailers have become increasingly selective "gatekeepers" to consumers, making innovation success contingent on adequate retail acceptance (Kaufman, Jayachandran, and Rose 2006). Second, the retailers' marketing-mix decisions in terms of price, promotions, and assortment - issues often bundled under the term "shopper marketing" (Ailawadi et al. 2009; Grocery Management Association 2007; Shankar 2011; Shankar et al. 2011) - are increasingly recognized as crucial determinants of consumers' buying behavior. Shopper marketing refers to all marketing activities directed at influencing an individual at the point of purchase (Shankar 2011). Marketing stimuli at the point of purchase can serve as a memory cue and trigger purchases (Bell, Corsten, and Knox 2011; Hui et al. 2013). With about 70% of CPG purchase decisions made in-store, it is clear that the role of the retailer in shaping buying behavior can – and will - be substantial. If anything, this applies especially to decisions related to the purchase of new products, as these decisions are not yet part of consumers' habitual buying behavior that characterizes most CPG purchases (Hoyer 1984). As a result, innovations can be very successful in some retail contexts but less so in others. To illustrate this, Table 1 (Tables below References throughout.) provides some examples taken from the U.K. market where we provide information on two distinct, but related, metrics of innovation success, viz., whether the innovation is adopted by a retailer, and what the subsequent market share at that retailer is.

Table 1 shows several interesting things. First, not all innovations get access to all retailers. For example, Gillette's Arctic Ice Shaving Gel was only accepted by Asda and Waitrose within the first year after its introduction on the U.K. market. Why did Asda and Waitrose adopt the Gillette innovation while the others did not? Could it be that Gillette's Arctic Ice Shaving Gel was too "new" to the assortment of the others? Or was it because the other retailers opt to not carry many (sub-)brands in the shaving-cream category, making them less willing to expand their assortment? Or was it perhaps because these two retailers have a strong banner reputation which they want to uphold by regularly adding new products to their assortment? Or all of the above?

Second, given adoption, the subsequent performance of the innovation differs widely between retailers. Continuing with the Gillette example, we note that its market share in the shaving-cream category was 4.78% at Asda versus 17.92% at Waitrose. Why was the Gillette innovation much more successful at Waitrose? Was the price charged by Waitrose (relative to its existing offerings in the category) lower than that of Asda? Or was it perhaps due to the larger market share Asda's own private label has in this category? And what role did the intrinsic strength of the retail banner play?

The purpose of this study is to answer these questions. We will examine the role of retailer-controlled drivers in the success of new-product introductions by CPG manufacturers, where we consider their effects on both the retailer's decision to adopt the new product or not – a necessary but not sufficient condition for innovation success – as well as the subsequent market share the new product acquires at the adopting retailer. To investigate these issues, we will analyze innovation success of over 100 major innovations in the U.K. grocery market in 13 leading grocery chains. The remainder of the paper is organized as follows. We will first discuss the framework that guided our research. Next, we describe the data sources, variables, and analytical approach. Then, we will present the empirical findings of our study. We conclude with a summary, implications for retailers and manufacturers, and issues for future research.

Research Framework

An innovation is offered in a particular category at a particular retailer. This logically leads to three groups of retailer-related factors that can influence the success of innovations initiated by CPG manufacturers: (1) the retailer's shopper-marketing mix associated with the innovation per se, (2) characteristics of the category in which the innovation is (or could be) introduced at the retailer in question, and (3) the overall reputation of the retailer, as the category is nested within the retailer, where the retail banner acts as a kind of umbrella brand endorsing specific categories (cf. Erdem 1998). These three groups of variables are posited to affect the retailer's decision to adopt a particular innovation or not, as well as the subsequent market share of the innovations at the adopting retailer (labeled jointly "innovation success"). Figure 1 (Figures follow References throughout.) provides the conceptual model that guided our research. We now turn to discussing each group of drivers of innovation success at a retailer.

Retailer's shopper-marketing drivers

Three key shopper-marketing activities that influence shoppers' in-store purchase decisions are the *price* at which the innovation is sold, the extent of *promotional support* for the innovation, and the *uniqueness* of the innovation in the retail assortment. While decisions regarding pricing and promotions are influenced (and, in case of promotions, often funded) by the manufacturer, it is the retailer who has the final decision on what prices to charge on the store floor (Ailawadi et al. 2009, p. 43). Competition laws in many countries, including the U.S. and U.K., have limited the ability of manufacturers to enforce the retail prices of their goods. Moreover, literature on retailer pass through (see, e.g., Ailawadi and Harlam 2009) shows considerable variability in promotional pass-through: many manufacturer brands receive a pass-through rate well below 100%, while a small fraction enjoys pass-through rates greater than 100%, or receives promotions without any manufacturing funding. This supports the notion that it is the retailer who ultimately is in control of pricing and promotional decisions in its stores. This also applies to the composition of its assortment, and hence, the *uniqueness* of the innovation versus competing offerings on a retailer's shelves. Retailers are selective as to what products they add to their assortment. Depending on the characteristics of the incumbent products, the innovation may be more or less unique within a certain retail banner category.

We expect that innovations that are more unique relative to the existing assortment of the retailer, and innovations for which the retailer can anticipate heavy promotional support have a higher likelihood of being adopted by that retailer (Rao and McLaughlin 1989; van Everdingen et al. 2011) and will experience a higher market share at the adopting retailers (Gielens and Steenkamp 2007). Innovations that are offered at a relatively high price may be attractive to the retailer because of a possible higher margin, but a high price could also reduce in-store sales.

Retailer-category drivers

Retailers differ on several structural characteristics of the category that can influence consumers' brand choice and/or retailer adoption. We characterize the composition of the category at a given retailer in terms of three factors: (1) the expertise of the retailer with the category, (2) the brand proliferation in the category, and (3) the strength of its private-label offering. First, some retailers have developed a special expertise in certain categories. Because of their higher category knowledge, they may be in a better position to assess the relative benefits of the innovations, while consumers may be more willing to try new products at retailers that have extensive experience in the category (Draganska and Klapper 2007; Gielens, Gijsbrechts, and Dekimpe 2014). Second, high brand proliferation in the category with a retailer may imply that there are several market segments for the category among its shoppers, and therefore ample room for product differentiation (Schmalensee 1978). But it could also imply that it becomes more difficult for the innovation to stand out and influence brand choice (Srinivasan et al. 2004). Finally, in categories where the retailer's private label has succeeded in capturing a large share of total sales, the retailer may be more reluctant to adopt a new product of a brand manufacturer because of the potential cannibalization of his private-label sales (ter Braak, Dekimpe, and Geyskens 2014). However, in every category, there remain consumers who are national-brand buyers (Ailawadi, Neslin, and Gedenk 2001) and consumers who are on the look-out for new products (Steenkamp and Gielens 2003). In categories where the retailer's private label has captured a large portion of sales, the retailer may have an incentive to adopt national-brand innovations to serve these segments. But in either scenario, subsequent innovation performance may be modest, because in categories where the private label is very strong, many people have gotten used to buying private labels, and become less inclined to even consider buying branded products (Lamey et al. 2007).

Retail-banner brand equity

Brand equity refers to the differential effect of brand knowledge on consumer response to the marketing of the brand (Keller 1993, p. 2). While brand-equity research has typically focused on manufacturer brands, increasingly, academics and practitioners acknowledge that the retail banner is a brand in its own right possessing brand equity, affecting consumer response, and creating value to the company (Ailawadi and Keller 2004). Retail-banner brand equity (RBBE) exists if consumers react more favorably to the marketing mix of the retailer (products offered, pricing, promotion, etc.) when the retail banner is identified compared to when it is not identified.

Academic and applied evidence support the existence of RBBE. Render and O'Connor (1976) and Dodds, Monroe, and Grewal (1991) show that the reputation of the retailer in which the manufacturer brand is offered affects consumers' perceptions of the brand's product quality, while Dodds and colleagues also document its effect on consumers' willingness to buy the product. Further, each year, market research agency MillwardBrown calculates the financial value of hundreds of brands around the world, including the "Top-20 Retail." A critical component in their brand-value calculations is what they call "brand contribution." It refers to a quantitative measurement (on a scale of 1 to 5, with 5 being the most positive) of "the impact of the brand alone on brand value with financials and all other factors stripped away" (MillwardBrown 2013, p. 28). Its 2013 list of most valuable retailers includes Tesco and Whole Foods, which received a brand contribution rating of 4 (the same score as, e.g., Budweiser, Gillette, and Colgate), Asda and Target, which received a rating of 3 (similar to, e.g., Nivea and Minute Maid), and Aldi and Wal-Mart, which received a rating of 2 (similar to, e.g., Pond's and Sprite).

Conceptually, the retail banner acts as an umbrella brand spanning the entire assortment. From an information-economics perspective (Erdem 1998; Montgomery and Wernerfelt 1992), when consumers are uncertain about the product's quality, purchasing the product at a retailer with high RBBE lowers their perceived purchase risk, which is especially important for new products, as they are inherently more risky than existing ones (Erdem 1998; Steenkamp and

Gielens 2003). We further expect that retailers with high RBBE have a greater inclination to add new products to the assortment to maintain their differentiated positioning in the minds of the consumers.

Contingency effects

Previous research has documented that the effectiveness of marketing activities can vary across the context in which they take place (e.g., Steenkamp and Gielens 2003; van Heerde et al. 2013). The context in the present study is (1) the characteristics of the category in which the innovation is introduced, and (2) the banner of the retailer. We expect that these contextual variables will moderate the effects of the shopper-marketing variables on innovation adoption and subsequent performance at the adopting retailers. That is, we propose that these characteristics have the potential to make shopper-marketing instruments more or less effective in stimulating innovation success.

Marketing theory is not sufficiently developed to allow us to posit a comprehensive set of a-priori expectations concerning (1) which retail-context drivers will moderate the effect of (2) which shopper-marketing mix variable on (3) which innovation-success dimension. Therefore, we will examine the moderating role of the retail-context variables using an inductive approach. This approach is philosophically backed by Bass (1995) and more recently by Alba (2012, p. 984) who writes admiringly about marketing scientists' "*ability to produce empirical generalizations about fundamental marketing phenomena [that] has advanced understanding and practice, irrespective of underlying theory*." However, we will offer a post-hoc deductive rationale for the inductively obtained results.

Control variables

Even though our main focus is on the impact of the aforementioned drivers to explain differences in innovation success across chains, we control for the impact of various manufacturer and other control factors that have already been found in earlier studies to affect innovation success. While these are not the focus of our study, controlling for them will provide a stronger test for our key findings.

First, manufacturer power in the category is likely to impact the retailer-manufacturer negotiations related to new-product adoption by the retailer (Kaufman, Jayachandran, and Rose

2006). Second, both retailers (Lin and Chang 2012) and consumers (Gielens 2012) are more inclined to accept innovations by high-equity brands. For such brands, consumers can capitalize on their knowledge inferred from earlier brand experiences, while retailers expect a positive spillover effect. Third, earlier adoptions by other retailers are also expected to influence retailers' innovation adoption decision (Rao and McLaughlin 1989) and its subsequent success at the retailer (Kalyanaram, Robinson, and Urban 1995). Fourth, following work by Ma et al. (2011), we control for the impact of gasoline prices on the retailer's adoption decisions and consumers' grocery purchases. Finally, in line with Steenkamp and Geyskens (2014), we control for unobserved category effects through category dummies (foods, beverages, personal care, and household care).

Method

Research setting

Our research setting is the U.K., one of the largest European grocery markets. It is the home market of one of the world's largest and most sophisticated global retail chains, Tesco. Other leading retailers in the U.K. market include Asda, the most important wholly-owned subsidiary of Walmart, and Sainsbury's, one of the world's pioneers in private-label development. The world's leading discounters, Germany's Aldi and Lidl, are also active in the U.K.

Data and measurement

Our main data source is six years of scanner panel data (from June 2004 until June 2010) covering the grocery purchases from a representative sample of 15,000+ U.K. households, provided by Kantar Worldpanel. We augmented this database with consumer survey data and secondary data to operationalize the variables included in our research framework.

Identification of innovations. Category experts from Kantar Worldpanel identified 105 major innovations launched by leading European national-brand manufacturers in the U.K. market across 21 grocery categories during the period June 2005 to June 2008. [1] The categories cover a mix of foods, beverages, personal-care products, and household-care products. The introductions

[1] The period between June 2004 and June 2005 is used to initialize certain covariates. The data after June 2008 are used to assess the post-introduction performance: we consider whether retailers accept the product within one year after market entry, and determine consumer acceptance in the first year following a retailer's adoption.

reflect major innovations (often introduced as an entire product line), and abstract from minor product modifications and pure SKU proliferations such as a new flavor or packaging (see Gielens 2012 for a similar practice). Some examples were listed in Table 1.

Retailer innovation adoption. From the panel data, we first assessed whether (when) these innovations were adopted in the first year after their market launch by each of the 13 largest retail banners in the U.K. grocery business. In 2007, these retailers collectively represented more than 80% of U.K. grocery sales. This resulted in a set of 105x13=1,365 innovation-retailer combinations. In two instances, the retailer did not offer the specific category in its stores, leaving us with 1,363 observations for further analysis. On average, a retailer accepted 66% of the innovations, with discounter Lidl accepting the fewest innovations (17%), and Asda, Morrisons, Sainsbury's, and Tesco accepting around 90% of all innovations. Table 2 offers descriptive statistics on innovation acceptance and performance at each retailer.

Retailer innovation performance. We operationalized retailer innovation performance as the innovation's category volume share at the retailer in the first year after its listing at that specific retailer. This one-year focus is in line with Gielens and Steenkamp (2007) and ter Braa, Geyskens and Dekimpe (2014), and is consistent with the view of industry analysts who consider the first-year performance of innovations crucial in the CPG industry (Ernst&Young/ACNielsen 2000). Across the 13 retailers, the average market share of the innovation in the first year is 4.69%, but again considerable variation across retailers is observed. In particular, discounters Aldi and Lidl show first-year shares of around .5%, while innovations at Waitrose obtain an average share of 7.60%.

Shopper-marketing and retailer-category drivers and control variables. From the panel data, we derived the shopper-marketing variables associated with the innovation (price, promotion, and uniqueness in the assortment), the retailer-category drivers (expertise, proliferation, and private-label strength), as well as several other control factors (manufacturer power, category type, and order of retailer adoption). As indicated in Table 3, category expertise, category proliferation, private-label strength, and manufacturer power were all operationalized on the year prior to the retailer's adoption (or, in case of non-adoption, the year prior to the right-censoring date).[2]

[2] Determined as one year after the innovation's initial launch in the U.K. market.

RBBE and brand equity. Both RBBE and the equity of the brand under which the innovation was introduced were measured in an online consumer survey. RBBE was measured with 17 items, pertaining to the four components of brand equity included in the Brand Asset Valuator (Keller 2008, pp. 393-399) – differentiation, energy, relevance, and esteem – using items developed by Lehmann, Keller, and Farley (2008). See Appendix for details on the measurement instrument. This measurement instrument (with appropriate modification) was also used to measure the equity of the innovating brands. Each retail banner was evaluated by at least 250 respondents, and each innovating brand by 45 to 50 respondents, in a survey among Kantar Worldpanel's online panel, conditional on their awareness of the retailer or brand (see Dodds, Monroe and Grewal1991 for a similar practice). Ratings were averaged across respondents to arrive at overall RBBE and brand-equity scores.

Gasoline price. Data on the price of gasoline were obtained from the U.K. Department of Energy and Climate Change (DECC), which publishes quarterly an index of real gasoline prices in the U.K. (www.decc.gov.uk). To model the adoption decision, the average gasoline price in the year prior to the adoption (or censoring date) was used, while the gasoline price in the year following the adoption was used for predicting innovation performance. We refer to Table 3 for more details on the operationalization and data source for the variables.

Model specification

Innovation adoption by a retailer is likely to be a strategic choice driven by various motives, among which (potentially) the expected innovation performance in its stores. If innovations that secure shelf presence at a particular retailer differ in important, but unobserved characteristics from those that fail to obtain shelf presence, a problem of sample selection arises (Hamilton and Nickerson 2003). Therefore, we simultaneously model the retailer's decision to adopt the innovation and, conditional upon adoption, innovation performance at the retailer with a Heckman (1979) selection model. More specifically, our model consists of the following system of equations:

$$\begin{bmatrix}\text{ACCEPT}_{ir}\\ \text{SHARE}^*_{ir}\end{bmatrix} = \underbrace{\begin{bmatrix}\gamma_{11} & \gamma_{12} & \gamma_{13}\\ \gamma_{21} & \gamma_{22} & \gamma_{23}\end{bmatrix}.\begin{bmatrix}\ln(\text{PRICE}_{ir})\\ \ln(\text{PROMO}_{ir})\\ \ln(\text{UNIQ}_{ir})\end{bmatrix}}_{\text{Shopper-marketing drivers}} + \underbrace{\begin{bmatrix}\gamma_{14} & \gamma_{15} & \gamma_{16}\\ \gamma_{24} & \gamma_{25} & \gamma_{26}\end{bmatrix}.\begin{bmatrix}\ln(\text{CDI}_{ir})\\ \ln(\text{PROLIF}_{ir})\\ \ln(\text{PLMS}_{ir})\end{bmatrix}}_{\text{Retail-category drivers}} + \underbrace{\begin{bmatrix}\gamma_{17}\\ \gamma_{27}\end{bmatrix}.[\ln(\text{RBBE}_r)]}_{\text{Retailer-banner brand equity}}$$

$$+\underbrace{\Delta\mathbf{X}}_{\text{Control variables}} + \underbrace{\text{B}\mathbf{Z}}_{\text{Inter-actions}} + \begin{bmatrix}\varepsilon_{1ir}\\ \varepsilon_{2ir}\end{bmatrix}, \qquad (1)$$

with $\Delta\mathbf{X} = \begin{bmatrix}\delta_{10} & \delta_{11} & \delta_{12} & \delta_{13} & \delta_{14}\\ \delta_{20} & 0 & \delta_{22} & \delta_{23} & \delta_{24}\end{bmatrix}.\begin{bmatrix}1\\ \ln(\text{MPOW}_{ir})\\ \ln(\text{BE}_i)\\ \ln(\text{ORDER}_{ir})\\ \ln(\text{PRGAS}_{ir})\end{bmatrix} + \begin{bmatrix}\sum_{c=1}^{3}\delta_{15}^{c}\,.\,\text{CAT}_i\\ \sum_{c=1}^{3}\delta_{25}^{c}\,.\,\text{CAT}_i\end{bmatrix}$

ACCEPT and SHARE* refer, respectively, to the retailer adoption and the (logit-transformed) market share of innovation *i* (= 1…105) at retailer *r* (= 1…13). These two success measures are linked to three groups of retailer drivers. The shopper-marketing drivers are the innovation price premium at that retailer (PRICE), retailer promotion intensity for the innovation (PROMO), and the uniqueness of the innovation in the retailer's assortment (UNIQ). The retailer-category drivers include category expertise of the retailer (CDI), brand proliferation in the category at the retailer (PROLIF), and the strength of the private label in the assortment of the retailer (PLMS). The retailer umbrella-brand driver is RBBE.

Matrix ***X*** refers to the effects of the control variables, and includes an intercept, manufacturer power (MPOW), brand equity (BE), number of retailers that have already adopted the innovation (ORDER), gasoline price (PRGAS), and three category dummies (CAT) for foods, household-care products, and personal-care products, with beverages as baseline. Note that in our model, MPOW is only included in the innovation acceptance equation. While consumers are typically familiar with the brand under which a product is sold, they are less knowledgeable about the producing manufacturer. This is consistent with the view by Kapferer (2008, p. 319) that national brands in CPG follow mostly a 'house of brands' rather than a 'branded house' strategy.[3] Finally, matrix ***Z*** contains the relevant interaction terms between, respectively, the shopper-marketing and retail-context drivers, as discussed in more detail below.

[3] This exclusion restriction, while not absolutely necessary, is useful for identification purposes (Johnston and Dinardo 1997, p. 450).

In the first equation, ACCEPT_{ir} captures whether innovation *i* obtains shelf presence with retailer *r*. This equation models the innovation-adoption stage, and is estimated on the full sample of all 1,363 possible innovation-retailer combinations. It takes the form of a probit model where ACCEPT_{ir} is a binary variable taking the value of 1 if the retailer added the innovation to its assortment in the first year after the national or market launch, and 0 otherwise. In the second equation, the dependent variable is the performance of innovation *i* at retailer *r*. This equation corresponds to the outcome stage, and includes a subsample of the original innovation-retailer combinations used in estimating the adoption equation (i.e., those innovations that were adopted by a retailer). Since retailer innovation performance is quantified by its volume market share (MS_{ir}), it can only take on values in the range between 0 and 1. To account for this range constraint, we use the logistic transformation of the innovation's volume share, i.e. $\mathrm{SHARE}^{*}_{\mathrm{ir}} = \ln(\frac{\mathrm{MS}_{\mathrm{ir}}}{1-\mathrm{MS}_{\mathrm{ir}}})$, as dependent variable.

To allow for the possibility that unobserved characteristics may affect both retailer innovation adoption and performance, no restrictions are imposed on the correlation (ρ) between the error terms $\varepsilon_{1\mathrm{ir}}$ and $\varepsilon_{2\mathrm{ir}}$.

Estimation

We estimate our model with a joint Maximum Likelihood estimation, which has been shown to be more efficient than the more traditional two-stage estimation (Breen 1996). In estimating our model, we take into account several additional issues. First, to limit the influence of outlying observations in our analysis, we log-transform all continuous predictors (Ruppert and Aldershof 1989), and mean-center these variables for ease of interpretation (Cohen et al. 2003). Effects coding is used for the category dummies.

Second, even though we focus on three key shopper-marketing instruments for the innovation (price, promotional intensity, and uniqueness), there may be other shopper-marketing activities (such as aisle and display-management strategies) that are not explicitly measured, but which could have important effects on the sales of innovations in that chain. To control for potential within-retailer correlations across the different innovations, we follow Mizik and

Jacobson (2009), and employ cluster-robust standard errors, in which the error terms are allowed to be correlated across the innovations within a retail banner.[4]

Third, in the *adoption equation*, the post-adoption price and promotion variables are not yet known at the time of the adoption decision (and are never observed in case of rejection). In the spirit of Lamey et al. (2012), we develop a proxy for these not-yet-observed/missing values: the price premium for the innovation prior to adoption is measured as the average price of the innovation at all other adopting retailers relative to the weighted national category price (with the respective brands' value share as weight). This measure captures whether the focal innovation is relatively expensive compared to current category offerings in the market. Since promotional intensity differs widely between HiLO, EDLP and discount-oriented retailers, we derive the promotional proxy as the average promotional intensity across all other innovations in our sample adopted by a given retailer.

Finally, we tested for the possible endogeneity of the three shopper-marketing variables in the *outcome equation*. We regressed each shopper-marketing variable on three instruments along with the other (exogenous) variables. As instruments, we use the mean price premium of the innovation at other adopting retailers (cf. Lamey et al. 2012), the mean promotional intensity at other adopting retailers, and the uniqueness of the innovation in the retailer assortment one year prior to its introduction at the retailer (see Villas-Boas and Winer 1999, or Dhar and Hoch 1997 for a conceptually similar practice). All three auxiliary regressions showed satisfactory levels for their R^2 and F-values (price premium: $R^2 = .70$, $F(13,893) = 159.98$ ($p < .001$); promotional intensity: $R^2 = .48$, $F(13,893) = 62.32$ ($p < .001$); uniqueness: $R^2 = .67$, $F(13, 893) = 136.47$ ($p < .001$). The Hausman-Wu test indicated that there is no evidence for the endogeneity of promotional support ($p = .30$) and innovation uniqueness ($p = .43$).[5] Retailer innovation price,

[4] Note that Tesco operates four separate chain formats in the U.K. market: Tesco (regular), Tesco Express, Tesco Extra, and Tesco Metro. In our analysis, we treat these four Tesco formats as separate retail banners, since they vary considerably on multiple dimensions such as store size (e.g., hypermarkets vs. supermarkets), perceived RBBE, retailer innovation adoption, and average innovation performance at the chain. Nonetheless, there may be a closer relationship in innovation acceptance and innovation performance among the Tesco formats than with other U.K. retail chains. Therefore, we also estimated the model with an alternative error structure, i.e. where we allow the error terms of all Tesco observations to be correlated with one another (irrespective of the specific Tesco banner), while those of the non-Tesco observations remain correlated within their respective banner (hence, allowing for 10 rather than 13 clusters). The results were robust, apart from one additional interaction effect (between category proliferation and the innovation's promotional support) that became marginally significant ($p = .094$) in the outcome equation.

[5] In line with Hoetker and Mellewigt (2009) and ter Braak, Dekimpe and Geyskens (2013a), we report on the endogeneity tests for the main-effects model.

however, was found to be endogenous (p = .02). In our further analyses, innovation price will therefore be instrumented in the outcome equation by its corresponding estimate from the auxiliary regression.

Model-building approach

Following Palmatier, Gopalakrishna, and Houston (2006), we build our model by successively adding blocks of predictors. We start with a selection model which includes only an intercept and the control variables (i.e., $\boldsymbol{X}$ in Equation 1). In subsequent steps, we successively add the shopper-marketing variables (Model 2), and the retail-context drivers (Model 3, where we add both the retailer-category drivers and the RBBE). Finally, we allow (Model 4) for interactions between the shopper-marketing variables and these retail-context drivers (i.e., $\boldsymbol{Z}$ in Equation 1). However, retaining all 24 such interactions would lead to excessive multicollinearity and unstable results. In the spirit of Bijmolt, van Heerde, and Pieters (2005), we first augmented Model 3 with the interactions between each shopper-marketing variable and one of the four retail-context drivers. Following the estimation of four such extended models, we estimated a final model containing all main effects as well as all significant (p < .10) interactions in the previous models (see van Heerde et al. 2013 and Steenkamp and Geyskens 2014 for a similar practice).

Results

Model fit

Of the 1,363 innovation-retailer combinations considered, there were 456 instances where the retailer decided not to accept the innovation. Accordingly, while the innovation acceptance model includes all 1,363 observations, the innovation performance equation is estimated on 907 innovation-retailer combinations. Table 4 provides the results of the incremental model testing approach. Since the models are nested, we can assess whether model fit improves significantly by means of a likelihood-ratio test. Moving from Model 1 to Model 4, this was the case in every instance (p < .01). These findings clearly support the importance of considering the retail context in which the new product is introduced as driver of innovation success. Also an evaluation in terms of the AIC and BIC leads to the same conclusion that all blocks of variables contribute to

Model 4's explanatory power. Moreover, all VIF factors in Model 4 remain below the critical value of 5 advocated by Judge et al. (1988), suggesting multicollinearity is not a major issue.

In model 4, we obtain a hit rate of 84% in the adoption equation, which clearly exceeds the value that would be expected by chance alone of 55% (= $\alpha^2 + (1- \alpha)^2$ with α = 66%; Morrison 1969). The fit of the final outcome equation resulted in an R^2 of 54%.

The error-correlation between ε_{1ir} and ε_{2ir} is significant ($p < .05$), which underscores the importance of accounting for unobserved factors that affect both success metrics. Interestingly, this correlation is negative, suggesting that, on average, unobserved factors that make the adoption decision more (less) likely, tend to have an opposite effect on the outcome equation. As discussed below, this is also the case for several of the included drivers.

Main effects

The parameter estimates for Model 4 are reported in Table 5. The higher the price premium of the innovation, when evaluated at the mean level of the relevant moderating variables,[6] the more likely that the retailer adopts the innovation (γ = .484, $p < .01$). As argued before, higher price premiums offer the (appealing) prospect of higher margins on such innovations for the retailer. However, price premium has no effect on subsequent performance at the adopting retailers (γ = .002, n.s.). As we shall see below, its effect on consumer purchases is highly dependent on the retail setting. Promotional intensity has a significant positive impact on the retailer's adoption decision (γ = 8.835, $p < .01$) as well as on the market share obtained in the category at the adopting retailers (γ = 1.117, $p < .01$). The third shopper-marketing variable, uniqueness, has opposite effects on the two dimensions of innovation success. More unique products are less likely to be accepted by retailers (γ = -.519, $p < .10$), but once accepted, turn out to be more successful at those retailers (γ = .311, $p < .01$). At first sight, the negative effect of uniqueness on likelihood of adoption is contrary to prior expectations. We will revisit this below when we consider the interplay with RBBE.

Turning to the retailer-category drivers, we find that although the effect of category expertise is in the expected direction for both innovation success metrics, it does not reach statistical significance. However, the main effects of the other two category drivers are significant. Retailers are more likely to adopt innovations in categories with a high degree of

[6] This applies to all main effects discussed in the current section.

proliferation ($\gamma = .581$, $p < .01$), which turns out to be a smart decision as also subsequent innovation performance is greater in these categories ($\gamma = .334$, $p < .01$). This provides support for the notion that high category proliferation is an indication of the existence of multiple niches in the market (Schmalensee 1978). Further, in categories where the retailer's own private label is more successful, it is more prone to adopt a national-brand innovation ($\gamma = 1.340$, $p < .05$), possibly in the hope to still attract (keep) customers that do not want to purchase a private label in that category. However, subsequent performance in those categories is less ($\gamma = -2.677$, $p < .01$). The dominant presence of private labels may already have conditioned many consumers to buy the retailer's own brand (Lamey et al. 2007), making them less receptive to national-brand innovations. Innovations are more likely to be adopted by high-RBBE retailers ($\gamma = 2.613$, $p < .01$), whereas innovation performance seems unrelated to the level of RBBE ($\gamma = -.527$, n.s.). Still, the role of RBBE in shaping innovation performance becomes clearer when considering the interplay with the shopper-marketing variables (see below).

Finally, in terms of the control variables, retailers are more likely to adopt innovations offered by powerful manufacturers ($\delta = 1.823$, $p < .01$). Brand equity matters too. Retailers are more likely to accept innovations if they are offered under a strong brand name ($\delta = 3.516$, $p < .01$), and with good reason as their subsequent performance with the retailer is also higher ($\delta = 2.055$, $p < .01$). Further, retailers' likelihood of adoption increases with the number of retailers that have already adopted the innovation ($\delta = 1.199$, $p < .01$), which is an example of the bandwagon effect (cf. Deleersnyder et al. 2009), even though subsequent performance at the laggards is lower ($\delta = -.411$, $p < .01$). Finally, innovation success is influenced by the level of the gasoline prices: when gasoline prices go up, retailers exhibit a reduced willingness to adopt new products ($\delta = -16.680$, $p < .01$), which appears justified, as the subsequent performance of the innovations at the retailer is lower as well in these circumstances ($\delta = -1.769$, $p < .01$). While these substantive control variables are not the focus of this paper, the fact that their effects are consistent with expectations increases the confidence in the validity of our focal parameter estimates. Finally, across both performance metrics, significant differences are found among the various product types.

Contingency effects

To enhance our understanding of the influence of shopper-marketing activities on innovation success, we further explore how their effectiveness differs across retail contexts. In line with Greene (2010) and Mallapragada, Grewal, and Lilien (2012), we focus on the significance of the relevant product terms in Table 5.[7] We graphically depict these interactions in Figure 2 where we show the impact of a gradual increase in the three shopper-marketing instruments (across the data ranges observed in our data) for two levels (one standard deviation above and below the means in each equation)[8] of three moderator variables: the RBBE, and the category's proliferation and private-label strength.[9]

There is clear evidence in Table 5 that the effectiveness of all three shopper-marketing variables is moderated by retail-context variables. Of the 24 potential interactions in our equations, 12 interactions are significant in our final model (6 out of 8 interactions included in the adoption equation, and 6 out of 8 interactions added in the performance equation). They lead to new insights on how the effectiveness of commonly-used shopper-marketing activities for the innovation varies (i) by retailer, and (ii) within a retailer, by category.

Category proliferation. We have pointed out earlier that (for average values of the moderating context variables) retailers are less prone to adopt highly-distinctive products. However, this effect is due to the strong negative effect of uniqueness on innovation adoption in categories characterized by low proliferation (Panel A.1). The adoption probability decreases over the sample range (Panel A.1) by 35 percentage points as the uniqueness increases in low-proliferated categories (from an adoption probability of 84% to 49%), as opposed to an increase of 20 percentage points in highly-proliferated categories (from an adoption probability of 75% to 95%). In highly-proliferated categories, higher uniqueness becomes an asset that increases the adoption probability ($\beta = .911$, $p < .01$). Further, while high innovation uniqueness was found to have a positive main effect on innovation's subsequent performance at the retailer, this becomes especially pronounced (Panel A.2) in highly-proliferated categories ($\beta = .334$, $p < .10$). These

[7] As such, we do not focus on the significance of changes in the partial effects, as these can be seen as an artifact of the adopted non-linear functional form (see Mallapragada, Grewal and Lilien 2012, p. 485 or Greene 2010, p. 295 for a similar reasoning).

[8] For the retailer variable RBBE, we take the mean across the 13 retailer values, instead of the grand mean used for the retailer-category variables.

[9] No significant product term with category expertise was found (see Table 5). In the graphs, all continuous variables are set at their mean level, while effects coding is used for the category dummies to reflect average values across the entire sample for the adoption probability and innovation market share in Figure 2.

results can be explained from the point of view of competitive clutter (cf. Danaher, Bonfrer, and Dhar 2008). In highly-proliferated categories, being unique and different from other offerings may be one of the few ways to get noticed. However, being very different in categories with few offerings may deter retailers from carrying the product, for fear of undermining the cohesiveness of their category.

Private-label strength in category. The effectiveness of innovation price and promotion vary in function of the strength of national brands' greatest competitor in the category, the retailer's own brand. An increase in the price premium has a stronger effect (Panel B.1) on the retailer's decision to adopt the innovation in categories where the retailer's own private label is not particularly successful (β = -1.265, $p < .01$), while retailers appreciate increased promotional support more in categories where their private label is dominant (β = 14.551, $p < .05$) (Panel C.1). This also has a greater impact (Panel C.2) on innovation sales in categories with a strong private label (β = 6.333, $p < .01$). Also, in categories with a high private-label share, having a high price premium starts to hurt (Panel B.2) the innovation's performance (β = -.883, $p < .05$). These findings corroborate Pauwels and Srinivasan (2004), who show that the presence of a strong private label at the retailer increases consumers' sensitivity to price-related instruments.

Retail-banner brand equity. The prominent role of RBBE is highlighted by the finding that it moderates the effects of all three shopper-marketing instruments on both innovation- success dimensions. First, the impact of an increase in the innovation's price premium on the retailer's adoption decision is more pronounced (β = 3.519, $p < .01$) in high RBBE settings (Panel D.1). Even though no significant main price effect was found in the outcome equation, we find (β =.867, $p < .01$) that a higher price stimulates subsequent innovation sales at high-RBBE retailers, while the reverse is true for low-RBBE retailers (Panel D.2). Promotional support for the innovation, in turn, increases the chances of acceptance by low-RBBE retailers, and has a strong effect on subsequent sales, but has little effect on innovation success at high-RBBE retailers (β = -51.863, $p < .01$ and -11.306, $p < .01$, respectively; see also Panels E.1 & E.2). These findings are broadly consistent with the information-economics view of umbrella branding. In general, uncertainty about product quality and the associated perceived risk of the new product decrease consumer expected utility (Erdem 1998). Decreased utility should translate into a lower reservation price absent the countervailing power of a strong umbrella brand, something low-RBBE retailers lack. Hence, price considerations become more important to innovation success at these retailers: they are less enticed by (and receive smaller performance rewards from) higher price premiums, but react more extensively to (and obtain higher performance gains from) an increased promotional support.

Finally, innovation uniqueness plays a larger role (Panel F.2) in stimulating sales at high-RBBE retailers than at low-RBBE retailers ($\beta = 2.267$, $p < .10$). In contrast, the interaction between uniqueness and RBBE in the adoption equation is negative ($\beta = -8.358$, $p < .01$). This causes the adoption likelihood among high-RBBE retailers to decline with uniqueness (Panel F.1). Closer inspection of the interaction effect reveals that it is driven by the finding that high-RBBE retailers exhibit a high likelihood of adopting new products that are low on uniqueness. An explanation for this finding could be that a key component of high-RBBE retailers is their need to maintain high levels of "energy". To signal a highly dynamic assortment (see, e.g., items 13, 16, and 17 of the RBBE construct in Appendix A), they need a high level of assortment rotation (Deleersnyder and Koll 2012), for which they rely on the regular addition of often less-distinctive innovations.

Discussion

Despite the billions of dollars spent on new-product development and related marketing activities by national-brand manufacturers, it is the retailer who is the gatekeeper to consumers. PlanetRetail (2010, p. 7) puts it as follows: "*the ball is in the retailers' court when it comes to influencing or even deciding which products consumers should buy*." Yet, previous research has largely focused on the manufacturers' and consumers' roles in new-product success. The present study adds to existing insights by studying the dual role of the retailer in new-product success. First, the retailer has to decide whether or not to include the innovation in its assortment. Second, the retailer has to employ its shopper-marketing instruments to move the innovation off its shelves. While the manufacturer can attempt to influence the shopper-marketing activities, e.g., by subsidizing consumer promotions, it is ultimately the retailer who decides upon pricing, promotions, and assortment composition (Ailawadi et al. 2009; Inman, Winer, and Ferraro 2009).

Understanding the retailer's role in innovation success is complicated by three additional factors. First, this role materializes through two distinct performance metrics, which are not independent of one another, and therefore should be studied in tandem. Second, both the adoption decision and subsequent sales performance at the retailer depend on category characteristics, which differ across retailers, and on the general strength of the retail banner, which acts as an umbrella brand. Third, also the efficacy of the various shopper-marketing instruments may not always be the same across categories and retailers. On the contrary, there is every reason to believe that their effectiveness differs as a function of the characteristics of a given category at a specific retailer and the latter's RBBE.

In this study, we made an attempt to identify and estimate these different effects. Using data from the U.K. grocery market, our study provides evidence for the key role of the retailer in new-product success, and documents that this success is systematically affected by the complex interplay between a set of retailer-controlled factors, pertaining to shopper-marketing instruments used in conjunction with the retailer-category characteristics and the retailer umbrella brand. Our findings provide broad support for our research framework (Figure 1), with three groups of drivers contributing significantly to the explanation of innovation success. The effect of some variables (innovation price premium and RBBE in the innovation performance equation) work completely through interactions, while the effect of most other variables works through both main effects and the interplay between the shopper-marketing instruments and retail-context characteristics. The important moderating role of RBBE is testimony to the fact that retail banners have become strong brands in their own right (Ailawadi and Keller 2004), exerting effects on market outcomes for national brands over and above the equity these brands possess. Finally, we show that it is important to simultaneously consider both metrics of innovation success - retailer innovation adoption and retailer innovation performance - given that a sole focus on the innovation performance without considering the retailer's prior selection decision could be misleading, as the effect of several variables is found to differ, and for some to even work in opposite direction, across both success metrics. In combination, our results provide tools for both retailers and manufacturers how to tailor their innovations' marketing mix to the retailer in question and, if necessary, also at the more granular category level within the retailer.

Implications for retailers

Retailers exert a strong influence on the success of innovations at their outlets, but the effectiveness of their shopper-marketing instruments is context dependent. Our findings call for tailor-made strategic recommendations where retailers need to adapt their innovation-related shopper-marketing activities in function of their RBBE, while also considering the composition of the category in question within their banner.

In general, high-RBBE retailers can set a higher price premium for their innovations, a strategy that is especially effective in categories where the retailer's private label is less successful. In contrast, low-RBBE retailers can boost innovation sales by setting competitive prices and/or by offering promotions for the innovations more frequently, as their shoppers are found to be more responsive to prices, especially in categories where their private labels compete strongly with the national brands. High-RBBE retailers are also encouraged to include innovations that are more unique and stand out in their assortment. Note that a high number of established offerings already available in the categories should not refrain the retailer from adding an additional innovation, and we encourage retailers to embrace especially more unique offerings into already highly-proliferated assortments. Finally, we advise retailers to include innovations in categories where their own private labels are still less developed. Also, they should act quickly and not postpone the adoption of an innovation, as the latter's performance at their outlets will decrease as more competing retailers have already adopted the innovation.

Over and above these general recommendations, we illustrate how our findings can be used to provide recommendations to specific retailers. In Table 6, we present for each individual banner the combined effect, consisting of the main-effect augmented with the different contingency effects for the three shopper-marketing instruments. The contingency effects are evaluated at the banner-specific means (across all innovations adopted by that retailer) for the log-transformed category variables and at the specific RBBE level. In addition, we present the proportion of categories, relative to the number of categories in which at least one innovation was adopted, with a significant positive and negative combined impact for every instrument (now evaluated at the category-specific means within that banner). Since there are real managerial costs associated with type II errors (i.e., unjustifiably rejecting the alternative hypothesis), we follow (Lodish et al. 1995, p. 128) and use the more liberal p <.20 (2-sided) as cutoff. Significance levels are determined on the basis of the Delta rule.

The results show that the effectiveness of the shopper-marketing variables differs considerably between retailers. Concerning price, the message for discounters Aldi and Lidl is clear – a higher price premium always (i.e., in 100% of the categories considered) leads to lower innovation performance at their stores, and thus, these chains are advised to be cautious in adopting premium-priced innovations, unless their introduction is accompanied by heavy promotional effort, which has a large effect in these chains. For the Asda, Tesco, and Sainsbury's banners, a premium price works positively on average (.079, $p < .10$; .154, $p < .05$; and .135, $p < .05$, respectively) and in the majority of the categories (65%, 67%, and 85%, respectively).[10] For Iceland, on average, price has little effect on innovation performance but a higher price does not hurt, as exemplified by the finding that it never works (significantly) negatively, and in 71% of cases works positively. In sum, these four banners are the strongest beneficiaries of a high-price strategy. For Waitrose, pricing should be closely tailored to the characteristics of the category in which the innovation is introduced, as it has a significantly positive effect on innovation performance in 42% of the categories examined, but for 16% of the categories in which an innovation was accepted, the relationship is significantly negative. Similar findings are observed for Tesco Express, Tesco Extra, and Tesco Metro.

Promotions are very effective in stimulating innovation sales in discounters Aldi, Lidl, and Netto, and in smaller neighborhood stores such as Tesco Metro and Tesco Express. As for the latter, these are especially targeted towards impulse and last-minute buying, where promotions can be expected to be quite effective. Discounters, in contrast, are known to mostly follow an EDLP strategy (also confirmed in our dataset as having the lowest promotional intensity). The high percentage of cases with a positive promotion effect suggests that there are opportunities for collaboration between manufacturers and discounters to use the promotion instrument more intensively (Deleersnyder et al. 2007). In Asda (Sainsbury's), price promotions should be tailored to the category, since it helps innovations in 15% (10%) of the categories where the retailer accepted innovations, while it hurts innovation performance in 20% (40%) of the categories [and has no significant impact in the remaining 65% (50%)].

Uniqueness, on average, has a strong positive effect on performance at Asda, Morrisons, Sainsbury's, Waitrose, and the four Tesco banners, and for none of the categories is higher uniqueness detrimental to innovation performance. For the other chains, a tailored (category-dependent) strategy is called for, something especially pertinent for Aldi where positive (28%) and negative (11%) effects occur with some frequency.

[10] Unless noted otherwise, in this section, percentages refer to the proportion of significant (positive or negative) effects.

Implications for national-brand manufacturers

Our results may help manufacturers to understand which retailers are more prone to accept their innovations. Such information can be taken into account when negotiating with retailers on the terms of agreement for the new products. In general, manufacturers will have more easy access with their innovations in categories with more established offerings, at higher-RBBE retailers, when they are more powerful, and when the innovation is launched under a strong brand name. In addition, more expensive innovations are more readily accepted by high-RBBE retailers, who may also require less promotional support for these innovations. Finally, to the extent possible, manufacturers are recommended to shift their promotional support for the innovation to lower-RBBE retailers (and encourage these retailers to pass on these promotions to their consumers), and to retailers with a stronger private-label presence in the category in which the new product is introduced.

Using a similar procedure as before, we present in Table 7, for each of the 13 retail banners, the combined effect of the various shopper-marketing instruments on retailer innovation acceptance (evaluated at the banner-specific means across all innovations), and present the proportion of categories, relative to the number of categories in our sample offered by the retailer, with a significant positive and negative impact for every instrument (evaluated at the category-specific mean values at that banner). Table 7 reveals that higher prices and more promotional support for the innovation typically increase the chances of getting access to the retailer. But there are exceptions. A tailor-made pricing approach is called for with discounters Aldi, Lidl, and Netto: while the overall effect is non-significant, it is nearly always negative in those categories for which there is a significant pricing effect. Further, promotion support is not often an important consideration for Sainsbury's (38%) and even less so for Tesco (5%). The aggregate effect of uniqueness differs in magnitude and significance across retailers but the dominant thrust across retailers is that it is negative. However, for retail banners Netto, Somerfield and Waitrose, a more category-specific strategy is called for, as both positive and negative effects occur across categories.

Comparing Tables 6 and 7 shows that there is greater within-retailer consistency in the effects of the shopper-marketing variables on the adoption decision than on the performance at the retailer. This makes sense. The adoption decision is made by the retailer itself, which may have coordinated policy guidelines across categories regarding criteria of adoption, while the market share at the retailer critically depends on decisions by many individual consumers, who may respond differently to the retailer's marketing instruments. This suggests that manufacturers need to tailor their innovation support to a specific retailer, but less tailoring is needed in function of the category in which the manufacturer operates. However, retailers need to tailor that shopper-marketing mix more closely to the category in question in order to make the innovation a success with shoppers at their banner.

Limitations and directions for further research

Several areas for future research remain open. First, retailer innovation performance was conceptualized by the volume share of the innovation in the category at the retailer. Our performance metric is not informative on the sources of the innovation's sales at the retailer. These may, for example, come at the expense of the mother brand (which is undesirable for the manufacturer), at the expense of the private-label offering (undesirable for the retailer), and/or from category expansion. Future research should examine alternative innovation performance measures at the level of the retailer to also identify the origin of the innovations' sales.

Second, other in-store factors may have an impact on innovation performance at the retailer. The assigned shelf space (both the number of facings as well as their position) and store atmosphere will affect the salience of the innovation among the retailer's incumbent offerings. We were unable to obtain such information in the context of this project, but these factors deserve more research attention.

Third, we found no significant effects for category expertise. This may be due to the particular measure employed (CDI), even though this measure has been used successfully in previous research (Dhar and Hoch 1997; Draganska and Klapper 2007). Future research could employ other operationalizations, such as expert judgments.

Finally, our study focused on the U.K. grocery market. However, the retailers in our sample covered a broad spectrum of formats (ranging from price-oriented hard discounters to high-end, service-oriented supermarkets) and sizes (from smaller neighborhood stores to large hypermarkets), as also found in many other (developed) retail markets. Similarly, many of the innovating manufacturers in our sample (such as Unilever and Procter & Gamble) are active, and offer their innovations, in a multitude of other markets, and also the categories studied are diverse enough to make the general insights applicable beyond our specific sample. Still, it would be useful to extend our analysis to more retailers (to have more variation regarding the general-retailer characteristics) across multiple (also non-European and developing) countries, using more categories and industries (also non-grocery), while also considering other innovations. As for the latter, especially the growing practice of retailers to introduce their own (private-label) innovations (Gielens 2012) is expected to further complicate retailers' shopper-marketing decisions, as their own innovations are likely to be handled differently than national-brand innovations. Such retailer-owned private-label innovations are not yet part of the current study, and represent an interesting area for further research on the topic.

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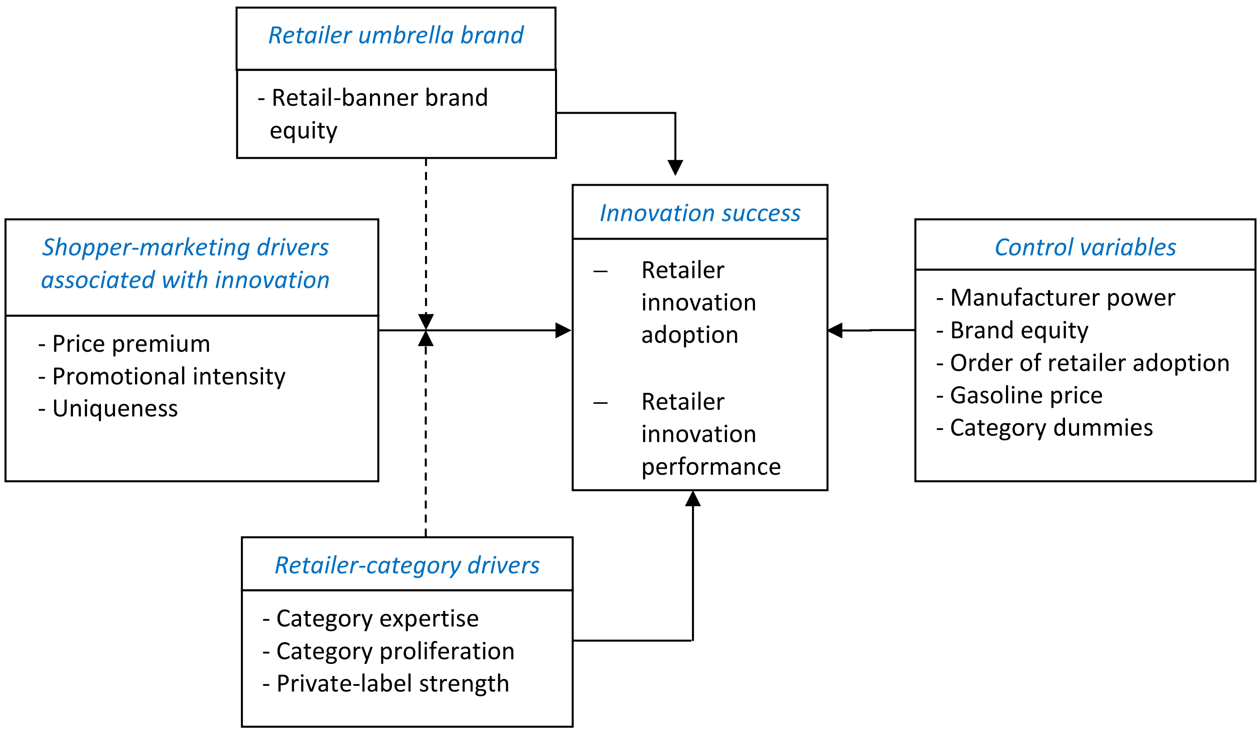
Figure 1
Research Framework



Key:

main effects: ⟶

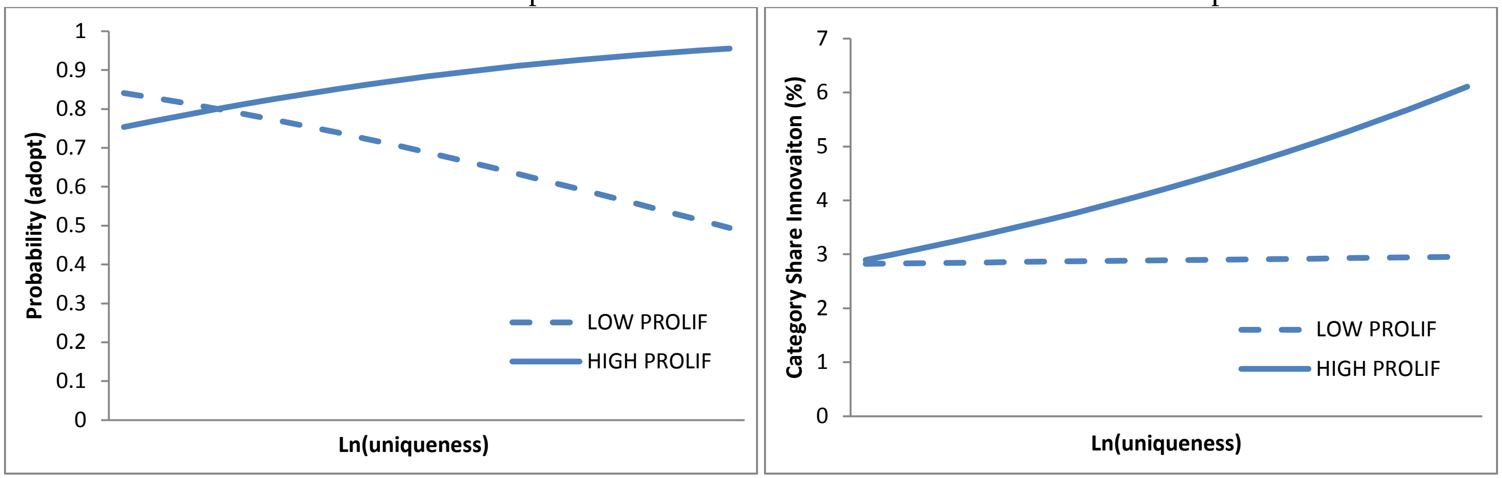
moderating effects : - - - - -▸

Figure 2
Moderating Effect of Retail Context on the Impact of Shopper-Marketing Variables on Innovation Acceptance (Left) and Performance (Right)

PANEL A
Category proliferation (PROLIF) x Uniqueness

A.1 Retailer innovation adoption

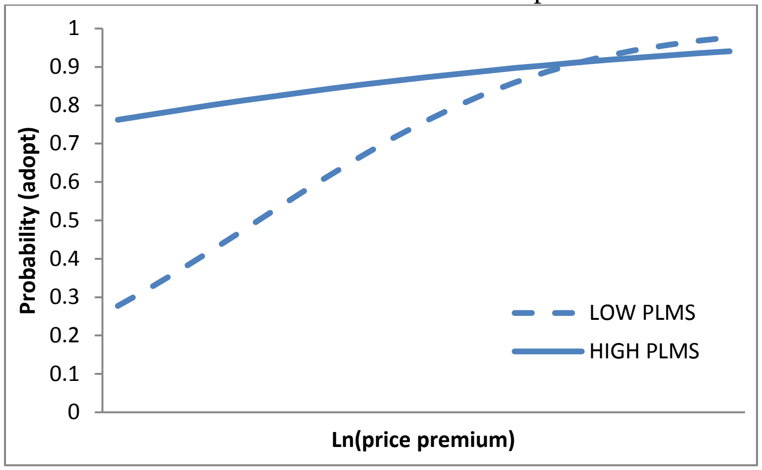
A.2 Retailer innovation performance



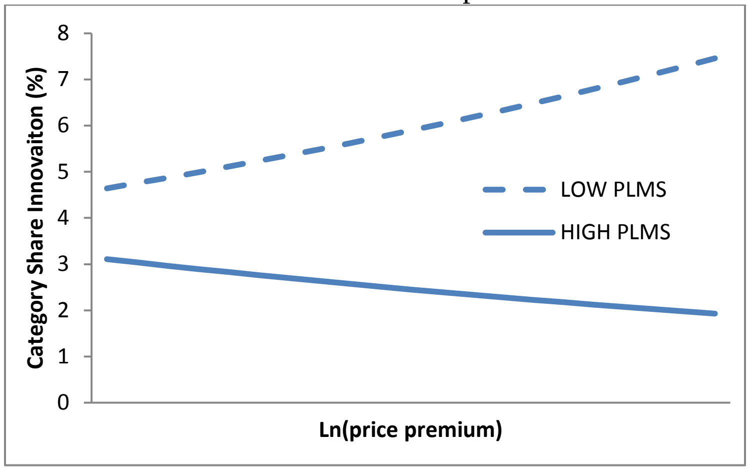
PANEL B

Private-label Strength (PLMS) x Price Premium

B.1 Retailer innovation adoption



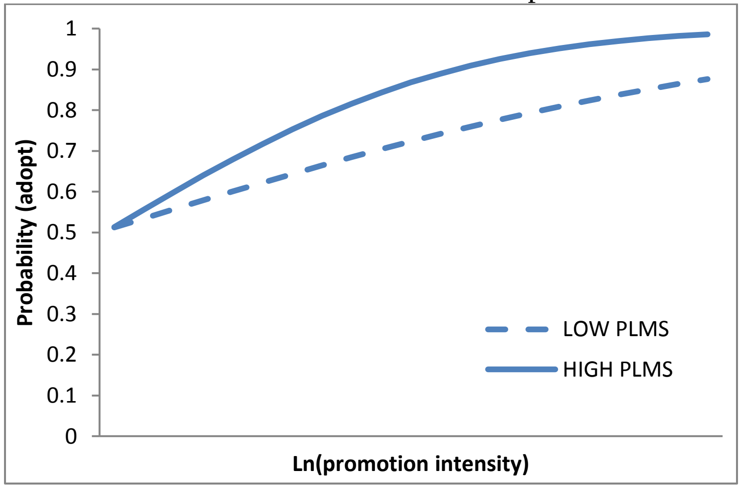
B.2 Retailer innovation performance



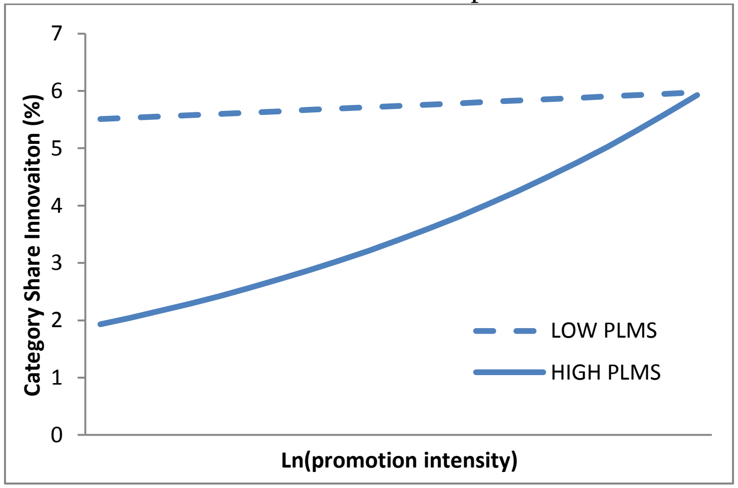
PANEL C

Private-label Strength (PLMS) x Promotion Intensity

C.1 Retailer innovation adoption



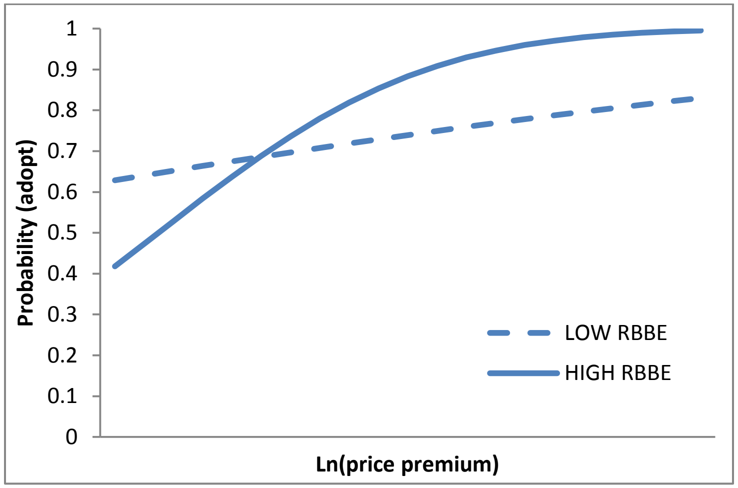
C.2 Retailer innovation performance



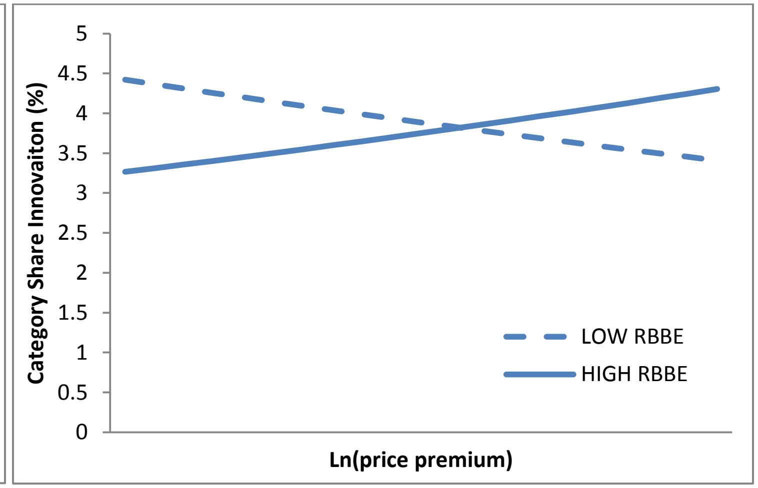
PANEL D

Retailer umbrella brand (RBBE) x Price premium

D.1 Retailer innovation adoption



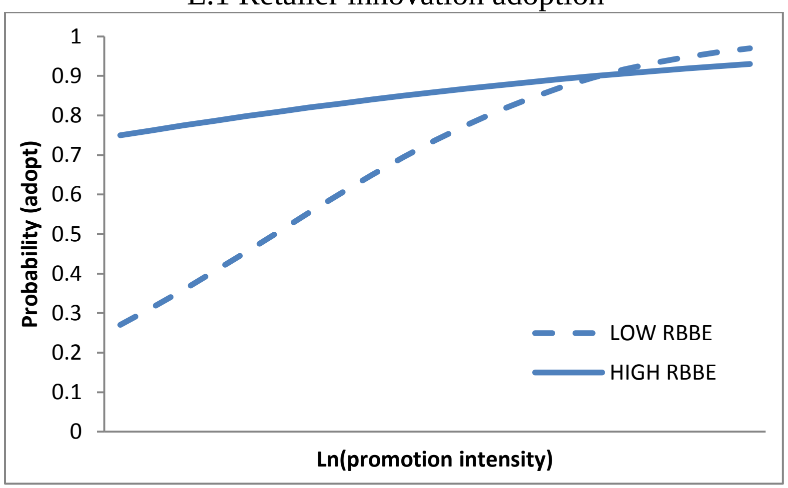
D.2 Retailer innovation performance



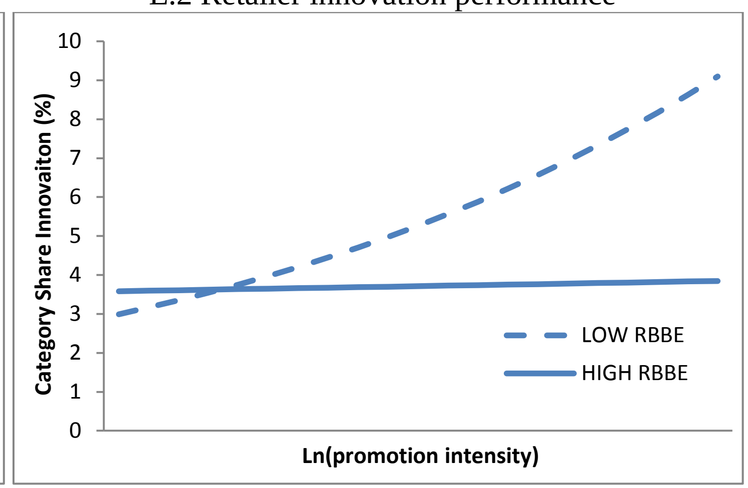
PANEL E

Retailer umbrella brand (RBBE) x Promotion intensity

E.1 Retailer innovation adoption

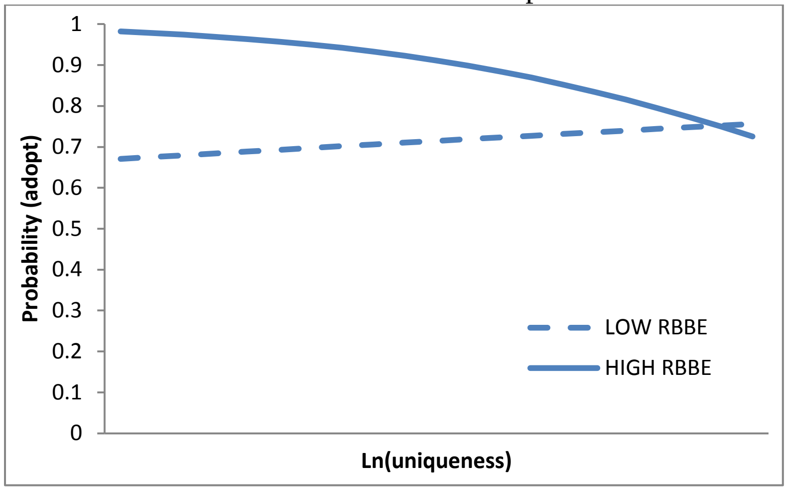


E.2 Retailer innovation performance



PANEL F
Retailer umbrella brand (RBBE) x Uniqueness

F.1 Retailer innovation adoption



F.2 Retailer innovation performance

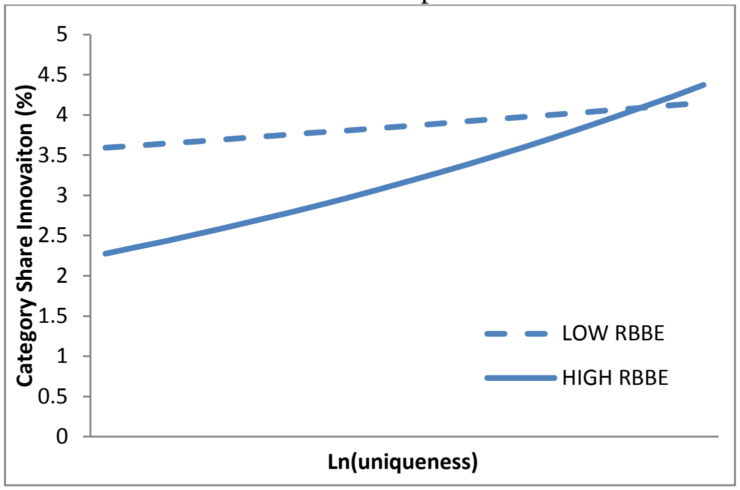


Table 1
Innovation Success at 6 Leading U.K. Grocery Retailers

Example innovations	**Category**	**U.K. market introduction**	**(Volume) share in 1st year following adoption at retailer (%)**					
			Tesco	*Sainsbury's*	*Asda*	*Morrisons*	*Somerfield*	*Waitrose*
Lenor Pure Oxygen Freshness	fabric softener	01-2006	5.20	6.02	. [a]	6.59	.	.
Gillette Arctic Ice	shaving gel	04-2006	.	.	4.78	.	.	17.92
Huggies Little Walkers	diaper	06-2006	1.77	3.11	1.77	1.47	5.84	4.31
Gillette Fusion	razor	08-2006	6.76	8.73	4.75	5.61	4.06	12.35
Garnier Fructis Fortifying	shampoo	02-2007	5.71	7.79	.	6.12	7.52	7.46
Wilkinson Quattro Titanium Energy	razor	02-2007	7.09	8.93	4.72	5.33	.	.
Listerine Total Care Antiseptic	mouthwash	07-2007	5.85	7.52	9.07	9.52	7.57	12.98

[a] A '.' means that the innovation was not accepted by that retailer in the year following its market entry.

Table 2
Innovation Success at the top-13 U.K. Grocery Retailers

	Number of adopted innovations[a] (n=105)	Percentage of innovations adopted	Average innovation performance[b]
Aldi	50	48%	.64%
Asda	92	88%	5.04%
Iceland	26	25%	4.55%
Lidl	18	17%	.42%
Morrisons	95	90%	6.00%
Netto	40	38%	3.26%
Sainsbury's	94	90%	6.28%
Somerfield	80	76%	5.67%
Tesco	94	90%	5.15%
Tesco Express	77	73%	5.63%
Tesco Extra	95	90%	6.02%
Tesco Metro	70	67%	4.73%
Waitrose	76	72%	7.60%
Mean	*70*	*66%*	*4.69%*

[a] An innovation is adopted if the retailer adds the product to its assortment within the first year following the innovation's market entry.
[b] Innovation performance is the volume share (%) of an adopted innovation in the category at the retailer in the first year after its adoption by that retailer.

Table 3: Measures and Data Source

Construct	Operationalization	Reference	Data Source
	RETAILER DRIVERS		
Innovation price premium (*PRICE*)	Ratio of the post-introduction innovation price (per equivalent unit) at the retailer to the corresponding weighted category price at the retailer.	Lamey et al. (2012)	Panel data
Innovation promotion intensity (*PROMO*)	Number of post-introduction weeks with a negative price shock of more than 5% of the innovation's regular (average) price at the retailer (relative to a maximum of 52 weeks).	Raju (1992); Nijs et al. (2001)	Panel data
Innovation uniqueness in the assortment (*UNIQ*)	$= 1 - [\sum_{k=1}^{2}(\frac{S_{kj}}{N_j})]/2$ with S_{kj} the number of sub-brands with a similar value on attribute *k* in category *j* at the retailer, and N_j the total number of sub-brands in category *j* at the retailer, both in the post-introduction year. The two attributes are price and volume. While the (discrete) volume sizes need to be identical between an established sub-brand and the innovation, prices are considered to be similar if they are in the same price tier at the retailer -- where we considered three price tiers per category (low, medium, high), with the low- (high-) tier defined as being more than one standard deviation below (above) the average price in the category.	ter Braak, Dekimpe and Geyskens (2013a)	Panel data
Category expertise (*CDI*)	The Category Development Index (CDI) or fair share of the retailer in the category in the year prior to adoption: [retailer sales in the category / U.K. market sales in the category] / [total retailer sales / total grocery sales for the entire U.K. market].	Dhar and Hoch (1997)	Panel data
Category proliferation (*PROLIF*)	Total number of sub-brands offered in the category at the retailer in the year prior to adoption.	Gielens (2012)	Panel data
PL strength (PLMS)	Value share of PLs in the category at the retailer in the year prior to adoption.	Dhar and Hoch (1997)	Panel data
Retail-banner brand equity (*RBBE*)	Average of 4 constructs underlying the retailer-equity measure: [Esteem + Differentiation + Relevance + Energy] / 4	Adapted from Lehmann et al. (2008)	Consumer survey
	CONTROL VARIABLES		
Manufacturer power at retailer (*MPOW*)	Value share of the manufacturer in the category at the retailer in the year prior to adoption.	ter Braak et al. (2013b)	Panel data
Brand equity (*BE*)	Average of 4 constructs underlying the brand-equity measure: [Esteem + Differentiation + Relevance + Energy] / 4	Adapted from Lehmann, Keller and Farley (2008)	Consumer survey
Order of retailer adoption of innovation (*ORDER*)	Number of other retailers adopting the innovation prior to the focal retailer. If the focal retailer did not accept the innovation within the 1st year after its market launch, it represents the total number of the top 13 U.K. retailers that accepted the innovation within that time span.	Heeler, Kearney, and Mehaffey (1973)	Panel data
Gasoline price (*PRGAS*)	Index of real gasoline prices.	Ma et al. (2011)	DECC
Category type (*CAT*)	Dummy variables for food, personal-care and household-care grocery categories with beverages as benchmark (using effects coding).	Lamey et al. (2012)	Panel data

Note: NB = National Brand; PL = Private Label.

Table 4
Model Fit

Model	LL	- 2Δ(LL)[a]	df	AIC	BIC
Model 1 (M1) = intercept + control variables	-1,879.88			3,783.77	3,846.39
Model 2 (M2) = M1+ retailer shopper-marketing drivers	-1,777.78	204.21***	6	3,579.56	3,642.17
Model 3 (M3) = M2 + retail-context drivers	-1,575.46	404.63***	8	3,174.93	3,237.54
Model 4 (M4) = M3 + interaction effects	-1,516.26	118.40***	16	3,056.52	3,119.13

[a] Likelihood-ratio test versus the preceding model; *** $p < .01$.

Table 5
Drivers of Innovation Success at Retailers

	Retailer innovation adoption			Retailer innovation performance		
Shopper-marketing variables						
Price premium	.484	***	(5.71)	.002		(.05)
Promotion intensity	8.835	***	(5.64)	1.117	***	(2.84)
Uniqueness	-.519	*	(-1.75)	.311	***	(2.90)
Retailer-category drivers						
Category expertise	.105		(.97)	.148		(1.06)
** Uniqueness*	.452		(1.13)	-.841		(-.83)
Category proliferation	.581	***	(5.91)	.334	***	(3.31)
** Price premium*	.124		(1.43)			
** Promotion intensity*				-.308		(-.88)
**Uniqueness*	.911	***	(5.76)	.334	*	(1.83)
Private-label strength	1.340	**	(2.46)	-2.677	***	(-6.70)
** Price premium*	-1.265	***	(-4.88)	-.883	**	(-1.99)
** Promotion intensity*	14.551	**	(2.10)	6.333	***	(2.72)
Retailer umbrella brand						
Retail-banner brand equity	2.613	***	(3.75)	-.527		(-1.00)
** Price premium*	3.519	***	(2.62)	.867	***	(3.07)
** Promotion intensity*	-51.863	***	(-4.42)	-11.306	***	(-3.14)
** Uniqueness*	-8.358	***	(-3.20)	2.267	*	(1.81)
Control variables						
Manufacturer power	1.823	***	(7.20)			
Brand equity	3.516	***	(4.86)	2.055	***	(4.72)
Order of retailer adoption	1.199	***	(3.81)	-.411	***	(-7.95)
Gasoline price	-16.680	***	(-9.83)	-1.769	***	(-4.46)
Dummy food	-.700	***	(-4.54)	-.381	***	(-3.84)
Dummy personal care	.431	***	(3.64)	.602	***	(4.60)
Dummy household care	.597	***	(3.17)	.522	***	(8.31)
Intercept	.842	***	(9.63)	-3.228	***	(-37.58)
Selection parameter (ρ)	-.247**					
Log-likelihood	-1,516.26					
N	1,363			907		

t-values in parentheses; *** $p < .01$, ** $p < .05$, * $p < .10$ (two-sided).

Table 6
Retailer and Category-specific Effectiveness of the Shopper-marketing Instruments in terms of Innovation Performance

Retailer	# categories with innovation adoption[a]	Price: Average combined effect[b]		Price: - (%)	Price: + (%)	Promotion: Average combined effect		Promotion: - (%)	Promotion: + (%)	Uniqueness: Average combined effect		Uniqueness: - (%)	Uniqueness: + (%)
Aldi	18	-.407	**	100%[c]	0%	4.345	***	0%	100%	.444		11%	28%
Asda	20	.079	*	5%	65%	-.090		20%	15%	.596	***	0%	85%
Iceland	14	.127		0%	71%	.501		0%	21%	.880		0%	14%
Lidl	14	-.399	**	100%	0%	4.402	***	0%	100%	.497		0%	7%
Morrisons	21	.064		5%	38%	.397		0%	57%	.394	***	0%	67%
Netto	14	-.093		43%	0%	2.516	***	0%	100%	-.225		14%	0%
Sainsbury's	20	.135	**	0%	85%	-.620		40%	10%	.676	***	0%	90%
Somerfield	21	-.015		29%	0%	1.727	***	0%	100%	.290		10%	0%
Tesco	21	.154	**	0%	67%	-1.024	**	57%	0%	.725	***	0%	81%
Tesco Express	19	.040		21%	37%	.791	**	0%	74%	.448	*	0%	42%
Tesco Extra	21	.051		10%	33%	.381		0%	43%	.374	**	0%	62%
Tesco Metro	19	.001		32%	5%	1.054	***	0%	95%	.362	**	0%	47%
Waitrose	19	.049		16%	42%	.820	**	0%	58%	.418	*	0%	37%

*** $p<.01$, ** $p<.05$, * $p<.10$ (two-sided).
[a] Total number of categories out of the 21 categories in our sample where the retailer accepted at least one innovation from our sample.
[b] The combined effect is derived as the sum of the main effect and the various moderated effects. The latter are computed using that retailer's observed RBBE value and the retailer-specific mean values (across all accepted innovations) for the (log-transformed) retailer-category drivers. Significance is determined using the Delta rule.
[c] In 100% of the adopted categories (18 out of 18) at Aldi, price has a negative effect (two sided p-value <.20), based on the combined effect (cf. footnote b above), but now using the category-specific mean values for the respective (log-transformed) category drivers for each retailer.

Table 7
Retailer and Category-specific Effectiveness of the Shopper-marketing Instruments in terms of Retailer Acceptance

		Price				Promotion				Uniqueness			
Retailer	**# categories offered by retailer [a]**	**Average combined effect[b]**		**- (%)**	**+ (%)**	**Average combined effect**		**- (%)**	**+ (%)**	**Average combined effect**		**- (%)**	**+ (%)**
Aldi	21	-.188		48%[c]	5%	16.628	***	0%	100%	-.454		57%	0%
Asda	21	.902	***	0%	100%	3.614	**	0%	81%	-.756	**	71%	0%
Iceland	20	.532	***	0%	95%	7.396	***	0%	100%	-1.654	***	100%	0%
Lidl	21	-.148		57%	10%	15.052	***	0%	100%	-1.323	***	95%	0%
Morrisons	21	.709	***	0%	100%	6.528	***	0%	100%	-.232		52%	5%
Netto	20	.022		25%	0%	14.987	***	0%	100%	.178		20%	25%
Sainsbury's	21	1.033	***	0%	100%	1.832		0%	38%	-.966	**	76%	0%
Somerfield	21	.257		0%	57%	12.681	***	0%	100%	.347		29%	38%
Tesco	21	1.185	***	0%	100%	-.359		0%	5%	-1.266	**	100%	0%
Tesco Express	21	.576	***	0%	95%	7.687	***	0%	100%	-.556	*	67%	0%
Tesco Extra	21	.741	***	0%	100%	6.003	***	0%	100%	-.309		57%	0%
Tesco Metro	21	.516	***	0%	90%	8.517	***	0%	100%	-.433		57%	5%
Waitrose	21	.544	***	0%	100%	8.482	***	0%	100%	-.259		57%	14%

*** $p<.01$, ** $p<.05$, * $p<.10$ (two-sided).

[a] Total number of categories out of the 21 categories in our sample that are offered by the retailer.

[b] The combined effect is derived as the sum of the main-effect parameter and the various moderated effects. The latter are computed using that retailer's observed RBBE value and the retailer-specific mean values (across all innovations) for the (log-transformed) retailer-category drivers. Significance is determined using the Delta rule.

[c] In 48% of the adopted categories (10 out of 21) at Aldi, price has a negative effect (two sided p-value <.20), based on the combined effect (cf. footnote b above), but now using the category-specific mean values for the respective (log-transformed) category drivers for each retailer.

Appendix

Retail-Banner Brand Equity Measurement Instrument[a]

Items are rated on a 7-point scale (1=strongly disagree, …, 7=strongly agree) with the following instruction "*Indicate to what extent you agree with the following statements*."

Retail-banner brand esteem

1. I hold XXX in high regards.
2. XXX is a leader in its field.
3. XXX has earned a strong reputation.
4. XXX respects me.

Retail-banner brand differentiation

5. XXX stands out from its competitors.
6. XXX stands for something unique.
7. XXX is in a class by itself.

Retail-banner brand relevance

8. XXX is relevant to me.
9. XXX is relevant to my family and/or close friends.
10. XXX is a good one for me.
11. r XXX fits my lifestyle.

Retail-banner brand energy

12. I would be tempted to buy in any store of XXX.
13. XXX is innovative.
14. I would buy in any type of store concept introduced by XXX.
15. Based on my experience with XXX, I would strongly consider looking for a XXX outlet when I move to a new area.
16. XXX constantly introduces new products.
17. XXX constantly introduces new services.[b]

[a] XXX refers to the retail banner in question. In case of the brand survey, it refers to the brand under which the innovation was introduced.
[b] This item was not included in the brand survey.