



The impact of new product entry on brand sales volatility at the retailer: A Detailed Look into volatility drivers^{☆,☆}

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ABSTRACT

Volatile sales patterns with large and uncertain peaks and drops significantly increase operational complexity and complicate inventory activities tremendously. This study examines whether and to what extent the addition of a new product into the assortment of a grocery retailer is responsible for an increase in sales volatility for incumbent offerings and which brand and retailer factors underlie this change. Using time-series models of eight years of sales data from brands in nine categories at six German grocery retailers, a significant and persistent rise in volatility is observed in sales after a new product enters the store for the majority of these brands. National brands are affected the most by the addition of an entirely new brand, whereas sub-brands introduced under an existing national brand name have a more limited impact on sales volatility. Interestingly, the opposite is found for retailers' private labels, where volatility increases more after the entry of a new sub-brand (rather than a new brand). Several other brand and assortment characteristics can be linked to changes in the sales volatility of incumbent brands at the retailer. Based on this, two prediction tools are developed to anticipate before product entry if—and by how much—brand sales volatility will change. These insights can assist retailers and brand suppliers in managing their inventories and brand operations and provide relevant input for planning marketing support when new products arrive.

1. Introduction

Growing a business in mature industries such as consumer packaged goods (CPG) is hard to realize (KPMG 2018). CPG manufacturers continue to treat new products as a top priority to spur growth and lift their customer base (McKinsey 2019; Sorescu and Spanjol 2008). Retailers, in turn, embrace new products to offer shoppers an attractive assortment and enhance their store image, which can further strengthen their competitive position (Lamey et al. 2018). However, growing a customer base is rarely a smooth path forward. Marketing has traditionally examined the impact of new products on the performance level of (own and competing) brands using classic metrics such as brand sales, market share, and sales growth. However, these studies mask the fact that (positive and negative) sales changes are often associated with an

increase in uncertainty, where sudden sales swings with large peaks and drops alternate (Fischer, Shin, and Hanssens 2016; Vakratsas 2008).

As an illustration, in the CPG market, the introduction of Coke Zero, a sugar-free cola that preserves the original taste, tremendously surprised the cola category in 2006 (Marketing Week 2008). Retailers worldwide embraced the new product into their assortment. Consequently, not only the Coca-Cola brand but also its main competitors (Pepsi and retailers' private labels (PLs)) faced larger post-entry sales swings at the retailer (Fig. 1). In other words, rapid changes in brand sales (where high sales peaks were followed by steep drops) became more severe after Coke Zero entered the market.

Unstable sales patterns, also referred to as sales volatility, can be defined as the degree of variation in sales over time after accounting for expected changes; they capture the rate at which sales move up or down

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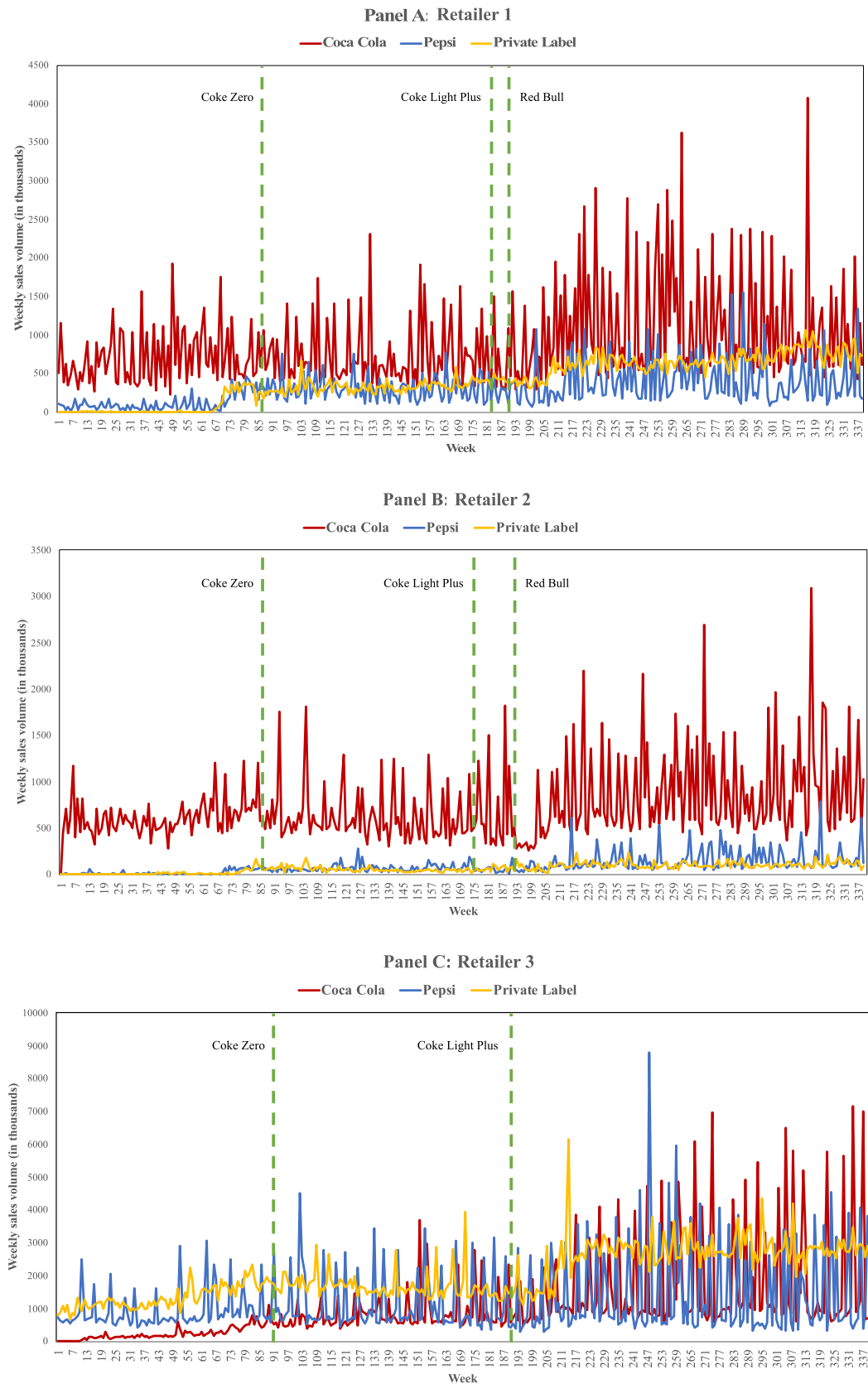


Fig. 1. Weekly Volume Sales of Coca-Cola, Pepsi, and Private Label Cola by Retailer. Note: The plots cover the entire period before the introduction of the first new product (Coke Zero) and three years after the last new product was adopted by the retailers. The vertical dashed lines in green refer to the adoption time of each new product by the respective retailer. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

around a long-term sales path in an unpredictable way (Raju 1992; Tuli, Bharadwaj, and Kohli 2010).¹ Volatile sales patterns in an assortment with many brands obstruct accurate brand sales predictions, complicate retailer inventory planning, and hinder effective marketing operations (Forbes 2017). Although managers prefer smooth but growing sales and want to avoid volatile sales fluctuations around it, they realize that marketing interventions such as new product introductions, the source of their future growth, trigger changes in customer behavior that have been associated with uncertain sales for existing brands (Dyer, Furr, and Lefrandt 2014). Thus, understanding whether and when sales fluctuations are amplified after new product entry and which brands are affected the most is critical to effectively manage brand-level operations at the retailer. Based on these insights, brand managers and retailers can account for changes in sales volatility and develop marketing and operational strategies to handle more uncertainty in brand sales.

Similarly, marketing scholars recognize that interventions that change performance levels can affect the surrounding volatility or uncertainty (Raju 1992; Tuli, Bharadwaj, and Kohli 2010). Unfortunately, this has rarely been examined in the context of new products that have the potential to overhaul consumers' habitual buying and break purchase habits (van Heerde, Mela, and Manchanda 2004). The few studies that consider sales volatility have examined it at the market (van Heerde, Mela, and Manchanda 2004) or category level (Raju 1992), while the impact on individual brands and retailers has been left understudied. This is surprising given that retailers and manufacturers still manage their activities at the brand level. Moreover, not all brands are affected by every new product in the same way. Against this background, no systematic investigation has been conducted of the presence, scale, or sources of change in brand sales volatility in the context of new product entry.

These observations led us to formulate the following research questions. First, would all new products that enter the assortment increase the sales volatility of incumbent brands at the retailer? Not every new product has the same potential to influence existing brands or disrupt the market. Most new products in the CPG market are still launched by manufacturers under an existing and often well-established parent brand name (Morgan and Rego 2009; Peng, Bijmolt, Völckner, and Zhao 2023). Apart from these *new sub-brands*, an entirely new brand occasionally enters the category (i.e., *new brand* introduction). Second, which incumbent brands are confronted with an increase in sales volatility once a retailer adds a new product into its assortment? Retailers mostly offer a mix of national brands (NBs) and PLs in their assortment. Sales spillovers following product entry likely vary between them and between NBs that may or may not share the same brand name as the new entrant. Third, can we identify other brand or retail factors that drive changes in an incumbent brand's sales volatility after a new product enters the assortment? These questions constituted the impetus for this study.

We identified 182 new products launched by manufacturers in nine grocery categories in Germany between 2006 and 2010. For each, we examine how the sales volatility of incumbent offerings changed when these new products were added into the assortments of six German retailers. We further link the observed changes in sales volatility to a set of drivers to understand which new products systematically change volatility in brand sales and which existing brands and retailers are the most affected.

¹ Part of the up- and downward movements in brand sales over time can be attributed to recurring seasonal fluctuations and/or regular business actions such as price changes and advertising. However, a significant proportion of sales fluctuations remains unexplained. In this study, we focus on this "unexplained" sales variation after accounting for any predictable sales movements. In the Method section, we formally distinguish between conditional and unconditional sales volatility in this context.

2. Background

Table 1 provides an overview of marketing studies that focus on the volatility in brand sales or revenue in response to different marketing actions, including product introduction.² For instance, van Heerde, Mela, and Manchanda (2004) showed that a major new product in the frozen pizza category has the potential to significantly disrupt consumer choices and alter the market structure, which (temporarily) increases sales variance in the category around the time of introduction. Vakratsas (2008) extended these results to the impact of advertising, price, and distribution decisions on monthly market share volatility in the SUV market. More recently, Fischer, Shin, and Hanssens (2016) linked combined marketing spending levels and spending volatility to quarterly unit sales of prescription drugs. Finally, Esteban-Bravo, Vidal-Sanz, and Yildirim (2017) showed that brand prices and promotional actions can be used to smooth volatility in grocery sales.

Our study differs from the limited research on sales volatility in relation to new products and contributes to the literature in three important ways. First, while van Heerde, Mela, and Manchanda (2004) showed that new products can increase market-level volatility, this volatility is not linked to individual brands or retailers. Fluctuations in brand sales can dampen or even disappear at the category or market level if swings in competing brands alternate (Fischer, Shin, and Hanssens 2018). Given that grocery retailers manage an assortment of many brands, we evaluate sales volatility at the individual brand level, where fluctuations directly influence retailer brand operations related to ordering, warehousing, and marketing support. Moreover, brand sales volatility at retailers is often amplified at manufacturers due to the bullwhip effect (Lee et al. 1997). This is because large and unexpected brand orders from retailers can mislead upstream suppliers in their production and investment decisions, with substantial adverse cost implications. If manufacturers correctly assign brand sales spikes to new product entry and realize that these are temporary uplifts that are offset by sales drops afterward, they can avoid over- or underproduction, abstain from investments in idle capacity, and diminish the waste of (perishable) groceries. Second, while earlier work merely established whether sales volatility changes, we undertake a systematic investigation to evaluate which new products are likely to change sales volatility for what incumbent brands at which retailers. Uncovering the drivers underlying volatility changes can help academics better understand when and why volatility increases. We examine volatility changes not only for the parent brand (that launched the new product), but also for competing NBs and retailers' PL, where the effects likely differ. Finally, we show how volatility models can be used to predict whether and to what extent the volatility of each brand in a retailer's assortment changes after product entry. Given the frequent entry of new products into the CPG market, these insights can guide retailers and manufacturers to better manage their brand operations and inventory activities by building larger stock buffers, avoiding excessive warehousing costs and waste, and refraining from marketing spending bursts when brands face rising sales volatility.

3. Research framework

We advance two key underlying mechanisms that drive volatility in brand sales and propose that new products that enter a retailer can change volatility in incumbent brand sales through both mechanisms. Next, we examine whether (and how) changes in sales volatility vary

² The marketing literature on volatility often takes a financial focus, linking marketing variables such as marketing mix instruments, customer satisfaction, and channel relationships to volatility in financial performance metrics rather than volatility in sales (e.g., Srivastava, Shervani, and Fahey 1998; Gruca and Rego 2005; Tuli and Bharadwaj 2009; Tarasi et al. 2011). This study focuses on sales-related brand performance rather than firm financial performance.

Table 1
Literature Review.

Article	Research objective	Key marketing variables (IVs)	Performance variable (DV)	Main findings	Focus		Impact studied	
					NPI	Retailer	IV → own brand volatility	IV → competing brand volatility
van Heerde et al. (2004)	How do product innovations change market dynamics?	Price, promotion, and innovation	Own and competing brand sales	*A major innovation increases brand similarities, decreases brand differentiation for existing brands, and increases uncertainty in sales responses.	✓	×	✓	✓
Vakratsas (2008)	How do marketing mix actions affect market share volatility?	Advertising, price, and distribution	Market share and market share volatility	* Market share volatility is influenced by advertising, pricing, and distribution decisions.	×	×	✓	×
Fischer, Shin, and Hanssens (2016)	How are revenues and cash flow volatility influenced by own and competitive marketing spending volatility, by the level of marketing spending, by the responsiveness of own marketing spending, and by competitive reactivity?	Aggregate marketing expenditure on detailing, journal advertising, and other media communications as well as competitors' marketing expenditure	Own brand sales, revenues, and cash flows	*Volatile marketing spending can have negative financial side effects such as higher financing costs and higher opportunity costs of cash holdings. *Common volatility-increasing marketing practices such as advertising pulsing may be effective at the top line, but could be ineffective after all costs are considered.	×	×	✓	×
Esteban-Bravo, Vidal-Sanz, and Yildirim (2017)	What is the impact of marketing mix actions on sales volatility in the short and long term?	Price and promotion	Own brand sales	* Price and promotions affect sales and vice versa in both mean and volatility. * Price growth and promotion growth have positive impacts on sales growth volatility.	×	×	✓	×
This study	What is the impact of new product entry at a retailer on own and competing brand sales volatility?	Retailer new product entry	Own and competing brand sales and sales volatility	*Adding a new product into the retailer's assortment increases sales volatility for both innovating and competing brands. * New product, brand, and retailer drivers explain the difference in the rise in volatility.	✓	✓	✓	✓

Note: This review includes marketing studies on sales volatility following a marketing intervention. NPI = new product introduction; IV = independent variable; DV = dependent variable.

across brands, new products, and retailers.

3.1. Behavioral mechanisms

Two behavioral mechanisms identified in the marketing and promotion literature underlie brand sales volatility: (i) *brand switching* by consumers and (ii) consumer *concentrated buying behavior* where they shift their brand purchases to certain periods. First, more (less) *brand switching* is associated with higher (lower) brand sales volatility. In mature CPG categories, consumers tend to have stable preferences and mostly engage in habitual repeat purchases, whereby they choose products they have purchased in the past (Dubé, Hirsch and Rossi 2000). Brand managers employ a variety of strategies to differentiate their offers and provide consumers with reasons to favor their brands over competing ones (Kumar and Kaushik 2022). This makes consumers more brand loyal and less likely to switch even if competing brands offer attractive deals. This form of inertia in brand choice contributes to stable and predictable aggregate sales patterns over time (Srivastava, Shervani, and Fahey 1997). By contrast, a lack of differentiation reduces a product

to commodity status and consumers will substitute brands regularly driven by variety-seeking tendencies, prices, and other (marketing) considerations. Frequent brand switching contributes to less predictable sales patterns over time and, hence, higher sales volatility.

Second, even with stable brand preferences and repeated brand choices, consumers are often observed to *concentrate brand buying* in a given week, where they buy larger quantities, and/or there is an incentive for consumers to buy at the same time. Apart from (predictable) seasonal influences, marketing interventions often stimulate purchase peaks. Next to own brand actions, those of competing brands and retailers that managers cannot always foresee have been shown in the promotion literature to contribute to unexpected sales peaks for brands at the retailer (Bijmolt, van Heerde, and Pieters 2005). Such peaks are alternated by offsetting sales drops with brand sales below normal demand levels, induced by consumer stockpiling behavior, buyers leaving the market, or switching back to their original brand in non-promotion weeks (e.g., Ailawadi et al. 2007; Gauri et al. 2017). This exacerbates sales fluctuations and increases brand sales volatility. Evidence for concentrated buying behavior is abundant in the marketing and

promotion literature (Macé and Neslin 2004; Ailawadi, Neslin, and Gedenk 2001; Manzur et al. 2011).

3.2. New product entry and brand sales volatility at the retailer

When new products enter the assortment, consumer preferences can shift as shoppers are “shaken out” of their habitual buying patterns, resulting in more *brand switching* (van Heerde, Mela, and Manchanda 2004). New products are introduced to satisfy new or unmet consumer needs and shoppers have an incentive to reconsider their choices when new information becomes available. This raises uncertainty about overall brand quality due to consumer learning, leading to more brand switching (van Ewijk, Gijbrecchts, and Steenkamp 2022). Moreover, retailers typically reorder shelf space when new products arrive, encouraging a more deliberate choice by shoppers among all alternatives rather than an automatic selection of the same product they purchased before. With more options and an incentive to reconsider habitual choices, brand switching by the retailer increases when new products arrive. This is likely to persist as consumers become accustomed to buying different brands on consecutive shopping occasions.

At the same time, product launches are often accompanied by heavy marketing, both by the new brand through advertising and in-store marketing by the retailer using promotions and displays, in-store signage, and other merchandising support (Lamey et al. 2018). More intense marketing spending accompanying a product launch is often responsible for “spending bursts” (Chapman and Steenburgh 2011) because competitors are likely to react to it (Esteban-Bravo, Vidal-Sanz, and Yildirim 2017; Tuli, Bharadwaj, and Kohli 2010). This chain of intense actions and reactions among competitors can *concentrate shoppers’ purchases* during promotion weeks, while they refrain from buying in subsequent weeks. Indeed, with more price promotions, infrequent or new buyers are attracted to the category and consumers’ reference prices can decrease after launch (Han, Gupta, and Lehmann 2001; Pauwels, Hanssens, and Siddarth 2002). In anticipating new deals, regular buyers are less likely to purchase without any support, pushing brands to maintain a higher level of marketing activity afterwards. Ailawadi et al. (2001) supports that increasing competitive marketing activity in a mature CPG market is difficult to stop or reverse and that more intense marketing is (partly) maintained after the launch period.

Thus, new products are expected to activate brand switching, whereas more intense marketing following product entry induces purchase concentration, which raises volatility and makes it harder for the retailer to predict sales patterns for incumbent brands.

H1: The entry of a new product increases volatility in incumbent brand sales at the retailer.

3.3. Moderating role of brand type (NB vs. PL) and new product type (existing vs. New brand)

The increase in volatility after product entry is unlikely to be the same for all incumbent brands. Brand switching and concentrated buying following the entry of a new brand or sub-brand under an existing NB name are expected to be more intense for incumbent NBs than for the PL available at the retailer. Through the neighborhood price effect, which predicts higher competition between brands more closely aligned in price (Auer and Papies 2020; Sethuraman, Srinivasan, and Kim 1999), brand switching between NBs is expected to be more intense than that between PLs and NBs, which compete less directly because of differences in price, positioning, and target consumer characteristics (Choi and Coughlan 2006; Gielens 2012). The average PL buyer is more price-sensitive and less involved in the category, and brand differences are not always observed or appreciated (Richardson 1997; Ailawadi, Pauwels, and Steenkamp 2008). Therefore, PL buyers are less likely to reconsider their choices than NB buyers when new products arrive, even if clear quality or other intrinsic benefits are observed for NBs over the PL (Steenkamp, van Heerde, and Geyskens 2010).

Furthermore, NBs engage more in marketing than PLs (Steiner 2004), resulting in more concentrated buying for NBs. Advertising can serve as a quality signal that consumers appreciate (Abe 1995) and can be used together with other support tools to communicate unique brand associations and value, which is even more relevant when a new competitor arrives. While such marketing campaigns are unevenly spread over time, managers typically engage in heavy spending alternated with periods of low or no brand support (Gijnsberg and Nijs 2019). By contrast, PLs rely on the reputation and popularity of the retailer but invest less in marketing support (Garretson, Fisher, and Burton 2002). Thus,

H2: The increase in sales volatility at the retailer following new product entry is larger for incumbent NBs than for PLs.

Previous research has demonstrated that not all new products are equally disruptive and not all competitors lose (proportionally) when new products enter (Gielens 2012, p. 409). We argue that entirely new brands have a different effect on brand switching and concentrated buying than new sub-brands that enter the assortment; yet, opposing effects are proposed for NBs and PLs.

Entirely new brands have a more severe impact on incumbent NBs than do new sub-brands. Apart from the uncertainty about innovative features, no prior knowledge of the brand and its quality is available to consumers when an entirely new brand enters (Lei, Dawar, and Lemmink 2008). When consumers are unfamiliar with a brand and no clear reference point in the market exists, they evaluate it relative to existing NBs with well-established associations. As a result, the entry of a new brand has the potential to move preferences for existing NBs in the category and create structural change (van Heerde, Mela, and Manchanda 2004; Pauwels and Hanssens 2007). Initially, stable brand preferences and choices are updated and consumers are more likely to try out other brands, resulting in more switching between NBs. Moreover, with more brands to choose from and more intense in-store support and shelf rearrangement aimed at acquainting shoppers with new brands, NBs have a greater incentive to respond.

By contrast, a new sub-brand is primarily evaluated against its parent brand (Peng, Bijmolt, Völckner, and Zhao 2023). Quality perceptions can be inferred from the parent brand, whereas other associations are typically transferred to new offers (Völckner and Sattler 2006). They create less uncertainty and their ability to change consumer preferences for other incumbent NBs is limited. Furthermore, known and recognized brands require less new product support such as advertising, trade deals, and promotions (Collins-Dodd and Louviere 1999; Völckner and Sattler 2006). This is different for entirely new brands. Heavy marketing accompanying the entry of entirely new brands and the reactions it provokes from existing NBs boost consumers’ brand-switching tendencies and encourage more consumers to concentrate their brand purchases in promotion weeks compared with new sub-brands where marketing support and reactions from other brands are more modest.

H3a: The increase in the sales volatility of an incumbent NB at the retailer is larger after the entry of an entirely new brand into the retail assortment than after the entry of a new sub-brand.

For PLs, we argue the opposite. Consumers are uncertain about their preferences when an entirely new brand becomes available. Through the well-known contrast effect (Schwarz and Bles 1992), the entry of an entirely new brand can push PLs away from other NBs, making them more distant and, hence, less substitutable. For instance, Geyskens, Gielens, and Gijbrecchts (2010) showed that product entry can change the perceptions of all brands, with the largest shift for PLs given that they are positioned at the end of the quality and price dimensions. Therefore, a new brand fosters a comparison between more similar incumbent NBs, but away from the retailer’s PL (Huber and Puto 1983).

New sub-brands, in turn, are compared mostly with the parent NB and the existing associations of the latter are transferred to the new product. Therefore, the ability to increase preference uncertainty and change the perceptions of other brands, including PLs, is more limited. If the PL remains a competitor to incumbent NBs, it stimulates more

switching and marketing reactions even on the part of the PL when a new sub-brand enters the assortment.

H3b: The increase in the sales volatility of an incumbent PL at the retailer is smaller after the entry of an entirely new brand into the retail assortment than after the entry of a new sub-brand.

3.4. Other drivers of new product-induced volatility in brand sales at the retailer

Finally, not all incumbent NBs in every retailer experience a sizable change in sales volatility after entry, even for the same new product. To understand what drives these differences, we further link potential changes in new product-induced volatility to a set of other brand and retailer drivers.

Stronger brands are expected to be more resilient to shocks in the environment related to competitors' marketing actions and other external events because these brands are valued and appreciated by a steady group of regular buyers who are less likely to switch (Ailawadi, Lehmann, and Neslin 2003). We follow the literature and evaluate the impact of *brand position* (i.e., its ranking in the category) as a proxy for brand strength in the market. Alternatively, *brand innovativeness* can influence consumer loyalty and switching behavior (e.g., Pappu and Quester 2016). Buyers of innovative brands are frequently exposed to new products. They are used to regularly trying new offerings and have more confidence in them. These brands also appeal especially to consumers who appreciate the greater variety in their choices. The entry of a new product therefore raises sales volatility more for innovative brands than for less innovative brands for which consumers are not accustomed and face a higher risk of trying new products in the first place. We examine brand innovativeness using the number of new products launched by the brand as a separate brand-level driver.

In addition to brand factors, the retail environment in which a new product is introduced may be important. The increase in volatility induced by a new product is largely determined by the competition between incumbent brands in the assortment (Draganska and Klapper 2007). Consumers may be less loyal to individual brands in *larger assortments* consisting of diverse (sub-)brands to cater to shoppers' heterogeneous needs or variety-seeking tendencies (Bell, Chiang, and Padmanabhan 1999; Vakratsas 2008). The entry of a new product exacerbates these brand-switching tendencies, as it provides another incentive for consumers to revisit their choices with more options. Small assortments appeal to consumers with a lower need for variety; hence, they are less likely to value new brands. This manifests in more volatile brand sales after new product entry in larger assortment environments than in limited ones. Finally, higher *price variability* at the retailer (reflected in the price variation between brands) shows that brands are heterogeneous and, hence, less substitutable at the retailer, resulting in less brand switching. The entry of a new brand or sub-brand is unlikely to shift the perceptions of clearly differentiated brands in different price tiers, and sales volatility hardly changes.

4. Data

Setting and data source. We acquired German household panel data from GfK across nine frequently purchased CPG categories: bath and shower gel, biscuits, cola, coffee, chips, diapers, razors, tea, and yoghurts. Data were available from January 2005 to December 2012 for purchases made in six major German retail chains.³ During the data period, all six retailers were active in the national market. The retailers have different business models, including hypermarkets (i.e., a combination of a supermarket and department store), retailers that mostly operate in the supermarket format, and two representative hard

Table 2

Brand New Products by Category, Germany, 2006–2010.

Category	Total No. of New Products	New Sub-Brands	New Brands
Bath & shower gel	15	13	2
Biscuits	27	27	0
Coffee	27	25	2
Cola	3	2	1
Chips	21	21	0
Diapers	15	11	4
Razors	20	19	1
Tea	30	30	0
Yoghurts	24	23	1
Total	182	171	11

discounters.

New product identification. In each category, we first identified whether and when entirely new manufacturer brands entered the market between January 2006 and December 2010. We used the 12-month initialization period before January 2006 to determine which NBs in 2006–2010 were not already available for sale in Germany in 2005. Using the 24-month period after December 2010 ensured we had sufficient observations to study the performance and volatility in the post-launch period for all new products and brands.⁴ Across all nine categories, only 11 new brands were launched in the German market, with three categories that had no new brands (biscuits, chips, and tea), and up to four new brands entering the diaper category between 2006 and 2010. As the majority of new CPG products are still launched under an existing and often well-established NB name, we further screened the top five manufacturer brands in each category in terms of their sales across the six retailers over 2005 and 2006. For this set of five top brands $\times$ nine categories, all the new sub-brands launched in the market between 2006 and 2010 were identified using the same procedure as for new brands. Table 2 summarizes all the new products launched in the German market across these categories between January 2006 and December 2010: in total, 182 new products were identified, consisting of 171 sub-brands introduced by 45 established manufacturer brands and 11 entirely new manufacturer brands. The addition of each of these new products by the retailer to its assortment is used as the new product entry date in the analysis.

Time series. To study brand sales volatility at the retailer, household purchase data were aggregated at the weekly level for each brand at a given retailer and time series by retailer-brand-week over the 417-week period from January 2, 2005 to December 29, 2012. For each retailer and category, we evaluated the five leading German NBs and the retailer's own PL, resulting in 324 (six brands $\times$ six retailers $\times$ nine categories) potential combinations for further analysis. However, not all brands were sold by every retailer (not surprisingly, hard discounters carried only a few of the top five NBs in some categories), and we dropped combinations where the new brand or sub-brand was not added by the retailer. Finally, we excluded combinations with fewer than 50 weekly observations.⁵ As a result, 214 brand–retailer combinations were retained for further analysis. Sales and price series were generated for

⁴ While the focus of our study is not on brand performance following new product entry, but rather the impact on the sales volatility of incumbent brands at the retailer, we realize that these selection criteria exclude unsuccessful new products with poor sales from our analysis. Still, the market performance of the 182 new products in our sample differ greatly, with the best performing achieving a 9% market share in its first year of launch compared with an average share of only 0.7%. In one of the validations, we check if our main results are driven by a few successful new products in our sample, but this turns out not to be the case (see the Model validations subsection).

⁵ Our 50-week cut-off is driven by model convergence considerations. With more missing values, model estimation turned out problematic in many instances (especially when we checked for longer lag lengths in the models).

³ An NDA prohibited us from disclosing the names of the retailers. We refer to them as Retailers 1 to 6 instead.

each combination. Weekly value and sales volume for each brand were obtained by summing all household spending and volume sold at the retailer in a week, respectively. Similarly, as prices were obtained by dividing value by sales volume, they were expressed per volume equivalent (e.g., €/liter or €/gram) to make offerings with varying package sizes comparable. We deflated all prices using the monthly consumer price index from the World Bank for the reference year of 2010.

Drivers of sales volatility. From our screening, we distinguished between NBs and PLs and identified whether a new product was launched by an established NB (i.e., a new sub-brand vs. entirely new brands). We further derived the brand ranking, its price, and overall brand innovativeness using data one year before the introduction of the focal new product to avoid endogeneity concerns, except for the 11 new brands for which no prior brand data were available. Their brand variables were measured in the first year after market entry. Similarly, all retailer drivers were measured one year before launch. Finally, we controlled for the differences between discounters and traditional retailers, between own brand and competing brand introductions, and between food and non-food categories. All the drivers, together with their descriptions and summary statistics, are presented in Table 4.

5. Model-free insights

We use the cola category as an example to provide initial insights into the impact of product entry on brand sales volatility. During the data period, the cola category faced three new products that were adopted by most retailers.⁶ Coca-Cola Zero (launched in Germany in July 2006) and Coke Light Plus (March 2008) were introduced worldwide by the Coca-Cola Company to target increasingly health-conscious customers, whereas Red Bull Cola, a genuine new brand, entered the cola market in Germany in July 2008. Fig. 1 plots the sales volume of Coca-Cola, Pepsi, and the retailer's PL cola for three example retailers from the beginning of the data period until three years after the last entry at the retailers. The dashed vertical lines in Fig. 1 indicate the retailer's adoption time for each new product (note that Red Bull Cola was not adopted by Retailer R3). The introduction of Coke Zero turned out to be successful, both from a brand and a retailer perspective, as evidenced by the rise in Coca-Cola sales after the launch in all three retailers. However, we are more interested in sales volatility after product launch. As expected, the introduction of all three new products led to instability in incumbent brand sales at the retailers afterwards, generating a series of effects on the Coca-Cola brand, its main competing brand, Pepsi, and the retailers' PLs. The increase in volatility was also reflected in the increase in the standard deviation of Coke brand sales. When we compare the 16-week period before and after the Coke Zero entry, we find that the standard deviation of Coca-Cola sales, for instance, rose by 8.4 % in Retailer R1, by 28.0 % in R2, and by 30.9 % in R3. The increase in the sales volatility of Pepsi and PLs also suggests more unstable sales patterns for competing brands after entry. Here, we also observe a lower increase in volatility for PLs than for the Coca-Cola and Pepsi brands for all three retailers.

6. Method

Our modeling approach consists of two main stages. The *first-stage* (time-series) analysis measures the volatility in brand sales at the retailer over time. For each of the 214 incumbent brand–retailer combinations, we estimate a standard vector autoregressive (VAR) model combined with a multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model to assess the impact of new product

entry on sales volatility over time for various incumbent brands at each retailer. Retailers in every category added multiple new products. For each, we assess the impact on the sales of several incumbent brands, resulting in 821 estimated volatility changes. The estimates from Stage 1 across all brands, retailers, and new products are further linked in a *second-stage* (cross-sectional) analysis to a set of moderators to understand what drives volatility changes across new products, brands, and retailers.

6.1. Stage 1: Modeling brand sales volatility in relation to new product entry over time

Volatility cannot be observed directly, but it represents the fluctuations in a series around its expected value or “conditional mean” (Franses and van Dijk 1996). Accordingly, this requires a model that first determines the expected value of a brand sales series, Y , conditional on factors X that drive changes in Y over time, after which volatility can be determined. Changes in sales volatility are linked to the market events associated with, among others, new product entry. To model this, for each brand–retailer combination, we simultaneously estimate the series conditional mean using a standard VAR model and its volatility around this mean using a multivariate GARCH model extended with exogenous product entry variables in each equation. Eq. (1) shows the VAR model formulation that captures the dynamic interactions between brand sales and the price variables, with the matrix Z representing the controls specified in Eq. (2). In this VAR, the conditional mean brand (volume) sales and brand price at the retailer are a function of their own past, the new products that entered the assortment, and a number of standard controls. Owing to the scaling of our sales variable (with large numbers), we mean-center the sales series to reach model convergence in our estimations. Table 3 describes the variables in the models and their measurements:

$$\begin{bmatrix} Sales_t \\ Price_t \end{bmatrix} = \begin{bmatrix} \alpha_{01} \\ \alpha_{02} \end{bmatrix} + \sum_{i=1}^I \begin{bmatrix} \alpha_{11}^i & \alpha_{12}^i \\ \alpha_{21}^i & \alpha_{22}^i \end{bmatrix} \begin{bmatrix} Sales_{t-i} \\ Price_{t-i} \end{bmatrix} \\ + \begin{bmatrix} \beta_{11} \cdots \beta_{1n} \\ \beta_{21} \cdots \beta_{2n} \end{bmatrix} \begin{bmatrix} dBR_ENTRY1_t \\ \vdots \\ dBR_ENTRYn_t \end{bmatrix} \\ + \begin{bmatrix} \beta_{31} \cdots \beta_{3m} \\ \beta_{41} \cdots \beta_{4m} \end{bmatrix} \begin{bmatrix} dNP_ENTRY1_t \\ \vdots \\ dNP_ENTRYm_t \end{bmatrix} + \begin{bmatrix} \beta_5 \\ \beta_6 \end{bmatrix} [CNP_ENTRY_t] \\ + \Gamma \cdot Z_t + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad (1)$$

where t denotes the time index for week, i stands for the number of lags used for the sales and price variables, and the indices n and m represent the number of entirely new brands and the number of own new sub-brand entries, respectively. We use three sets of entry variables in Eq. (1) to separate the effect of entry on brand sales and prices by (1) entirely new brands in the category (dBR_ENTRY), (2) own new sub-brand entries with the same NB name (dNP_ENTRY), and (3) new sub-brands entered by competing NBs (CNP_ENTRY). While we use separate dummies to capture the effect of each new brand and each own new sub-brand introduced at the retailer, we combine the effect of the new sub-brands launched by competing NBs. Using separate dummies to assess the impact of each product entry by a competitor turns out to be

⁶ One of the hard discounters did not include any of the new products during the data period. Hence, the cola analysis includes five of the six retailers in our dataset.

Table 3

Variables and their Measurement in the Brand VAR and GARCH Models.

Variable	Measurement
Brand sales $Sales_t$	(Mean-centered) total brand sales volume at the retailer in week t .
Brand price $Price_t$	Average (deflated) regular price of the brand at the retailer in week t (average price used in promotion weeks).
New brand entry dBR_ENTRYn_t	Step dummy taking 1 in the weeks after a completely new brand n enters the retailer and 0 before entry.
Own sub-brand entry dNP_ENTRYm_t	Step dummy taking 1 in the weeks after new sub-brand m introduced by the focal brand enters the retailer and 0 before entry.
Competing sub-brand entry CNP_ENTRY_t	Count variable starting from 0 in week 1 and increasing by 1 in each week t when a new sub-brand from one of the competing top five brands available from the retailer enters the assortment.
Competing brand price $CPRI_t$	Weighted average (deflated) regular price (in volume equivalents) of the other top five competing brands available at the retailer in week t (average price used in promotion weeks). Static weights are used to construct the weighted competitive price variables, with the average brand market share (in terms of sales) over the entire data period as the weight.
Private label price $PLPRI_t$	Average (deflated) regular price (in volume equivalents) of the private label at the retailer in week t (average price used in promotion weeks). If more private labels are available at the retailer, we take a weighted price with the average retail share in the respective year as the weight.
Focal brand promotion $dFPRO_t$	Promotion dummy is 1 if the actual price of the focal brand in week t shows a negative shock of at least 1 standard deviation below the brand's average (non-promoted) price at that retailer and 0 otherwise.
Competing brand promotion $CPRO_t$	Number of competing top five brands available from the retailer that are offered in a promotion in week t at the retailer.
Private label promotion $dPLPRO_t$	Dummy is 1 if the private label is offered with a promotion in week t and 0 otherwise. If more private labels are available at the retailer, the dummy is 1 if any of these private labels is on promotion that week.
Change in assortment $RASCH_t$	Count variable with the number of sub-brands offered in the category at the retailer in week t .
Seasonal variables $SEASq_t$	Two trigonometric terms are used to capture seasonal fluctuations ($q = 1, 2$). The variable is constructed as $\sin(2\pi t/52)$ for $q = 1$ and $\cos(2\pi t/52)$ for $q = 2$, with t the corresponding week number.

Notes: Prices of all SKUs belonging to a brand are weighted using as the weight each SKU's volume share in total brand sales at that retailer in that week. In line with Nijs, Srinivasan, and Pauwels (2007), a promotion week for a brand in a retailer is identified when a brand's weekly price is lower than one standard deviation below its average price at that retailer (average price over the entire data period at that retailer).

problematic for the many new competitive sub-brands that were often added by the retailer around the same time.⁷ To capture the effect of sub-brand entry by competing NBs, we use a count variable that starts with the value 0 in the first week and in each week in which one of the competing NBs launched a new product, its value grows by + 1. The resulting parameter estimate shows the average effect of a new sub-brand entry by a competing NB on the respective brand's sales and prices. The controls in Z_t are specified in Eq. (2):

$$Z_t = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} \end{bmatrix} \begin{bmatrix} CPRI_t \\ PLPRI_t \\ dFPRO_t \\ CPRO_t \\ dPLPRO_t \end{bmatrix} + \begin{bmatrix} \delta_{11} \\ \delta_{21} \end{bmatrix} [RASCH_t] + \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} \begin{bmatrix} SEAS1_t \\ SEAS2_t \end{bmatrix} \quad (2)$$

These controls account for the impact of changes in the regular prices of competing brands ($CPRI$) as well as the retailer's own PL ($PLPRI$) and the impact of price promotions at the retailer by the focal brand ($dFPRO$), competing NBs ($dCPRO$), and the retailer's PL ($dPLPRO$). They are commonly used in the retail and promotion response literature to explain variations in brand sales and prices (Widdecke et al. 2023). Retailers also regularly remove offerings; therefore, the model further controls for changes in assortment size over time ($RASCH$), following van der Maelen, Breugelmans, and Cleeren (2017). Finally, following Gielens (2012), two trigonometric seasonal terms are added to account in a parsimonious way for seasonal fluctuations in brand sales and

prices. Table 3 provides further details on the measurements of the variables.

The error terms $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ in Eq. (1) are normally distributed with a zero mean and time-varying (heteroscedastic) variance: $\varepsilon_{1,t} \sim N(0, h_{1,t})$ and $\varepsilon_{2,t} \sim N(0, h_{2,t})$. We denote the conditional covariance matrix of these residuals using H_t . In GARCH models, H_t is decomposed into conditional standard deviations (i.e., volatility) and correlations. In matrix form, it is expressed as

$$H_t = D_t^{1/2} S D_t^{1/2},$$

where S is the time-invariant conditional correlation matrix:

$$S = \begin{bmatrix} 1 & s_{12} \\ s_{12} & 1 \end{bmatrix},$$

and D_t , the focus of this study, is a diagonal matrix with conditional variances:

$$D_t = \begin{bmatrix} h_{1,t} & 0 \\ 0 & h_{2,t} \end{bmatrix}$$

Each element in D_t evolves according to the following GARCH process:

$$h_{1,t} = \sum_{j=1}^J \phi_{1j} \varepsilon_{1,t-j}^2 + \sum_{k=1}^K \psi_{1,k} h_{1,t-k} + \exp \left(\tau_{11} + \sum_{n=1}^N \tau_{12n} dBR_ENTRYn_t + \sum_{m=1}^M \tau_{13m} dNP_ENTRYm_t + \tau_{14} CNP_ENTRY_t + T_1 \cdot Z_t \right) + v_{1,t} \quad (3a)$$

$$h_{2,t} = \sum_{j=1}^J \phi_{2j} \varepsilon_{2,t-j}^2 + \sum_{k=1}^K \psi_{2,k} h_{2,t-k} + \exp \left(\tau_{21} + \sum_{n=1}^N \tau_{22n} dBR_ENTRYn_t + \sum_{m=1}^M \tau_{23m} dNP_ENTRYm_t + \tau_{24} CNP_ENTRY_t + T_2 \cdot Z_t \right) + v_{2,t} \quad (3b)$$

⁷ The average number of new products that entered the category over our data period was 18, with up to 30 new sub-brands in the tea category. If separate entry dummies were used for each, it would seriously affect model convergence, as it becomes problematic to isolate the individual effect of each entry due to multicollinearity among the many dummies.

Table 4
Volatility Drivers and their Measurements.

	Measurement	Mean ^a	S.D.	Min	Max
New product variables					
Private-label brand dPL_b	Dummy = 1 if brand b is a private label brand and 0 otherwise	11.57 %		0	1
New brand $dNEWBRD_b$	Dummy = 1 for the introduction of an entirely new brand in the category of brand b and 0 otherwise	17.15 %		0	1
Brand variables					
Brand rank $BRDRANK_b$	National rank of brand b in the category in terms of total sales value in the market	3.305	1.630	1	8
Brand innovativeness $BRDINV_b$	Total number of new products launched in the market by brand b in each year	4.746	3.087	0	11
Retailer variables					
Retailer assortment size $RETSIZE_{br}$	Ln-transformed total number of sub-brands offered at retailer r in the category of brand b	57.207	98.710	1	479
Retailer price variability $RETPrVAR_{br}$	Measured by the coefficient of variation in the prices of the top five brands in the category of brand b at retailer r	9.522	34.803	0.016	173
Control variables					
Discounter retailer $dDISC_r$	Dummy = 1 if retailer r is a discounter and 0 otherwise	10.22 %		0	1
Competing new product $dCOMP_b$	Dummy = 1 for the introduction of a new (sub-)brand by a competitor of brand b and 0 otherwise	25.30 %		0	1
Food category $dFOOD_b$	Dummy = 1 if the category of brand b is a food category and 0 otherwise	74.60 %		0	1

Note: All the drivers are measured in the year before new product launch, except for the brand drivers of the 11 new brands that can only be measured one year after market entry. Summary statistics of the dummy variable for the new sub-brands are omitted from this table because they are used as the reference in Eq. (4).

^a Statistics are reported before weighting and ln transformations. For the dummy variables, we report the percentage of observations with a value of one.

$$BRD_VOL_{pbr} = c0 + c1.dPL_b + c2.dNEWBRD_b + c3.(dPL_b \times dNEWBRD_b) + c4.BRDRANK_b + c5.BRDINV_b + c6.RETSIZE_{br} + c7.RETPrVAR_{br} + c8.dDISC_r + c9.dCOMP_{pb} + c10.dFOOD_b + u_{pbr} \quad (4)$$

where $v_{1,t}$ and $v_{2,t}$ are normally distributed error terms with a zero mean and constant variance, respectively. In Eq. 3, the estimates τ_{11} and τ_{21} are constants to ensure that the volatility terms are non-negative. The estimates τ_{121} to τ_{14} capture the impact of new product entry on brand sales volatility. As retailers often adopt the same new product in different weeks, we can assert that our findings are not driven by unobserved time-specific factors. Finally, we estimate the VAR model in Eq. (1) and multivariate GARCH process in Eqs. (3a) and (3b) jointly. Conventional marketing actions (e.g., price and promotions) drive brand sales volatility (Vakratsas 2008; Fischer et al. 2016). By controlling for its impact on brand sales in the VAR models, the sales volatility in the subsequent GARCH models before product entry captures the volatility related to conventional marketing. The new product dummies in the GARCH models capture the change in sales volatility relative to volatility before product entry. Hence, this combines the effect of entry itself and the impact of marketing interventions associated with product entry, which are not already explained by conventional marketing activity.

6.2. Stage 2: Drivers of the estimated changes in sales volatility after product entry

Once the models in Stage 1 are estimated for our set of 214 incumbent brand–retailer combinations, we collect all the estimates (τ_{12n} , τ_{13m} , and τ_{14}) quantifying the volatility changes across brands, retailers, and new products and estimate a cross-sectional model to further explain the variability in these estimates. To estimate this model, we

stack all the brand volatility estimates across brands and retailers (BRD_VOL) and they become the dependent variable in a second-stage regression linking the estimated sales volatility change to the new product, brand, and retailer drivers as well as the controls in Eq. (4):

with all the indices as before and index $p = 2, 3, 4$ for new brands ($p = 2$), own new sub-brands under the same parent brand name ($p = 3$), and competing new sub-brands ($p = 4$) that enter the market, respectively; b is the brand index and r is the retailer index. Table 4 details all the independent variables in Eq. (4) and their measurements. Because the dependent variable contains estimated values characterized by different degrees of estimation accuracy, we use a weighted least squares (WLS) estimation approach where we weight all the observations by the inverse of the standard error of the estimate (acquired from the Stage 1 models) to offer more weight to observations with more precise estimates (i.e., with lower standard errors) (see Shankar and Krishnamurthy 1996; Kubler et al. 2018).

7. Results

7.1. Preliminary data analysis and model specification

Standard exploratory data analyses are conducted to assess stationarity and properly capture the autocorrelation patterns in our series (see the Web Appendix for details). Preliminary unit root tests reveal that our series are stationary, while there is clear evidence of a change in volatility over time. We follow a stepwise procedure in which we

Table 5

Model Results for the Example Coca-Cola Brand at Three Retailers.

Variable	Retailer 1		Retailer 2		Retailer 3	
	Mean Sales	Sales Volatility	Mean Sales	Sales Volatility	Mean Sales	Sales Volatility
<i>dREDBULL</i>	431,969 ^{***} (25,756)	3.299 ^{**} (0.219)	204,155 (127,965)	2.349 ^{***} (0.379)		
<i>dZERO</i>	67,145 ^{***} (11,960)	0.796 ^{***} (0.133)	-72,738 [*] (42,502)	0.227 (0.289)	373,814 ^{***} (44,506)	0.305 (0.255)
<i>dLIGHTPLUS</i>	13,950 (24,457)	1.574 ^{***} (0.211)	28,512 (53,586)	0.409 (0.386)	425,974 ^{***} (72,691)	2.676 ^{***} (0.324)
<i>sales(-1)</i>	-0.071 ^{***} (0.017)		0.101 ^{**} (0.048)		0.025 (0.0190)	
<i>price(-1)</i>	-121,083 ^{***} (27,285)		-133,014 ^{***} (31,068)		-26,853 [*] (17,134)	
<i>price competing NB</i>	6,727 (16,565)	0.113 (0.164)	6,820 (20,383)	-0.150 (0.099)	15,665 (19,710)	0.477 ^{***} (0.114)
<i>price PL</i>	8,296 ^{***} (2,955)	0.031 (0.079)	24,429 [*] (14,090)	0.167 (0.113)	-301,849 (195,275)	-1.570 (1.173)
<i>promo</i>	584,970 ^{***} (16,794)	1.670 ^{***} (0.222)	363,296 ^{***} (57,978)	1.370 ^{***} (0.210)	1.849e + 06 ^{***} (228,872)	3.690 ^{***} (0.197)
<i>promo other NB</i>	-48,611 ^{***} (17,604)	-0.061 (0.092)	-34,277 (22,723)	-0.248 ^{**} (0.116)	-32,002 (28,035)	-0.152 (0.206)
<i>promo PL</i>	-36,236 (27,745)	-0.344 (0.515)	-27,213 (58,226)	-0.704 ^{***} (0.207)	-134,530 (105,102)	-0.949 (0.588)
<i>assortment size</i>	31,649 (96,468)	-0.551 (1.113)	18,845 (93,008)	-0.090 (0.513)	-496,292 ^{**} (214,740)	-9.015 ^{***} (1.351)
<i>arch(-1)</i>		0.007 ^{***} (0.001)		-0.016 (0.020)		0.005 (0.004)
<i>garch(-1)</i>		-0.182 ^{***} (0.020)		-0.030 (0.097)		-0.004 ^{**} (0.002)
<i>season1</i>	22,621 (18,283)		3,887 (16,559)		-10,133 (18,233)	
<i>season2</i>	10,891 (7,026)		-12,187 (18,259)		-38,599 [*] (22,499)	
Constant	-1,503,000 ^{***} (245,921)	24.68 ^{***} (2.502)	-1,525,000 ^{***} (302,142)	24.47 ^{***} (1.101)	343,518 (665,717)	39.92 ^{***} (4.295)
Observations	414		414		414	

Notes: Standard errors in parentheses.

*** $p < 0.01$.** $p < 0.05$.* $p < 0.1$ (p -values, two-sided).

estimate models with different numbers of lags and use standard information criteria to choose among the models (cf. Dekimpe and Hanssens 1995; Lütkepohl 1993). In this procedure, we start with a first-order lag VAR model and sequentially increase the lag order by one until the (symmetric lag) VAR model no longer converges. For all the models in which convergence is reached, we compare model performance based on the log likelihood, AIC, and BIC to select the final lag order. Following this procedure, we find that a VAR model with one lag in both equations is the most appropriate in all instances. For the GARCH model, using the same procedure as in the VAR model, the information criteria suggest that between one and four lags are appropriate for the alternative sales and price GARCH specifications.

7.2. Model findings for the example cola category

Tables 5 and 6 respectively present the estimates of the sales equations in both the VAR and the GARCH models for the example cola category.⁸ To capture the impact of the introduction of three new products on mean sales and sales volatility at each retailer, three entry dummies are added to the Coca-Cola models (*dZERO*, *dLIGHTPLUS*, and *dREDBULL*). In the models for the other cola brands (i.e., Pepsi, Sina,

⁸ Although we jointly model brand sales and price in the VAR and GARCH models as outcome variables, we only report the results of the sales mean and sales volatility equations as these are our main interest. The estimation results for the price equations are available from the authors upon request.

Vita, and PLs⁹), we have one dummy for the new Red Bull brand and capture the new sub-brands of the Coca-Cola competitor with the count variable (*CNP_ENTRY*), which measures the incremental impact of adding new offers on both brand sales and volatility. The variable *CNP_ENTRY* ranges from 0 to 2 because Coca-Cola is the only competing brand that introduced new sub-brands in the cola category in the data period.

The results for the controls in the Coca-Cola model, shown in Table 5, are plausible. The estimate of the own brand regular price on Coca-Cola sales, captured by the (lagged) price variable in the mean sales equations, has the expected negative sign and is significant for all three retailers. The results in Table 5 also show that Coca-Cola sales and volatility are hardly affected by changes in the prices of competing NBs, with insignificant cross-price effects observed across all the retailers. Only the PLs compete with Coke, with significant positive effects on mean sales for two of the three retailers, as shown in Table 5. Own brand promotions have a dominant positive effect, consistent with a boost in sales in promotion weeks. Promotions by competing NBs and PLs have a consistently negative impact on Coca-Cola sales, although not always significant. Finally, changes in retailer assortment have a significant negative effect on brand sales and sales volatility only at Retailer R3. In the volatility models, own brand promotions clearly boost sales volatility (significant positive effects across all three models); however,

⁹ The 5th NB in the cola category had fewer than 50 observations at each retailer and was therefore omitted.

Table 6

Summary of the Volatility Results: All Brand–Retailer Models, Cola Category.

Model	Estimated variable	Retailer 1	Retailer 2	Retailer 3	Retailer 4	Retailer 5
Coca-Cola	volatility: <i>dREDBULL</i>	3.299 ^{***} (0.219)	2.349 ^{***} (0.379)		1.334 ^{***} (0.346)	0.464 ^{***} (0.178)
	volatility: <i>dZERO</i>	0.796 ^{***} (0.133)	0.227 (0.289)	0.305 (0.255)	0.104 (0.543)	1.264 ^{***} (0.227)
	volatility: <i>dLIGHTPLUS</i>	1.574 ^{***} (0.211)	0.409 (0.386)	2.676 ^{***} (0.324)	0.028 (0.106)	0.013 (0.169)
Pepsi	volatility: <i>dREDBULL</i>	0.181 (0.292)	0.275 (0.299)		0.332 (0.524)	1.499 ^{***} (0.179)
	volatility: <i>competitor entry</i>	0.768 ^{**} (0.197)	0.233 ^{**} (0.087)		0.487 (0.499)	0.348 [*] (0.193)
Sina	volatility: <i>dREDBULL</i>	0.921 ^{**} (0.359)	0.392 (0.332)		2.194 ^{***} (0.360)	0.246 (0.213)
	volatility: <i>competitor entry</i>	0.092 (0.232)	0.686 ^{**} (0.213)	1.127 ^{***} (0.419)	1.115 ^{***} (0.265)	0.234 (0.149)
Vita	volatility: <i>dREDBULL</i>	0.432 (0.348)	0.362 (0.373)		0.368 (0.134)	0.996 ^{**} (0.402)
	volatility: <i>competitor entry</i>	0.291 (0.213)	0.565 (0.359)	2.187 ^{***} (0.717)	0.111 (0.234)	0.314 ^{**} (0.123)
PL	volatility: <i>dREDBULL</i>	0.886 ^{**} (0.323)	0.415 (0.562)		0.716 [*] (0.431)	0.492 ^{**} (0.232)
	volatility: <i>competitor entry</i>	0.052 (0.971)	0.348 ^{**} (0.039)	0.928 ^{***} (0.146)	0.273 (0.427)	0.033 (0.138)

Notes: Standard errors in parentheses. The estimates for the sales volatility model refer to the introduction of the new Red Bull brand (*dREDBULL*) that was new in the cola category, the new sub-brand introductions by the Coke brand (*dZERO* and *dLIGHTPLUS*, only for Coca-Cola), and the new sub-brands from competing brands (*competitor entry*).

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$ (p -values, two-sided).

volatility is unrelated to competing brand prices or promotions and there is hardly any impact from the other variables.

The results in Tables 5 and 6 provide evidence that for the clear majority of cases, the entry of the new brand and sub-brands significantly increased sales volatility at the retailer, not only for the Coca-Cola parent brand but also for most of its competitors. Table 6 shows that of the 49 estimates related to the new product variables in the sales volatility models, 25 (51 %) are positive and significant. The general rise in brand sales volatility following new product entry, which was hypothesized in H1, is also confirmed for the cola category by a combined, meta-analytic test using the method of adding Z's (Rosenthal 1991) with a significant positive impact across all the cola brands (meta $Z = 10.435$; $p < 0.01$). This rise in volatility following brand entry was hypothesized in H2 to be larger for NBs than for PLs. While the average estimated rise in PL sales volatility across all the retailers of 0.327 is indeed lower than

the average rise of 0.555 across all the NBs, there are too few PL estimates to test this formally. Finally, the effect of new brand entry (i.e., Red Bull) at Retailers R1 ($\tau_{121} = 3.299$, $p < 0.01$) and R2 ($\tau_{121} = 2.349$, $p < 0.01$) generates an even higher increase in Coca-Cola's sales volatility than the entry of its own sub-brands (i.e., Coke Zero, $\tau_{131} = 0.796$, $p < 0.01$ in R1; n.s. in R2 and Coke Light Plus, $\tau_{132} = 1.574$, $p < 0.01$ in R1; n.s. in R2). Further, Table 6 shows that the reverse holds for PLs: the increase in sales volatility following the entry of Red Bull Cola is lower for PLs than for NBs, with an average estimate for $\tau_{121, PL}$ across the retailers of 0.886 compared with 0.978 for $\tau_{121, NB}$ across the four NBs and retailers. With only a few innovations and brands in the cola category, the number of relevant volatility estimates used to formally test the hypotheses is limited, especially for incumbent PLs. To provide generalizable insights, H1–H3 are formally tested based on a second-stage regression analysis, which includes all 821 volatility estimates from the 214 models. These estimates relate to the 182 innovations launched across the nine categories.

7.3. Model findings for all the categories

The cola results are consistent with the results from the other eight product categories, providing further support that the entry of new brands and new sub-brands is mostly followed by an increase in sales volatility for incumbent brands at the retailer. Table 7 summarizes the number of models with positive (significant) estimates of the impact of new product entry on sales volatility (derived from the new product entry variables in the GARCH models). Of the 821 model estimates that capture the change in brand sales volatility at the retailer after product entry, 427 (52 %) are positive and significant ($p < 0.10$, two-sided). This includes a significantly positive rise for 73 of the 141 (51.77 %) estimates related to entirely new brands that enter the assortment (i.e., τ_{12n}), 232 of the 472 (49.15 %) estimates capturing the volatility rise

Table 7

Frequencies by Categories of the New Product Induced Sales Volatility Estimates.

Category	No. of estimates	Significantly positive
Bath & shower gel	96	59
Biscuits	91	42
Coffee	143	68
Cola	49	25
Chips	91	51
Diapers	72	42
Razors	47	24
Tea	133	57
Yoghurts	99	59
Total	821	427

Notes: We report the number of (positive) estimates in each category as well as the number of significant positive estimates (p -value < 0.10 , two-sided).

Table 8

WLS Regression of the Volatility Drivers.

Variable	DV: Change in Brand Sales Volatility at the Retailer After Entry	
	(1) Main Effects	(2) Full Model
Constant [c0]	1.053*** (0.054)	1.055*** (0.054)
dPL [c1]	-0.106** (0.051)	-0.026 (0.054)
dNEWBRD [c2]	0.041*** (0.014)	0.062*** (0.020)
dPL × dNEWBRD [c3]		-0.193*** (0.051)
BRDRANK [c4]	0.029*** (0.004)	0.021*** (0.004)
BRDINV [c5]	0.011*** (0.003)	0.011*** (0.003)
RETSIZE [c6]	-0.00001 (0.00001)	-0.00001 (0.00001)
RETPVAR [c7]	-0.077*** (0.024)	-0.078*** (0.024)
dDISC [c8]	0.288*** (0.047)	0.286*** (0.047)
dCOMP [c9]	-0.535*** (0.050)	-0.548*** (0.043)
dFOOD [c10]	-0.293*** (0.044)	-0.294*** (0.044)
Observations	821	821
R-squared	0.160	0.160

Notes: Standard errors in parentheses. DV = dependent variable, which contains the estimates $\tau_{12}-\tau_{14}$ obtained from the first-stage analysis (see Eq. (3a)) that capture the change in brand sales volatility at a retailer after new product entry. The model is estimated using WLS with all the variables weighted by the inverse of the standard error of the dependent variables obtained from the first-stage analysis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (p -values, two-sided).

*** $p < 0.01$.

** $p < 0.05$.

following own sub-brand entry (i.e., τ_{13m}), and 122 of the 208 (58.65 %) estimates related to competing sub-brand entry (i.e., τ_{14}).

While these results indicate that new product entry is often associated with an increase in brand sales volatility, this is not observed for all the brands or new products. To provide further insights into when and for what brands the volatility rise is larger and test the hypotheses, these estimates are linked in a second-stage analysis to the proposed drivers and control variables using Eq. (4). In the model estimation, we consider two issues. First, because the dependent variable contains estimated coefficients, we check for the heteroscedasticity of the ordinary least squares (OLS) standard errors (Nijss et al. 2001). The White test indicates that the hypothesis of no heteroscedasticity is rejected ($p < 0.01$); therefore, WLS regression is used. Second, multicollinearity is not a concern given the maximum VIF value of 1.79 (mean VIF = 1.45).

Table 8 summarizes the WLS model results. The several significant estimates for the drivers and reasonable R-square values show that both models can explain the variation in the dependent variable. Model 1 contains only the main effects. Model 2 adds the interaction term between dPL and dNEWBRD to examine the difference in volatility changes between PLs and NBs when a new brand enters the market. The estimates for the additional brand and retailer drivers are highly similar in size and significance in both models; therefore, we focus our discussion on the general brand and retailer drivers based on Model 1 and then elaborate on the difference between PLs and NBs based on the estimates of Model 2.

Across all the brands, retailers, and new products examined, the model results show an overall significant positive intercept ($c_0 = 1.053$, $p < 0.01$), supporting H1 that new product entry increases volatility in incumbent brand sales at the retailer. However, the volatility increase is

not the same for each new product entry and brand and our model indicates that this volatility increase is further related, positively or negatively, to several of the proposed new product, brand, and retailer drivers. Therefore, an increase in volatility may also be absent in individual cases. To further understand the differences between incumbent NBs and PLs, we check the estimate of the PL dummy. Consistent with H2, sales volatility changes less for PLs than for NBs after new product entry given the significant negative estimate for dPL ($c_1 = -0.106$, $p < 0.05$). Furthermore, volatility rises more with the entry of an entirely new brand than with a sub-brand entry given the significant positive estimate of c2 (0.041 , $p < 0.01$). With respect to other brand differences, the volatility induced by new products threatens smaller market players more than brand leaders, as we find a positive and significant effect for the brand rank variable ($c_4 = 0.029$, $p < 0.01$). As expected, brands that frequently launch new products face higher sales volatility ($c_5 = 0.011$, $p < 0.01$). Moreover, the retail environment appears to drive volatility in brand sales. Although the retailers' assortment size does not influence a brand's sales volatility when new products enter (c_6 , n.s.), product entry has a smaller impact on brand sales volatility for retailers with more heterogeneous assortments in which brands belong to different price tiers ($c_7 = -0.077$, $p < 0.01$). Finally, significant effects are observed for the remaining controls, with larger volatility changes at hard discounters ($c_8 = 0.288$, $p < 0.01$) and for new products under the same parent brand name ($c_9 = -0.535$, $p < 0.01$), while volatility changes are lower in food categories ($c_{10} = -0.293$, $p < 0.01$).

Although PLs suffered significantly less from new product entry according to Model 1, the results of the full Model 2, including the interaction between the PL and type of new product (see Table 8), reveals a more complex and interesting relationship. In line with H3a, for NBs, the entry of a completely new brand into the assortment results in the largest shift in consumer preferences and is responsible for a rise in sales volatility that exceeds that from new sub-brands (=baseline) ($c_2 = 0.062$, $p < 0.01$). This relationship is reversed for PLs: in line with H3b, the increase in PL sales volatility caused by a new sub-brand entry is, on average, larger than that after the entry of an entirely new brand given the negative significant interaction estimate c3 that is larger, in absolute value, than the estimate c2 ($c_3 = -0.193$, $p < 0.01$; Model 2). To gain further insights into the size of these volatility changes and how they differ between NBs and PLs and between new brands and new sub-brands, the mean volatility changes for the four combinations are determined. Mean sales volatility for NBs when new sub-brands enter the assortment rises by 1.055 (=c0, Model 2, $p < 0.01$) compared with 1.117 (=1.055 + 0.062) after the entry of an entirely new brand. For PLs, volatility increases by 1.029 (=1.055–0.026) when new sub-brands enter compared with only 0.898 (=1.055–0.026 + 0.062–0.193) when they face an entirely new brand at the retailer. These results are consistent with the contrast effect in which PLs become more distant from NBs after the entry of an entirely new brand, decreasing the brand-switching tendencies between them.

7.4. Prediction tool

Apart from understanding the factors that drive changes in brand sales volatility, managers would greatly benefit from knowing, before new product entry, whether and to what extent sales volatility for each brand will rise within the assortment. To this end, we build two prediction tools that can be used by brand managers and retailers before new product entry to predict: (a) whether incumbent brands' sales volatility will rise at the retailer and (b) how much it will rise after store entry. To build the prediction tools, we randomly split our initial sample of 821 observations from the second-stage analysis into an estimation sample (containing 80 % of the combinations) and a holdout sample (containing the remaining 20 %). The estimated sample is subsequently used to train two models using the 10-fold cross-validation technique (Reguera-Alvarado, Blanco-Oliver, and Martin-Ruiz 2016; Wei, Hong, and Tellis 2022). In the first model, the dependent variable is a binary

variable that takes the value of 1 if the observation is related to a significant increase in sales volatility (based on the first-stage time-series analysis) and 0 otherwise. We link this binary dependent variable in a logistic regression model to the same brand, retailer, and new product driver, as in Eq. (4) (second-stage analysis). In the second prediction model, we link the sales volatility estimates from the initial time-series analysis to the same set of drivers in the OLS regression. Based on the estimates generated after training both models using 10-fold cross-validation, we predict the presence (logistic regression) and level (OLS regression) of sales volatility changes for each combination in the holdout sample. According to the prediction accuracy statistics, both models are useful for predicting volatility changes in brand sales at the retailer. First, the prediction tool based on logistic regression accurately predicts a significant increase in volatility for 58 of the 90 cases in the holdout sample that showed a true significant volatility rise, corresponding to a prediction accuracy of 64.44 %. The model is less accurate at correctly predicting insignificant estimates, but overall, 99 of the 164 observations in the holdout sample are classified correctly, corresponding to a hit rate (forecasting accuracy) of 60.37 %, significantly better than chance ($50\% = \alpha^2 + (1 - \alpha)^2$, with $\alpha = 52\%$ in our sample). Second, the accuracy of predicting the size of the volatility increase based on the regression prediction tool shows a mean average prediction error (MAPE) of 19.86 % for predictions in the holdout sample and a corresponding R^2 of 40.14 % (calculated as $1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$). Thus, the average prediction error from comparing the predictions with the actual values is less than 20 % of the true value, whereas the forecasting model explains over 40 % of the variation in volatility estimates in the holdout sample. In conclusion, both prediction models are useful for predicting (a) the presence and (b) the extent of the sales volatility rise and can be used by managers to assess the vulnerability of their brands to new products prior to entry based on observed factors related to the brand, retailer, and new product.

7.5. Model validations

Our results are robust to various alternative specifications of the models and variables.

Alternative new product screening approach. We adjust our screening approach and analyze only the top three (instead of top five) NBs in each category. This reduces the sample from 182 to 139 new products (128 new sub-brands and 11 new brands). Having re-estimated our models for the top three NBs and PL within each of the nine product categories, we obtain consistent results supporting our formal propositions. Specifically, across the 159 models, we have 633 estimates of the effect of new product entry on sales volatility, with 322 (50.71 %) being positive and significant. We re-estimate the second-stage WLS model using 635 estimates. The results for Model 1 in the second-stage analysis show that the model estimates are consistent in terms of sign and significance, validating our earlier findings.

Removing the most successful new products. To rule out the possibility that our results are driven by a few exceptionally successful new products, we re-estimate all the models after excluding the best-performing new products with the largest national market share in each category. Again, the results indicate that new products positively impact sales volatility (758 estimates, with 402 significantly positive).

8. Discussion

Despite the associated performance benefits, adding new products into a retailer's assortment can be a source of concern for managers if it results in higher uncertainty because of a significant rise in sales volatility for existing offerings. From an operational perspective, more volatile brand sales are undesirable for manufacturers that face difficulties in planning production and managing marketing support, while retailers

also experience increasing inventory complexity with larger sales swings, resulting in waste and costly stockouts.

Based on a sample of 182 new products across nine CPG categories, this study confirms that the addition of new products into the assortment of a retailer is indeed followed, in most instances, by a rise in brand sales volatility for incumbent offerings. This increase is larger for NBs than for PLs and clear differences are observed between new sub-brands and entirely new brands once they enter in the assortment. Interestingly, while NBs suffer more from entirely new brands as opposed to new sub-brand entries, PLs are affected more by new sub-brand entries that contain an established NB name, but are hardly affected by entirely new brands. In addition to these differences, other brand and retailer drivers explain a substantial proportion of the variation in the volatility changes.

8.1. Research implications

While the effect of new product entry on brand sales *levels* has been well documented in the literature (e.g., Sorescu and Spanjol 2008), its impact on sales *volatility* has received far less attention. Previous studies provide evidence that marketing interventions can concentrate store traffic and sales in certain weeks, making them responsible for a rise in brand sales volatility, and these large and uncertain sales peaks and drops are undesirable and to be avoided (Fischer, Shin, and Hanssens 2016; Estaban-Bravo, Vidal-Sanz, and Yildirim 2017). However, these studies rarely examine sales volatility in relation to new products and the analyses are mostly for the brand itself at the (aggregate) market level, instead of at the retailer level at which brands are managed. We extend this work by examining brand sales volatility at the retailer in relation to new products that become available and measure volatility changes not only for the parent brand that introduced the new product but also for competing brands in the assortment.

Our findings show that volatility for incumbent brands seems to increase at the retailer after new products enter the assortment. Interestingly, this volatility rise varies considerably, with higher volatility when entirely new brands enter the assortment; by contrast, the impact of new sub-brands under an existing parent brand name is lower, except for PLs. This variation can be linked to other brand and retailer variables. These findings provide more refined insights into when and for what brands and new products an increase in volatility can be expected. Researchers can use these insights to understand how and why new products change sales dynamics in the store and how this is shaped by the nature of a brand given the different effects on incumbent NBs and retailers' PLs.

8.2. Managerial implications

Brand sales volatility at the retailer is responsible for excess operational and inventory complexity, whereas manufacturers face production inefficiencies associated with higher ordering volatility, especially in the CPG market that has many perishable products. Retailers and brand managers in CPG businesses can use our findings in several ways. First, earlier studies encourage managers to smooth sales fluctuations using marketing interventions and offer guidelines on how to do so (e.g., Fischer, Shin, and Hanssens 2016; Estaban-Bravo, Vidal-Sanz, and Yildirim 2017). Additionally, practitioners openly plead to manage revenue volatility when an industry faces higher demand uncertainty (Dyer, Furr, and Lefrandt 2014). Given that new products play a pivotal role in future growth and development in the industry and that retailers rely on them to remain competitive, repulsing new products or breaking their marketing support may be undesirable, as it could hamper both product and store performance. Instead, retailers are encouraged to scan the environment for new products and prepare for greater uncertainty and its higher costs by developing marketing and operational strategies to handle larger peaks and drops in brand sales. They can reorganize their brand operations and inventory activities around entry by, for instance, building larger stock buffers and avoiding intense promotions when

brands face rising sales volatility. Similarly, manufacturers are encouraged to scan retailers' assortments for new products or even exchange information with retailers on when certain new products will arrive. In anticipation of large sales peaks, they can expand production of their brands in the weeks before entry. If a retailer sends large sales orders after extending its assortment, manufacturers can correctly assess the temporary nature and refrain from structurally investing in expanding their capacity. Given the frequent entry of new products into the CPG market, these insights are critical for retailers and manufacturers to better manage their brand activities at the retailer.

Second, our results show that the change in brand sales volatility after entry can differ substantially, with some brands being more heavily affected, while others may not even face any changes. The results on the drivers allow brand managers and retailers to map their business reality to our brand- and retailer-level drivers and quickly evaluate their vulnerability (in the form of sales turbulence) to new product entries to take relevant actions. Manufacturers and retailers should account for the larger rise in the sales volatility of incumbent NBs after the entry of an entirely new brand, whereas proper measures are more important for retailers' PLs when new sub-brands enter the assortment. Smaller and more innovative brands suffer more when new brands arrive in the assortment. Additionally, incumbent brands face lower volatility in retailers with higher price variability and at non-discounters. With limited stock space at retailers, this information is critical for managing inventories and organizing brand support, especially if stores want to avoid excessive brand sales volatility. In this context, it is strategic for retailers that aim to cultivate PLs and turn them "powerhouse brands" to favor entirely new brands over frequently introduced new sub-brands of an incumbent NB. This is because the former can further distance their PL from other offerings and protect it from fierce competition.

Finally, based on the two prediction tools developed, brand managers can predict the vulnerability of brand sales even before new product entry. Retailers, in turn, can rely on our prediction tools to determine the incumbent brands in their assortment that are most sensitive to volatility increases when a new product is added.

8.3. Limitations and future research

Our study has several limitations. First, we focus on volatility in sales volume (or quantity), as this is the basis for planning manufacturer operations and managing retailer inventory levels. However, a larger sales volume could be offset by the lower prices at which the offerings are sold, especially when price patterns change at the same time. In this context, the volatility in sales revenue and impact of sales volatility on profits deserve more research attention.

Second, although we empirically establish that product entry is followed by changes in sales volatility, establishing causality in a non-experimental setting remains challenging and requires further analysis to elucidate its relationship with the drivers. Part of this effect is argued to occur because of adjustments in marketing activity after the launch by the innovating brand and/or its competitors. Although we formally account for our own and competing regular prices and promotions, we do not trace what part of volatility changes can be attributed to each of these marketing (price) adjustments and whether this leads to more impactful effects. Further, we do not have access to data on other marketing actions (e.g., advertising) or pre-launch marketing support for a new product that could influence sales volatility. Hence, it is impossible to formally test the proposed underlying explanations for the observed increase in brand sales volatility.

Finally, we study new product entry and the subsequent volatility implications in the CPG industry for incumbent brands, where large sales peaks around launch may foster trial purchases that could be converted into repeat purchases and speed up sales growth. Future research is required to determine whether more volatile sales can further influence a brand's future performance and if similar volatility patterns occur in other industries that are less dependent on repeat purchases or

in which more elaborate decision-making by consumers takes place.

CRedit authorship contribution statement

Wanxin (Britney) Wang: Writing – original draft, Software, Data curation. **Barbara Deleersnyder:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Formal analysis, Conceptualization. **Gokhan Yildirim:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jbusres.2025.115267>.

Data availability

The authors do not have permission to share data.

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