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Promotion elasticities of national and store brands: The effect of price level and brand type on promotion elasticity

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ABSTRACT

Prior research suggests that price promotions by higher-priced products generate greater sales lift than those by lower-priced products. This view implies that higher-priced products should promote more often, all else equal. However, this assertion largely rests on the asymmetric price effect, which holds that promotions by higher-priced national brands (NBs) draw disproportionately from lower-priced store brands (SBs), thereby confounding price level (high vs. low) with brand type (NB vs. SB). In other words, it remains unclear whether higher-priced NBs are more promotion elastic because of their price level, or simply because they are NBs. This paper disentangles the effects of price level and brand type by analyzing nearly 700 million observations for 60,000 UPC products across 30 grocery categories (2016–2019). The authors find that while NBs are generally more promotion-elastic than SBs (promotion elasticities of −3.47 vs. −2.40), the role of price level depends critically on the brand type. For NBs, lower-priced products exhibit 3 % greater promotion elasticities, whereas for SBs, higher-priced products benefit from 12 % greater promotion elasticities, though there is sizeable heterogeneity across categories and markets in these effects. Thus, the paper also explores the sources of this heterogeneity and assesses the category-level sales lift of promotions.

1. Introduction

Retail price promotion—also known as deals, price cuts, or temporary price discounts—is a dominant element of the marketing mix that can increase sales. Nearly 30 % of U.S. grocery sales, totaling more than $850 billion, occur through price promotions (U.S. Census Bureau, 2025). Therefore, retailers must make appropriate discount decisions for their products while addressing a pertinent managerial question: Should higher-priced products be promoted more than lower-priced products? While there are many reasons why a product may be price promoted, such as competitor actions, inventory reduction, or seasonality (see Blattberg & Neslin, 1993, for a

We acknowledge the Kilts Center for Marketing at the University of Chicago Booth School of Business for providing access to the NielsenIQ RMS data. Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. We thank Ed Fox, Jonne Guyt, Arjen van Lin, Venkatesh Shankar, and Wayne Taylor for helpful comments on an earlier version, and Sushmitha Chakravarthigari for assistance with literature review.

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detailed analysis), one crucial consideration is the promotional sales lift – i.e., whether price promotions by higher-priced products are more (or less) effective in increasing the product's sales than price promotions by lower-priced products.[1]

In this context, Blattberg and Wisniewski (1989) proposed the asymmetric price effect, which posited that when higher-priced national brands (NBs) discount, they take more sales away from lower-priced store brands (SBs). However, when the lower-priced SBs discount, they take little sales away from the higher-priced NBs. Drawing on this general premise, subsequent early research has developed theoretical frameworks supporting the asymmetric effect (e.g., Allenby & Rossi, 1991; Hardie et al., Johnson & Fader, 1993) and built equilibrium models asserting that higher-priced NBs should be discounted more often and more deeply than lower-priced SBs (e.g., Raju et al., 1990; Rao, 1991).

However, this asymmetric price effect is predicated on the competition between higher-priced (higher-quality) NBs and lower-priced (lower-quality) SBs. This type of brand competition may have reflected marketplace reality in the 1980s and the 1990s, when the asymmetric effect was proposed and supported. But, since 2000, the retail landscape has changed significantly. In particular, standard SBs have evolved and increasingly represent products comparable to NBs in quality but at a lower price (Gielens et al., 2021; PLMA, 2016). Furthermore, the current marketplace also offers higher-priced SBs (also called premium private labels; Geyskens et al., 2010; Keller et al., 2022) that are about the same or higher in price and quality than NBs. With these higher-priced SBs, the product options faced by the consumer no longer fall neatly into the dichotomy of "high-priced NBs" and "low-priced SBs" discussed in the early literature from the 1980s; rather they include both high- and low-priced NBs as well as high- and low-priced SBs.

Indeed, the current retailscape in the U.S. reflects this scenario: a typical store carries nearly 70 orange juice products, including higher-priced NBs (e.g., Tropicana at $4.79 per 64 oz. bottle), lower-priced NBs (e.g., Twist at $2.99 per 64 oz. bottle),[2] as well as high- and lower-priced SBs. A pertinent managerial question faced by the retailer is: Should higher-priced products be promoted more than lower-priced products? The answer to this question depends critically on whether promotions by higher-priced products have greater (or less) sales impact than promotions by lower-priced products (Sethuraman & Tellis, 1991).

The asymmetric price effect provides some insights into this question and suggests that promotions by higher-priced NBs do yield greater product sales lift than promotions by lower-priced SBs (e.g., Blattberg & Wisniewski, 1989; Sethuraman, 1996). But this view confounds brand type (NB vs. SB) with a product's price level (high vs. low) and does not reflect market realities in the present time, which feature both high-priced and low-priced NBs and SBs. In this changed, recent market scenario, our key contribution is to understand whether price promotions by higher-priced products result in greater sales lift than promotions by lower-priced products, after separating out the effect of a product's brand type (NB vs. SB). To the best of our knowledge, the literature has not separated the brand type and price level effects, nor has it provided insights on the relative promotional sales effects of higher versus lower-priced products. Thus, the key question we address in this research is: *Do retail price promotions by higher-priced products result in greater product sales lift for the promoted product than promotions by lower-priced products and does this hold for both NBs and SBs?*

Our research approach is as follows. First, we review prior literature and develop hypotheses regarding the relationship between product price and brand type and the promotional effect. Second, we specify an econometric model that disentangles the sales effect of price promotions into that due to product price (higher vs. lower) and brand type (NB vs. SB). This model enables us to compare the promotional sales effects of NBs with SBs, as well as high-priced NBs with low-priced NBs, and high-priced SBs with low-priced SBs. Third, we undertake a comprehensive empirical analysis, estimate the model using weekly store-level scanner data of more than 60,000 products from 30 grocery categories (e.g., orange juice, canned soup, paper towels, pain remedies), covering 100 markets and more than 4000 stores in the U.S., during 2016–2019, resulting in nearly 700 million observations. We discuss the results from the model, draw insights, develop implications for promotions of high-priced and low-priced products, and suggest future research directions.

Additionally, in an exploratory fashion, we investigate the heterogeneity in the impact of promotions on sales across category and market factors. Our promotional sales impact estimates are based on data from 2610 category-market pairs; this extensive set of estimates allows us to explore in which types of categories and markets price promotions are more effective in increasing sales.

In a supplemental analysis, we also empirically investigate the relationship between product price and incremental category sales – i.e., whether price promotions by higher-priced products lead to greater category sales expansion than promotions by lower-priced products. This latter question may be especially useful to address for retailers who care about the net sales impact on both the promoted and nonpromoted products.

Overall, our comprehensive empirical analyses yield numerous results, which we summarize along with their managerial implications in the Conclusion section. In particular, we find that price promotions by NBs yield greater product sales lift and greater category sales lift than promotions by SBs of the same price level. However, promotions by higher-priced NB products result in lower sales lift than similar price promotions by lower-priced products, though the effect size is of smaller economic significance. Interestingly, a product's price level plays a different role for SBs: higher-priced SBs generate greater promotional sales lift than lower-priced SBs, highlighting the importance of taking the interplay of price level and brand type into account. These findings suggest that, other things equal, from a sales lift standpoint, it may be better to price promote NBs over SBs, though higher-priced SBs can often be successful as well.

The heterogeneity analysis shows that while these insights hold on average, several factors can shape them significantly. For

[1] Our focus is on retail price promotions or temporary price discounts. Our empirical analysis estimates the effect of price promotions on sales at the Universal Product Code (UPC) level. For brevity, we refer to price promotions as promotions, UPCs as products, and use sales lift, effectiveness, and elasticity to indicate the impact of price promotions on sales.

[2] These prices do not come from NIQ; they are hypothetical examples.

example, three category-market factors – SB share, the degree to which products in a category are bought on impulse, and the category's stockpilability – minimize (and sometimes even erode completely) the advantage NBs have in terms of promotional effectiveness. Put differently, in some categories and markets, high-priced SBs react just as well as some NBs to promotions. Thus, category and market factors play an important role in shaping the promotional effectiveness and the difference in effectiveness between NBs and SBs.

2. Hypotheses

In this section, we draw on prior literature and our intuition to develop hypotheses on the relative promotional sales effects of NBs and SBs, higher-priced versus lower-priced products, and whether the moderating role of a product's price level is different for NBs and SBs.

2.1. Existing research on the role of brand type and price level in promotional effectiveness

A fundamental assumption of complete, competitive markets in classical economics is that prices contain all necessary information for optimal decision making by individual economic units (Abbott, 1953; Fama, 1970). Kihlstrom and Mirman (1975) extend this argument to show that price is a directional indicator of quality so long as there are some knowledgeable consumers. Following this literature, marketing researchers have also documented the positive relationship between product price and its quality over its life cycle (e.g., Curry & Riesz, 1988).

The intuitions for the positive price-quality relationship are as follows. In the long-term, a firm selling a lower-quality product cannot charge a higher price, because consumers will realize the discrepancy (product with lower quality sold at higher price) and not buy the product. Hence higher-priced products will be higher in quality and lower-priced products will be lower in quality in equilibrium. Second, if a higher-quality product costs more to make, then the firm must charge a higher price to recover the higher costs.

Given this price-quality relationship, the asymmetric price effect of Blattberg and Wisniewski (1989), supported theoretically by Allenby and Rossi (1991) and Hardie et al. (1993), states that when the higher-priced (higher-quality) products discount, they will take more sales from the lower-priced (lower-quality) products because those consumers will switch to the promoted higher-quality product. However, when the lower-priced (lower-quality) products discount, consumers of higher-priced products will not switch as much because they will perceive a greater risk, resulting in lower promotional sales lift. Empirical research (e.g., Ailawadi et al., 2006; Ailawadi et al., 2001; Lemon & Nowlis, 2002) largely supports this view and shows that NBs, which are typically higher-priced, high-tier products, benefit from greater promotional effectiveness than SBs, which are typically considered to be lower-priced, low-tier products. Consequently, the product sales lift from price promotion will be greater for higher-priced NB products than for lower-priced SB products. However, existing research is unclear about whether these asymmetric switching effects and documented higher promotional effectiveness of NBs is due to their (inherent) brand type or their (typically) higher price level. Thus, we discuss first why brand type might affect promotional effectiveness, followed by price level, and then its interaction.

2.2. The effect of a product's brand type on promotion effectiveness

Rooted in much of the early research on price promotion effectiveness, conventional wisdom in the 1980s and 1990s held that a product's brand tier influences its promotional responsiveness. NBs are expected to have a higher promotion effectiveness than SBs (Ailawadi et al., 2009); we argue this may be due to their greater brand awareness, perceived quality, and combined trade support from manufacturers and retailers.

First, NBs typically enjoy greater brand awareness and salience than SBs (Steenkamp, 2024). NBs generally have stronger advertising support and top-of-mind awareness than SBs (Aaker, 1996; Keller, 1993). Thus, when an NB runs a price promotion, more consumers are likely to notice it because the brand is already cognitively salient. Put differently, a price promotion by a NB is more likely to pass the threshold needed to get through the competitive clutter than a SB without the same top-of-mind support.

Second, NBs' higher perceived quality (e.g., Brucks et al., 2000; Kirmani & Rao, 2000) can translate into a higher promotional effectiveness. Many consumers intrinsically prefer NBs for their perceived quality (e.g., taste or social signaling) but buy SBs for value reasons (e.g., Sethuraman & Cole, 1999). A promotion on a NB may reduce the psychological barrier to "switching up", not just because of price savings, but also because purchasing a NB feels like a lower-risk trial due to the higher quality perceptions. Thus, many SB buyers may be inclined to switch to NBs, while SBs, even at the same price level, do not benefit from this effect.

Finally, SB promotions are mostly supported by the retailer only, while NB promotions are typically supported by both the retailer and the brands' manufacturers (Ailawadi et al., 2006). This additional support may come in the form of trade promotions, but also by non-price promotional tools (such as in-store sampling, free gifts, or loyalty program integration; Foubert et al., 2018; Narasimhan et al., 1996; Vafainia et al., 2021) that magnify the promotion effect such that promotions are more likely to be noticed and/or noticed at multiple points in the purchase funnel.

In sum, NBs' greater brand awareness, perceived quality, and combined trade support from manufacturers and retailers may lead to greater promotional effectiveness than that of SBs:

H_1. The product sales lift from price promotion is greater for NB products than for SB products.

2.3. The effect of a product's price level on NB promotion effectiveness

A product's price level can, holding its brand type constant, influence the promotional effectiveness in a variety of ways and is theoretically ambiguous. Below, we discuss reasons that favor greater promotional effectiveness of higher-priced NB products and reasons that favor lower-priced products, resulting in competing perspectives.

Price influences consumers' utility, at least in part, in absolute terms (Heath et al., 1995; Thaler, 1985): the total dollar amount paid matters. For a given percentage discount, higher-priced NB products generate larger absolute savings, which increases perceived benefit and transaction utility more than the same percentage cut on a cheaper item.

In addition, promotions on higher-priced NB products narrow the price gap to mid- and value-tier alternatives, encouraging "trading up." Crossing such a price-point barrier can prompt consumers to reconsider options they normally deem too expensive (Kim et al., 2022). Because a significant share of buyers in the category already purchase lower-priced alternatives, discounting an expensive product can attract new customers who would not have considered it at its regular price; this effect is likely to be smaller when already-low-priced items are discounted, as the asymmetric price effect would argue (Blattberg & Wisniewski, 1989).

Finally, higher-priced NB products are more likely to be excluded from consumers' consideration sets because they stretch budgets or exceed salient price thresholds. A price promotion can bring these products within budget constraints or below key psychological thresholds, making them viable options for more shoppers (Dodds et al., 1991; Hauser & Wernerfelt, 1990). Lower-priced NB products, typically already more affordable, have less potential to benefit from this extensive-margin effect. In contrast to the "trading up" argument, which rests on product switching, expanding the consideration set may create new demand because consumers add promoted products or enter the category. In sum, these reasons imply that promotions on higher-priced NB products are likely to generate a greater promotional sales lift than promotions on lower-priced products.

Conversely, lower-priced NB products may benefit more than higher-priced products from price promotions because they can become the best deal in a category and may fall below the "impulse purchase" threshold.

First, a promotion on a lower-priced NB product frequently makes it the lowest-priced option in the category, widening its price advantage over competing products. This can be particularly effective at drawing store switchers, i.e., shoppers who are willing to change retail outlets in search of better deals (e.g., Ailawadi et al., 2001; Bell & Lattin, 1998; Gauri et al., 2017) even if such switches are only temporary (Kotschedoff et al., 2025). Such an effect is weaker for higher-priced NB products, which may remain above competing options even after the discount.

Second, price cuts on low-priced NB products are more likely to move the item below psychologically salient impulse-purchase thresholds (e.g., under $1). Crossing such thresholds can prompt unplanned purchases from shoppers who might not have otherwise considered the product (and are now purchasing it in addition to other options; Winer, 1986), further boosting sales volume.

Taken together, becoming the best deal in a category, or falling below an "impulse purchase" threshold may suggest that lower-priced NB products may generate greater promotional sales lift than higher-priced NB products; yet, higher absolute savings, price-quality associations, and budget constraints lead us to expect the opposite. Hence, we offer competing hypotheses:

H_{2a}. The product sales lift from price promotion is greater (lower) for higher (lower)-priced NB products than for mid-priced NB products.

H_{2b}. The product sales lift from price promotion is greater (lower) for lower (higher)-priced NB products than for mid-priced NB products.

2.4. The moderating effect of brand type on price level's effect on promotion effectiveness

The mechanisms through which price level influences promotional effectiveness are likely to operate differently for SBs than for NBs, owing to differences in perceived quality, competitive positioning, retailer margin structures, and promotional support patterns. We expect the effect of price level on promotional sales lift to be less negative or even positive for SBs (as compared to NBs), for the following reasons.

First, quality proximity and switching potential differ sharply between SBs and NBs. Within SBs, only premium tiers are perceived as close substitutes to NBs. A discount on a premium SB can therefore trigger meaningful switching from NB buyers, who may view it as an opportunity to obtain comparable quality for less. Lower-priced SBs, by contrast, lack this quality proximity and have limited ability to attract NB buyers even when discounted. As importantly, the quality differences among SBs are typically made clear through vertically differentiated branding architecture that delineates the various lines from one another (e.g., basic, standard, and premium; Keller et al., 2016). For NBs, however, both high- and low-priced products are often perceived as superior to SBs and any differences are less visible due to independent brand names across NBs (e.g., RC Cola and Pepsi Cola), so differences in price level within NBs have less incremental impact on switching behavior.

Second, retailer margin economics and promotional execution favor higher-priced SBs. Because retailers are more likely to capture the full margin on SBs, premium SBs (priced closer to NBs) often yield higher absolute margins per unit than lower-priced SBs (ter Braak et al., 2013). This margin cushion enables retailers to fund stronger non-price promotional support (e.g., in-store sampling or loyalty program tie-ins) for higher-priced SBs. Lower-priced SBs, with lower margins, are less likely to receive such executional intensity (Garrido-Morgado et al., 2016). For NBs, promotional execution is, in addition to any retailer support, also manufacturer-funded and may be larger overall than for SBs, but the level of support is less tied to the NB's own price tier, and the price-level effect is correspondingly weaker.

Third, for SBs, price level moderates promotional impact through a dual-barrier effect. Many shoppers exclude SBs not only for price reasons but also due to perceived quality gaps. Higher-priced SBs, often positioned as premium SBs, are close enough in perceived quality to NBs that a promotion can simultaneously reduce the price barrier and make the quality trade-off acceptable (Geyskens et al., 2010; Keller et al., 2022). This dual shift can expand the SB's buyer base by attracting NB buyers who would not consider lower-tier SBs even at deep discounts. Lower-priced SBs already appeal to price-focused shoppers, so discounts mainly stimulate larger basket sizes rather than new adoption. For NBs, where quality perceptions are typically higher across all price tiers, promotional gains from price-level differences primarily reflect the budget-barrier mechanism, making the incremental effect of price level smaller relative to SBs. Taken together, these mechanisms suggest that, for SBs, higher-priced products have greater potential than similarly-priced NBs to generate incremental sales from promotions. As such, we formulate H_3:

H_3. For SBs, the effect of price on promotional sales lift is less negative (or more positive) than for NBs.

We now proceed to empirically test these three hypotheses. We conduct the empirical analysis at the least aggregate (product-) level for which data is available. Analyzing at the brand or price-tier level may lead to aggregation issues and incorrect inferences about these effects (Halvorsen & Larsen, 2013). For instance, if a brand has ten UPCs, with different price levels and promotional intensities, aggregating across the ten UPCs would result in biased estimates. Furthermore, if five of the ten UPCs show higher promotional effect, and five show lower promotional effects, it is not clear what the net promotional effect would be, which would depend on the aggregation method and nature of estimation.

3. Empirical setting

3.1. Data

We gathered retail sales data from NielsenIQ Retail Measurement Services (RMS), provided by the Kilts Center for Marketing. The RMS data contain detailed information at the product–store–week level, including its (actual) price, which we use to determine the regular price and whether a product–store pair is on promotion in a given week. We focus on 30 grocery categories with an average SB market share of at least 5 %, which are a subset of the 40 categories studied by DellaVigna and Gentzkow (2019). These 30 categories

Table 1
Category overview with key summary statistics[a].

Category	# of markets	# of observations	# of unique products	# of product-store pairs	SB share	Promotion incidence	Promotion depth[b]
Baby Milk	65	2,047,518	326	14,413	6.7 %	8.4 %	10.9 %
Bacon	81	9,318,332	1008	55,883	36.3 %	28.7 %	20.2 %
Batteries	87	5,527,116	499	28,951	15.2 %	21.9 %	14.4 %
Bottled Water	100	36,652,234	2296	211,994	53.8 %	24.6 %	18.1 %
Canned Soup	78	39,104,651	2990	217,950	25.3 %	19.6 %	23.5 %
Cold Remedies	86	4,821,163	923	27,683	69.4 %	14.4 %	13.8 %
Cookies	98	54,156,338	4741	320,316	25.1 %	22.4 %	19.7 %
Diet Soft Drinks	98	57,452,171	3506	361,510	14.9 %	32.6 %	20.2 %
Dry Dog Food	60	6,377,716	889	40,369	20.5 %	13.9 %	12.3 %
Eggs	83	4,797,889	869	28,842	75.2 %	19.0 %	18.1 %
Fresh Cakes	80	15,134,610	3719	100,617	42.9 %	18.3 %	20.1 %
Frozen Novelties	79	27,684,179	2563	174,609	25.9 %	23.3 %	20.1 %
Frozen Pizza	91	26,368,225	2275	166,924	19.5 %	30.8 %	18.1 %
Ground Coffee	89	18,042,356	2405	99,196	18.4 %	29.6 %	18.6 %
Ice Cream	88	39,525,550	4682	229,047	36.4 %	37.1 %	22.9 %
Liquid Bleach	82	4,318,990	432	25,939	38.9 %	13.4 %	13.2 %
Lunchmeat in Deli Pouches	85	14,142,726	954	86,481	16.9 %	28.3 %	18.1 %
Milk	98	17,839,591	1937	100,253	70.6 %	13.9 %	15.1 %
Non-Chocolate Candy	99	41,489,311	2948	246,567	13.5 %	23.7 %	20.2 %
Orange Juice	84	11,116,664	884	82,669	31.6 %	24.5 %	19.1 %
Pain Remedies	87	9,096,680	1248	48,919	64.8 %	14.1 %	14.2 %
Paper Towels	97	9,459,579	1160	92,744	40.5 %	18.7 %	19.3 %
Potato Chips	98	37,085,094	2687	274,287	12.3 %	28.1 %	19.9 %
Ready-To-Eat Cereal	95	45,516,539	2855	303,135	11.6 %	21.5 %	22.9 %
Refrigerated Entrees	79	12,653,576	2634	92,349	56.1 %	24.5 %	19.9 %
Shredded Cheese	83	16,963,561	2477	104,127	76.2 %	33.3 %	21.2 %
Sliced Lunchmeat	76	15,497,742	1781	96,779	22.5 %	21.1 %	18.1 %
Toilet Tissue	100	15,809,171	1424	140,832	32.8 %	20.6 %	17.7 %
Tortilla Chips	98	17,680,185	1147	119,377	13.5 %	28.1 %	20.1 %
Yogurt	86	60,099,678	3891	416,172	13.6 %	26.0 %	18.2 %
TOTAL/MEAN	2,610	675,779,135	62,150	4,308,934[c]	33.4 %[a]	22.8 %[a]	18.3 %[b]

[a] Average values across 675,779,135 observations.
[b] Average values across 170,567,110 observations, conditional on a promotion occurring.
[c] 4,308,934 product-store pairs are observed for an average of 157 weeks and at least for 52 weeks.

feature several characteristics that make them attractive for our research. First, these product categories are mature, which reduces confounds due to category dynamics, such as changes in customer needs or new product introductions. Second, promotions happen often, with wide variations in discount depth. Third, SBs are important, with an average volume share of around 33 %. Fourth, these categories exhibit sufficient price variation across products and within each brand type (NB and SB). These factors permit us to estimate and investigate the promotional sales impact of high-priced and low-priced NBs and SBs, with mid-priced products serving as the baseline.

We use four years of weekly sales data, from 2016 to 2019 (i.e., prior to the COVID-19 outbreak but still relatively recent), gathered from all stores continuously open throughout the data period and that recorded more than $100 in weekly sales in a category (DellaVigna & Gentzkow, 2019). To keep the analyses tractable, we study a random selection of 100 (out of 892) markets in the US, defined at the three-digit zip code (Keller & Guyt, 2023), in which at least two retail chains are active, and one retail chain operates at least two stores. To ensure sufficiently large markets and stable parameter estimates, we choose those products and stores that have at least 10 SB and 10 NB product-store pairs in a market and category.

As is common practice when dealing with retail scanner data, we rely on sales data to infer product stocking decisions to overcome the lack of information about product availability (e.g., Keller & Guyt, 2025). Similar to Hwang et al., (2010, p. 865), we consider products even in the absence of sales as part of the assortment unless they show zero sales continuously for four weeks. We focus on non-seasonal products and, following DellaVigna and Gentzkow (2019), we retain all product–store pairs with greater than 80 % of product–store–weeks with non-zero sales.

The data consist of 62,150 unique products sold by 4648 brands in 4077 stores in 100 markets, for a total of 675,779,135 observations covering 30 grocery categories. For each product, we identify from the data whether the product is NB or SB and its actual price (price paid) in a given week and store. Similar to Datta et al. (2017), we calculate regular price as the highest actual price in the preceding four weeks, then define a product as being on price promotion in any week if the actual price is more than 5 % lower than the regular price (Hitsch et al., 2021) in that four-week period. We compute promotion as the ratio of the actual price to the regular price. For example, if a product's regular price is $1 and the actual (promotional) price is $.90, then the promotion value is .90.

Table 1 presents the key summary statistics for each of the 30 categories. On average, we observe each category in 87 markets for a total of 2610 category-market pairs. The number of observations in these 30 categories range from 2 million for baby milk to over 60 million for yogurt, with a total of 675.8 million used for estimation. Similarly, the number of unique products range from 326 for baby milk to 4741 for cookies.

Across categories, the average SB share is 33.4 %, ranging from less than 7 % (baby milk) to more than 75 % (eggs). On average, products are promoted in about 22.8 % of the weeks, indicating substantial promotional activity, with discount frequency (promotion incidence) across categories ranging from low (baby milk at 8.4 %) to high (ice cream at 37.1 %). If a promotion takes place, the average discount depth is 18.3 % of the regular price.

Because our research focus is on assessing the relationship between product price and promotional effectiveness by brand type (NB and SB), we also need to ensure that there are sufficient NB and SB observations that span the price range (from low to high price). To test this variation, we classified products by price quartiles. First, we arranged observations from all products by their regular price per volume for each category. Observations in the lowest 25 percentiles were classified as "low-priced" (1st quartile), 25–75th percentile as "mid-priced" (2nd and 3rd quartile), and the products in the highest 25 % of regular prices as "high-priced" (4th quartile). Note that because we pooled all (NB and SB) observations in setting the price quartile cutoffs, the cutoff prices for each quartile are the same for NB and SB. Then, we separated the observations by brand type. Table 2 presents the number of product observations by price quartile for NBs and SBs.

We observe sufficient price variation within each brand type. Over 28 % of NB observations are high-priced (top quartile), while more than 55 % of SB observations are low-priced (bottom quartile), consistent with the notion that NBs are high-priced and SBs are low-priced. But we also find almost 18 % of NBs (nearly 100 million weekly observations) that are low-priced (bottom price quartile), and 8 % of SBs (about 10 million weekly observations) that are high-priced (top price quartile). This price variation across NBs and SBs reemphasizes the need to empirically identify and investigate the relationship between product price levels and price promotions across brand type (NB and SB).

To assess the link between brand type, price level, and promotional effectiveness, we also need to ensure our data features sufficient promotional activity across the entire price range. Fig. 1 presents the average promotional incidence and depth by price quartile and brand type.

Both promotion incidence and depth (= 1-promotion, converted to percentage) are higher than 15 % across the entire price range, both for NBs and SBs, indicating we observe sufficient promotional activity for our estimation and analysis purposes.

In summary, Tables 1, 2, and Fig. 1, as well as other descriptive statistics, have established that there are sufficient NB and SB

Table 2
Distribution of observations across regular price range.

Number and share of observations by regular price quartile					
Brand Type	1st (low-priced)	2nd	3rd	4th (high-priced)	Total
NB	97,347,593 (17.93 %)	138,432,965 (25.50 %)	150,424,862 (27.71 %)	156,700,598 (28.86 %)	542,906,018 (100.00 %)
SB	73,566,063 (55.37 %)	31,496,436 (23.70 %)	17,895,472 (13.47 %)	9,915,146 (7.46 %)	132,873,117 (100.00 %)

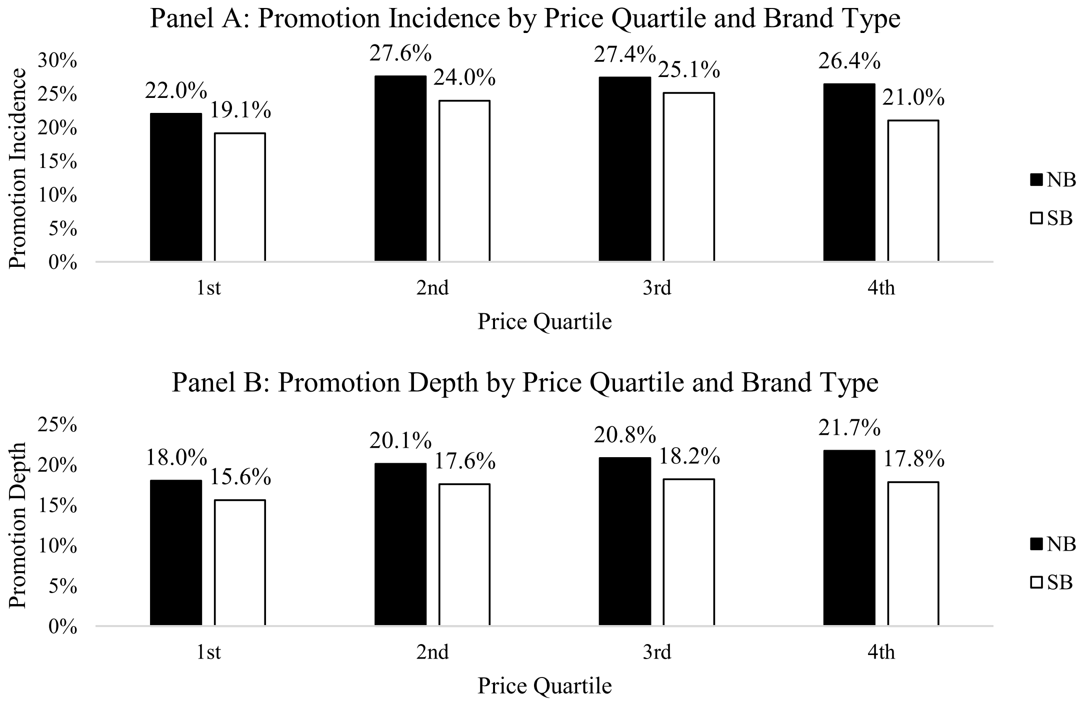

Fig. 1. Promotional conduct by brand type and price level.

observations with promotional activity to perform an empirical analysis to estimate the relationship between product price and promotion effectiveness after accounting for brand type.

3.2. Model-free evidence

Before we present our econometric model, we provide some model-free evidence on changes in product-level sales in response to price promotions, depending on their price level and brand type. We observe nearly 80,000,000 price promotions at the product-store level. Similar to Keller et al. (2019), we calculate for each of these price promotions the average sales level during the promotion and compare it to the average sales level in the four weeks prior to the beginning of the promotion, and express this as a percentage lift. As these price promotions vary drastically in promotional depth, which drives promotional sales lift, we focus on the model-free evidence on price promotions with a comparable promotional depth (from the 10^{th} (6.5 % promotion depth) to 90^{th} (37.5 %) percentile; 18.0 % on average, which is close to the grand mean of 18.3 % in Table 1).

Across all promotions (63,754,458, i.e., 80 %), the average sales lift is 69.4 %, with sales lifts for NBs being substantially higher than those for SBs (88.8 % for NBs vs. 57.2 % for SBs, t = 319.04, $p < .001$). Given the average discount depth of 18 %, these numbers translate into a promotional price elasticity of −3.86 overall (69.4/−18.0). We next assess the sales lift for higher-priced (4^{th} quartile) versus lower-priced (1^{st} quartile) products. The difference in sales lift between higher- and lower-priced products is statistically significant, with a somewhat higher lift for higher- than lower-priced products (72.0 % for higher-priced vs. 63.5 % lower-priced, t = -83.48, $p < .001$). This highlights that, in the aggregate, price level alone does not seem to meaningfully shape promotional responsiveness as compared to differences across brand types.

The more consequential differences only emerge once brand type is considered, where the interaction between price and brand type becomes central to explaining variation in promotional effectiveness. Among NBs, lower-priced products generate higher sales lift than higher-priced products (74.2 % lower-priced vs. 73.0 % higher-priced, t = 9.74, $p < .001$). Interestingly, the picture flips for SBs, where lower-priced products create noticeably lower sales lifts than higher-priced products (47.2 % lower-priced vs. 52.8 % higher-priced, t = −18.79, $p < .001$). Thus, the model-free evidence suggests that both brand type and price level affect the effectiveness of price promotions, and that their interaction is particularly important for SBs. This model-free evidence, however, disregards confounding effects at the product, brand, market, and time levels and the strategic setting of price promotions. In this light, we now proceed to develop the econometric model and empirically investigate the hypotheses linking product price with promotional sales lift.

4. Model development

We assess a product's sales lift due to promotion by specifying a sales-response model that allows for differential effects depending on a product's brand type and whether a product is high-priced or low-priced, with mid-priced products serving as baseline. Next, we describe the product-level sales model first followed by a discussion on how we treat potential endogeneity concerns, before we end with the model to assess heterogeneity in the promotional effectiveness.

4.1. Product Sales response model

We focus on estimating how a product's promotional conduct affects its own sales and if the effect differs for high- and low-priced products from mid-priced products, and between SBs and NBs, after controlling for other factors that might influence sales. The dependent variable in (Eq. 1) is volume sales of product (UPC) u in store s in week t ($VOLSALES_{ust}$). We log-transform and (grand) mean-center all continuous covariates so we can directly estimate their elasticities for each category (c) in market (m). We omit subscripts c and m in (Eq. 1) to avoid clutter. The model is:

$$\begin{aligned}VOLSALES_{ust} = &\underbrace{\beta_1 PROMO_{ust}}_{\text{promotion effect of mid-priced NBs}} + \underbrace{\beta_1 SB_u \times PROMO_{ust}}_{\text{promotion effect difference for mid-priced SBs}} + \\ &\underbrace{\beta_3^H HIGHPRICE_{us} \times PROMO_{ust}}_{\text{promotion effect difference for high-priced NBs}} + \underbrace{\beta_3^L LOWPRICE_{us} \times PROMO_{ust}}_{\text{promotion effect difference for low-priced NBs}} + \\ &\underbrace{\beta_4^H SB_u \times HIGHPRICE_{us} \times PROMO_{ust}}_{\text{promotion effect difference for high-priced SBs}} + \underbrace{\beta_4^L SB_u \times LOWPRICE_{us} \times PROMO_{ust}}_{\text{promotion effect difference for low-priced SBs}} + \\ &\underbrace{\sum\nolimits_{l=1}^{4} \beta_{4+l} PROMO_{us(t-l)} + \beta_{8+l} PROMO_{us(t+l)}}_{\text{intertemporal effects (lag\&lead)}} + \\ &\underbrace{\gamma_1 PRICE_{ust} + \gamma_2 SB_u \times PRICE_{ust} + \gamma_3 FEATURE_{ust} + \gamma_4 WSCOMPROMO_{ust} + \gamma_5 ORCOMPROMO_{ust}}_{\text{control variables}} + \\ &\underbrace{\sum\nolimits_{k=1}^{3} \delta_k CF\_\widehat{MKTG}_{k,ust} + \sum\nolimits_{k=1}^{3} \delta_{k+3} CF\_MKT\widehat{G}_{k,ust} \times SB_u}_{\text{control variables}} + \underbrace{\alpha_{u,s} + \alpha_t}_{\text{fixed effects}} + \varepsilon_{ust},\end{aligned} \tag{1}$$

Table 3 provides the operationalization of the variables in equation 1; Table W1 provides, by product category, summary statistics on the key variables. Multicollinearity does not appear to be an issue with average absolute correlations (across the 2610 estimations) being always below .4; Table W2 of the Web Appendix provides a correlation matrix.

Coefficients α are product-store and time(-category-market) fixed effects, and ε_{ust} is the error term. Here, β, γ, and δ are the parameters; As the model is estimated by category-market (c-m) pair, all parameters vary at that level, too.

In (Eq. 1), β_1 measures the main effect of promotional price for a mid-priced NB on volume sales for that product. Because both promotional price and volume sales are log-transformed, the estimate of β_1 represents own promotional price elasticity for that product in category (c) and market (m). Note that since price and sales move in opposite directions – i.e., as promotional price decreases, volume sales generally increases – we expect the promotional price elasticity $(\beta_1) < 0$.

Parameter β_2 is the interaction effect of promotional price with SB indicator (1 if SB; 0 if NB) on own volume sales. Because the SB indicator value is 0 for NB, parameter β_1 can be deemed as the promotional price elasticity of NBs, and β_2 measures the differential promotional effect (elasticity) of a mid-priced SB product from a mid-priced NB product. Thus, $\beta_1 + \beta_2$ represents the promotion elasticity of mid-priced SBs. If β_2 is positive, then the price promotion elasticity of SB is less negative compared to a similarly-priced NB product, i.e., the SB product is less elastic than an NB product. In other words, the sales lift from (the same) price promotion is lower for SBs than for NBs. If β_2 is negative, then the price promotion elasticity of SB is more negative compared to an NB product. Thus, the sales lift from (the same) price promotion is higher for SBs than for NBs. Based on H_1, we expect $\beta_2 > 0$.

We specify two interaction terms between promotion price and a product's price-tier indicator to allow for asymmetric promotional effects across NB price levels. Specifically, we include indicators for high-priced and low-priced NB products, with mid-priced NB products serving as the omitted (baseline) category. Let β_3^H (β_3^L) denote the interaction between promotion price and the indicator for high-priced (low-priced) products. These coefficients capture how the promotion elasticity of high-priced (low-priced) NB products differs from that of mid-priced NB products.

A positive β_3^H (β_3^L) implies that the promotion elasticity of high-priced (low-priced) products is less negative than that of mid-priced products: that is, high-priced (low-priced) products are less promotion-elastic, and therefore experience a smaller sales lift from an equivalent price promotion. Conversely, a negative β_3^H (β_3^L) indicates that high-priced (low-priced) products are more promotion-elastic than mid-priced products and exhibit a larger sales lift from the same price promotion.

Based on $H2_a$, we expect $\beta_3^H < 0$ and $\beta_3^L > 0$, implying that higher-priced NB products are more promotion-elastic and lower-priced NB products are less promotion-elastic than mid-priced NB products. In contrast, based on $H2_b$, we expect $\beta_3^H > 0$ and $\beta_3^L < 0$, implying the opposite pattern.

Parameters β_4^H and β_4^L capture the three-way interactions among price promotion, brand type (NB vs. SB), and a product's price-tier indicator (high- or low-priced, with mid-priced products as the baseline). These coefficients test whether the relationship between product price level and promotional effectiveness differs between NBs and SBs. Equivalently, they measure how the differential promotional effect of high- or low-priced products relative to mid-priced products varies across brand types, and thus identify the incremental role of regular price in shaping promotional response for SBs relative to NBs.

Table 3
Operationalization of variables in (Eq. 1).

Variable	Operationalization	Unit
VOLSALES	Volume Sales. Total volume (in comparable units such as fl. oz., oz., count, or pound) sold per product–store in a given week.	Comparable unit
PRICE	Regular Price. Highest actual price in the preceding four weeks in U.S. dollars per unit.	$/unit
PROMO	Promotional Price. Promotional price, normalized by regular price (Datta et al., 2017): ratio of the actual price to the regular price. We use promotional price instead of promotional depth to avoid zero values, since the logarithm is not defined for them.	Ratio
HIGHPRICE	High Price = 1 if product is high priced, 0 otherwise. A product is classified as high priced if its regular price exceeds the 75th percentile of regular prices of products sold in the same store and category. Classification is performed at the product–store–category level and fixed over time using the product's median price tier across weeks. Thus, the price tiers are defined relative to store-category-specific price distributions.	1/0
LOWPRICE	Low Price = 1 if product is low priced, 0 otherwise. A product is classified as low priced if its regular price falls below the 25th percentile of regular prices of products sold in the same store and category. Classification is performed at the product–store–category level and fixed over time using the product's median price tier across weeks. Thus, if both HIGHPRICE and LOWPRICE are 0, mid-price products serve as the baseline option.	1/0
SB	Store Brand Indicator = 1 if product is a SB, 0 otherwise.	1/0
FEATURE	Feature Indicator = 1 if product is featured in store circular by the store in a given week, 0 otherwise.	1/0
WSCOMPROMO	Within-Store Competitor Promotions of other Products. Market-share–weighted average promotion depth of all other products (UPCs) sold in the same category, store, and week, excluding the focal product. Market shares are computed at the store–week level and smoothed using a 13-week rolling mean. We orthogonalize within-store competitor promotions from own promotions by regressing them on PROMO and using the residuals in our analysis (for a similar partialing-out procedure see Batra and Sinha (2000) or ter Braak et al. (2013).	Ratio
ORCOMPROMO	Other-Retailer Competitor Promotions of same Product. Average promotion of a given product (UPC) at other retailers in the same market. We orthogonalize competitor promotions from own promotions by regressing them on PROMO and using the residuals in our analysis.	Ratio
CF_MKTG	Control Function Terms, accounting for intercept (main effect) and slope endogeneity (interaction effect with SB_u).	NA

A positive β_4^H (β_4^L) indicates that the difference in promotional sales lift between high- (low-) and mid-priced products is less negative (or more positive) for SBs than for NBs. Conversely, a negative β_4^H (β_4^L) implies that SBs exhibit a larger differential sales lift between high- (low-) and mid-priced products than do NBs. Based on H3, we expect $\beta_4^H < 0$ and $\beta_4^L > 0$.

Lag and Lead Effects. Price promotions may generate intertemporal sales reallocation such as stockpiling or purchase anticipation (e.g., Guyt & Gijsbrechts, 2014; van Heerde et al., 2004), which, if unaccounted for, can bias contemporaneous promotion effects. To mitigate this concern, we include four lagged and four lead terms (weeks t – 1 to t – 4) of promotional price as controls. Our objective is not to interpret these dynamics structurally, but to absorb residual intertemporal correlation in demand that could otherwise affect the estimation of contemporaneous promotion elasticities.[3]

Control Variables. We include regular price and feature indicator as control variables in the model (Eq. 1). In addition, a sales lift due to a price promotion might result from stealing sales from other products in the same period from competitive retail outlets. To account for this effect in the aggregate, we include an aggregate competitive promotional term $ORCOMPROMO_{ust}$, which measures the promotional price of the same product at other retailers in the same market and week, as a control variable. Finally, we control for price promotions of other products in the same store and week, by adding $WSCOMPROMO_{ust}$.

4.2. Handling endogeneity

Promotional price ($PROMO_{ust}$), regular price ($PRICE_{ust}$), and feature ($FEATURE_{ust}$) variables in (Eq. 1) are strategic managerial decisions that capture unobserved demand shocks and the firm's strategic intent. Thus, they may be endogenous. We use a combination of rich fixed effects and instrumental variables in a control function specification (Petrin & Train, 2010) to address endogeneity concerns. The following fixed effects are included in the model:

(i) Fixed Effects that vary with Time/Week. Week–category–market to account for unobserved time-varying demand shocks (α_t). These include overall sales trends or seasonality for a given category and market.
(ii) Fixed Effects that vary with Store/Category. Store–category level to account for unobserved differences in the importance of a category at a given store (α_s). This would reflect factors general to the store, such as its size or positioning (e.g., HiLo vs. EDLP), and factors specific to a store-category combination, such as the amount of shelf space or the store's expertise in a given category.
(iii) Fixed Effects that vary with Store/Product. Product-store fixed effects that reflect unobserved differences in products, which may vary across stores ($\alpha_{u,s}$). These fixed effects capture general product (or brand or manufacturer) characteristics such as the product's quality, the power of the brand or manufacturer (e.g., the support for price promotions through trade deals) and

[3] The choice of four lead and four lag indicators is motivated by the structure of the data. Approximately 25 % of all observations involve a promotion (see footnotes a and b to Table 1), suggesting an average promotion cycle of roughly four weeks.

characteristics that vary across stores for the same product, such as higher store-specific product preferences or competitive pressure.[4]

After accounting for these three groups of fixed effects, endogeneity could stem from unobserved factors that vary over time for a given product-store combination. This possibility could include time-varying trade support or strategic price setting (e.g., a higher regular price to allow for deeper promotions). We address these possibilities with a control function approach, where we adopt instruments for the three endogenous marketing conduct variables. Inclusion of these instruments should address concerns of unobserved factors driving the marketing conduct. For each product–store pair, we use as instruments the average value of the marketing conduct variables of the *same* product sold at the *same* retailer at stores across the five most similar peer markets in neighboring states that are not covered by the same Nielsen designated market area (DMA).[5]

These instruments must fulfill three criteria (Wooldridge, 2010): instrument relevance, exclusion restriction, and instrument granularity. First, an identifying assumption is that the peer markets represent similar economic environments and face similar cost structures. Thus, changes in marketing conduct in peer markets driven by cost shocks (e.g., transportation costs, which are similar within a region but may differ across regions) should be conceptually and empirically relevant to changes in marketing conduct in treated markets.

Second, the instrument cannot correlate with omitted variables that form part of the outcome equation's error term, to meet the exclusion restriction. Although the focal retailer's marketing conduct in a single peer market may affect its price in the focal market, it is unlikely that the average across all stores in all peer markets directly correlates with a product's idiosyncratic shock in one market (e.g., Keller & Guyt, 2023; Sridhar et al., 2016).

Third, peer group–based instruments need to exhibit sufficient granularity, such that they vary at the same level as the endogenous variables, and the peer group composition must exhibit sufficient systematic variation such that not the same set of (i.e., not perfectly overlapping) peer groups is used across markets (Angrist, 2014; Shi et al., 2021). The instruments vary at the product and week level (just as the endogenous variables), and we determine the peer markets with a matching procedure that produces different sets of peer markets for each market in our dataset, which fulfills this criterion. The first-stage regression for marketing conduct (*MKTG*, capturing the promotion, price, and feature) (k), for a given product (u), store (s), and week (t) combination, includes all fixed effects from (Eq. 1), and the instruments (other variables are potentially endogenous), resulting in:

$$MKTG_{k,ust} = \sum_{k'=1}^{3} \partial_{k,k'}\ INST\_MKTG_{k',ust} + \alpha_{k,u,s} + \alpha_{k,t} + \varepsilon_{k,ust}, \quad (2)$$

where $INST\_MKTG_{k',ust}$ is the average value of the marketing conduct variable k across all stores in the corresponding peer markets of product u in week t, and $\partial_{k,k'}$ is the corresponding parameter. We obtain the residuals from (Eq. 2), which we include in (Eq. 1) as control functions for each marketing conduct variable. In line with Luan and Sudhir (2010) and Keller et al. (2020), we account for both intercept and slope endogeneity. Intercept endogeneity reflects the strategic setting of the marketing mix in response to unobserved time-varying demand shifters, and is commonly accounted for. Slope endogeneity, in contrast, deals with endogenous marketing mix decisions that relate to the differential effectiveness of the marketing mix (e.g., across different brand types). Accordingly, $CF\_\widehat{MKTG}_{k,ust}$ indicates the estimated residuals from (Eq. 2). Because the control function terms are estimated quantities, we adjust the standard errors as recommended by Papies et al. (2017).[6] Next, we present the model results on the relationship of product price with promotional effectiveness.

5. Results

Table 4 presents the average parameter estimates (as the model is estimated separately for each of the 2610 category-market pairs) from (Eq. 1) that we use to examine the effect of product price on promotion effectiveness for NBs and SBs, along with the percentages of the 2610 estimates in three groups: (+) positive and significant ($p \leq .05$), (−) negative and significant ($p \leq .05$), and (ns) not significant ($p > .05$); we derive heteroskedasticity and autocorrelation consistent (HAC) standard errors (Wooldridge, 2012, p. 432) for determining significance.

[4] Erdem et al. (2008) convincingly argue that marketing conduct is not endogenous and does not covary with changes in taste (which remain relatively constant). Furthermore, retailers may be unable to respond in a timely way to weekly variations in taste. Following this reasoning, the marketing conduct variations should be driven predominately by intertemporal discrimination, making these changes exogenous to consumer preferences. Berry et al. (1995) further argue that the relevant omitted variables for marketing conduct decisions, such as price, are product characteristics. Because they are time-invariant, product fixed effects should account for them. Other unobserved shocks are accounted for with the store-category and week-category-market fixed effects.

[5] Specifically, we match markets on four market and consumer characteristics (market size in sqm, median home value, median household income, and number of housing units), using Euclidean distances. Potential peer markets that can provide instruments are (1) located in a neighboring state and (2) not covered by the same Nielsen DMA, because marketing actions can be coordinated at this level.

[6] In a robustness check, we assess the stability of our estimates to an approach that focused only on fixed effects and did not include control function. Results are robust to this alternative identification strategy.

Table 4
Parameter estimates of promotional sales-response model (Eq. 1).

Dep. Var. = ***VolSales***$_{ust}$	Par.	Mean		(+)	(−)	(ns)
Price/Brand Type Variables						
Promo	β_1	−3.466	***	1.00 %	95.29 %	3.72 %
Promo x SB	β_2	1.066	***	56.40 %	6.02 %	37.59 %
Promo x High Price	β_3^H	.057	*	24.21 %	24.10 %	51.69 %
Promo x Low Price	β_3^L	−.051	***	28.12 %	18.74 %	53.14 %
Promo x High Price x SB	β_4^H	−.218	***	12.08 %	17.03 %	70.89 %
Promo x Low Price x SB	β_4^L	.225	***	20.30 %	13.34 %	66.36 %
Control Variables						
Price	γ_1	−2.833	***	1.69 %	92.95 %	5.36 %
Price x SB	γ_2	.687	***	52.38 %	14.44 %	33.18 %
Feature	γ_3	.520	***	86.95 %	.88 %	12.17 %
Competitor Promo (within Store)	γ_4	.437	***	45.21 %	6.36 %	48.43 %
Competitor Promo (other Ret.)	γ_5	−.073	***	7.89 %	23.93 %	68.19 %
Lag/Lead Variables						
Promo (lag 1)	β_5	.180	***	54.98 %	5.29 %	39.73 %
Promo (lag 2)	β_6	.017	***	19.77 %	11.00 %	69.23 %
Promo (lag 3)	β_7	−.081	***	5.17 %	32.49 %	62.34 %
Promo (lag 4)	β_8	.024	***	18.08 %	9.23 %	72.68 %
Promo (lead 1)	β_9	−.096	***	14.37 %	34.94 %	50.69 %
Promo (lead 2)	β_{10}	−.078	***	14.10 %	28.05 %	57.85 %
Promo (lead 3)	β_{11}	.353	***	81.26 %	.00 %	18.74 %
Promo (lead 4)	β_{12}	.091	***	35.33 %	1.95 %	62.72 %
Control Function Terms						
Residuals	δ_{1-3}	✓				
Residuals x SB	δ_{4-6}	✓				
Fixed Effects						
Product-Store	$\alpha_{u,s}$	✓				
Week(-category-market)	α_t	✓				

.

Notes: "Par." = Parameter. "Mean" represent the trimmed (at 1st/99th percentiles) average parameter estimates across the 2610 category-markets pairs. The average number of observations per category-market pair is 258,919 (= 675,779,135 / 2610). Significance levels are derived using meta-analytic p-values (method of added Zs; Rosenthal, 1991). Pos. (Neg., Not Sig.) reflect the share of parameters that are significantly positive (negative, not significant) at $p < .05$. To handle endogeneity, we use fixed effects and instruments. On average, all instruments (Instr) relate positively to their corresponding variables: promotion depth ($\eta_{1,1'} = .852$), regular price ($\eta_{2,2'} = .849$), and feature ($\eta_{3,3'} = .777$); see Table W3 of the Web Appendix. Also, Sanderson-Windmeijer multivariate F-tests (all p-values < .01; Papies & van Heerde, 2017) attest to the strength of our instruments. ✓ = included in equation 1; to avoid clutter, we do not provide their estimates. Table W4 of the Web Appendix provides the results of a gradual buildup of the model where we add variables in groups.
* $p < .05$, ** $p < .01$, *** $p < .001$

5.1. The effect of product price and brand type and promotion effectiveness

By disentangling the promotional sales lift due to product price and brand type, we are able to assess whether promotions by higher-priced products yield greater sales lift than promotions by mid-priced (the baseline) or lower-priced products, after unconfounding the brand type (NB vs. SB) effect. The results are given in parameter estimates β_1 to β_4 in Table 4. The average promotional price elasticity across products, categories, and markets for a mid-priced NB product is −3.466 ($\beta_1 = -3.466$, $p < .001$); negative and significant in 95.29 % of 2610 category-market pairs. In other words, when an NB product's promotional price decreases by 1 %, its volume sales increases by 3.466 %, on average. This (promotional) price elasticity is in line with similar estimates in the marketing literature (e.g., average price elasticity of −2.62 based on a meta-analysis by Bijmolt et al. (2005)

Consistent with H_1, SB promotions are less price-elastic than NB promotions, on average ($\beta_2 = 1.066$, $p < .001$) with more than 55 % of the 2610 (c-m pair) estimates showing a positive sign consistent with the sign of the average estimate. The average estimate of 1.066 indicates that the corresponding price elasticity changes from −3.466 to −2.400 (=−3.466 + 1.066) for a mid-priced product. In other words, when a SB's promotional price (index) decreases by 1 %, its volume sales increases by 2.400 %, on average, as opposed to 3.466 % for NBs.

The estimates suggest that higher-priced NB products are slightly less promotion elastic than mid-priced NB products ($\beta_3^H = .057$, $p < .05$) and lower-priced NB products are more promotion elastic than mid-priced NB products ($\beta_3^L = -.051$, $p < .001$). Together they suggest that lower-priced NB products are more promotion elastic than mid-priced NBs, and high-priced NBs less elastic than mid-priced NBs, consistent with $H2_b$ (and contrary to $H2_a$), though there is considerable heterogeneity in the significance of their individual estimates with just over 50 % of the individual estimates being non-significant ($p > .05$).

Finally, the three-way interaction effects of promotion, price, and brand type (NB vs. SB) show a symmetric negative effect of higher prices: the moderating role of price is, on average, flipped for high-priced ($\beta_4^H = -.218$, $p < .001$; $\beta_3^H + \beta_4^H = -.161$, $p < .001$) and low-priced SBs ($\beta_4^L = .225, p < .001$; $\beta_3^L + \beta_4^L = .174, p < .001$), supporting H_3. Put differently, these results suggest that high-priced SBs have a higher promotion elasticity than mid-priced and lower-priced SBs, contrary to the results for NBs. As with β_3^H and β_3^L, there is considerable heterogeneity in the significance of the β_4 individual estimates, with many not reaching traditional levels of significance.

We have established that the promotion elasticity is lower for SBs (than for NBs) and for more (vs. less) expensive products. For SBs, the role of price tends to flip and more expensive products enjoy a greater promotion elasticity. But how economically meaningful is the moderating role of a product's price level? To shed light on this, we calculate the promotion elasticities (PE) for four types of products, as shown in Table 5.

Fig. 2 presents the average promotion elasticity for these four product types.

The average promotion elasticity for a low-priced NB is −3.524, which is 3 % more elastic than that of high-priced NBs (−3.409). A high-priced SB's promotion elasticity is considerably less elastic at −2.557, though it enjoys a 12 % higher elasticity than low-priced SBs at −2.249. Thus, the differences across brand types (NB vs. SB) seem to be much more relevant than differences across price levels. As importantly, these differences persist for both low- and high-priced SBs.

5.2. Effects of control and promotional lag/lead variables on sales

We used regular price (for NB and SB), feature, and competitor promotions as control variables in the promotion model (Eq. 1). The corresponding parameters are γ_1 to γ_5. We also included four lag promotion variables and four lead promotion variables in Eq. 1. The parameters for lag/lead variables are β_5 to β_{12}. We briefly state and interpret these parameter estimates below.

The average (regular) price elasticity for NBs is −2.833 ($\gamma_1 = -2.833, p < .001$), with 93 % negative and significant as expected. The regular price elasticity for SBs is less negative than for NBs ($\gamma_2 = .687$). In particular, the average regular price elasticity is −2.146 (= −2.833+.687) for SB products compared to −2.833 for NBs. In other words, (regular) price reductions may not yield the same increase in sales for SBs as the same 1 % price reduction for NBs. We note, however, that this parameter (γ_2) shows substantial variation in significance across markets and categories. Being featured in the retailer's store circular increases sales substantially ($\gamma_3 = .520, p < .01$), in the expected direction and fairly consistent across categories and markets. Price promotions for other products in the same store decrease own product volume sales on average – as explained by product cannibalization ($\gamma_4 = .437, p < .001$). Price promotions for the same product by competing retailers in the same market marginally increase own product volume sales on average ($\gamma_5 = -.073, p < .001$), possibly through increased awareness. However, this effect is not significant in more than two thirds of the cases.

Lag effect estimates of promotions (β_5 to β_8) are generally positive, indicating that sales are generally lower if there has been a promotion in prior (four) weeks ($\beta_5 - \beta_8$), e.g., because of stockpiling. For example, the β_5 estimate of .182 suggests that larger promotions in the previous week result in lower sales in the current week. Lead terms are included to account for potential anticipation effects. Their estimates are not stable across horizons and are not interpreted substantively as such effects are often hard to reliably detect in aggregate (sales level) data. Moreover, these lead and lag intertemporal promotion effects are generally small and exhibit considerable variation in their sign and significance.

5.3. Robustness checks

We assess the robustness of our findings in three ways: (i) by introducing past promotion intensity as a potential driver of our results, (ii) by adding additional interaction terms with the feature variable, and (iii) by focusing on rich fixed effects to tackle the endogenous nature of marketing conduct rather than control functions (e.g., Keller et al., 2024). All of the additional parameters have the expected directions and, most importantly, do not affect any of the focal parameter estimates or key insights. In the interest of model parsimony, we retain the focal model specification and provide detailed results in Table W5 of the Web Appendix.

5.4. Heterogeneity in promotion effectiveness across categories and markets

Our extensive empirical estimation yielded 2610 promotional price elasticities across categories and markets. On average, we find NBs to have a higher promotion elasticity than SBs; this difference is more pronounced for low-priced than for high-priced products. Across all category-market pairs, we find a noticeable share of cases where these patterns do not hold, however. For example, on more than 16 % (415) of category-market pairs, low-priced SBs' promotion elasticity is higher than that of low-priced NBs' promotion elasticity. Such cases include many markets in the tortilla chips (in 23 out of 98 markets the low-priced SB promotion elasticity is

Table 5
Description of product types and calculation of promotional elasticity.

Type #	Type Description	Calculation of Promotion Elasticity
1	LP-NB: Low-priced NB products	$\beta_1 + \beta_3^L$
2	HP-NB: High-priced NB products	$\beta_1 + \beta_3^H$
3	LP-SB: Low-priced SB products	$\beta_1 + \beta_2 + (\beta_3^L + \beta_4^L)$
4	HP-SB: High-priced SB products	$\beta_1 + \beta_2 + (\beta_3^H + \beta_4^H)$

Notes: We use the same price cutoffs for NBs and SBs within a store and category.

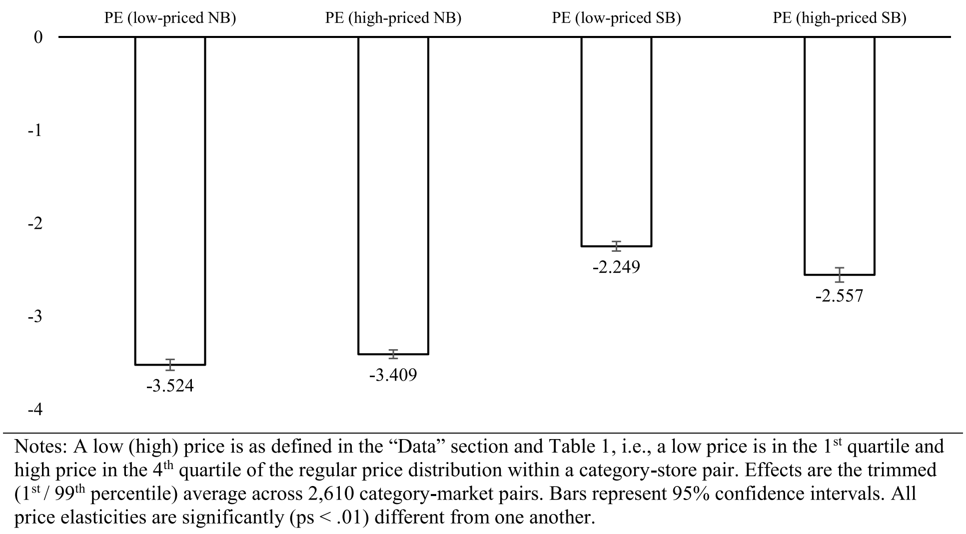

Fig. 2. Promotion elasticity (PE) by price level and brand type.
Notes: A low (high) price is as defined in the "Data" section and Table 1, i.e., a low price is in the 1st quartile and high price in the 4th quartile of the regular price distribution within a category-store pair. Effects are the trimmed (1st / 99th percentile) average across 2610 category-market pairs. Bars represent 95 % confidence intervals. All price elasticities are significantly (ps $<$ .01) different from one another.

greater than that of low-priced NBs), frozen novelties (20 out of 79 markets), and frozen pizza (33 out of 89 markets). Similarly, in more than 28 % of cases (727) high-priced SBs have a higher promotion elasticity than high-priced NBs.

What explains why in some categories and markets the promotion elasticity of SBs is a lot closer (or even greater) than that of NBs? This rich data set of promotion elasticities along with available variables compiled by us allows us to explore in what type of categories and markets price promotions are more impactful in increasing sales. Thus, in an exploratory fashion, we investigate the heterogeneity of product-level promotion elasticities across categories and markets next.

We calculate the promotion elasticities (PE) for the four types of products shown in Table 5 and explore their variation across

Table 6
Heterogeneity in promotion elasticities across categories and markets.

Par.	Dep. Var. = PE	Var. Description	Parameters			
			NB (low-priced)	NB (high-priced)	SB (low-priced)	SB (high-priced)
α	Constant		−3.427***	−3.399***	−2.317***	−2.601***
Market – Category Characteristics						
θ_1	PENETR	Penetration	−.003	.101**	−.097*	−.221***
θ_2	FREQ	Purchase Frequency	.500***	.517***	.481***	.532***
θ_3	SOB	Share of Budget	−.678***	−.756***	−.575***	−.665***
θ_4	PROMOFREQ	Promotion Frequency	−.093**	−.199***	−.082**	−.044
θ_5	PROMODEPTH	Promotion Depth	−.105***	.004	−.091**	−.151**
θ_6	BCONC	Brand Concentration	−.122*	.153***	−.064	.089
θ_7	RCONC	Retail Concentration	.099***	.113***	.092***	.032
θ_8	NBRANDS	Number of Brands	.045*	−.030	.036	.173***
θ_9	NSTORES	Number of Stores	.010	.049**	−.001	.021
θ_{10}	IMPULSE	Impulse Purchase	−.203***	−.092***	.110***	−.003
θ_{11}	STOCKPILE	Stockpilability	−.176***	−.039	.148***	.045
θ_{12}	CATSALES	Category Sales	.137***	−.035**	.008	−.128***
θ_{13}	SBSHARE	SB Share	−.208***	−.254***	.117***	.201***
Market – Household Characteristics						
θ_{14}	HHAGE	Household Age	−.065**	−.080***	−.058**	−.003
θ_{15}	HHINC	Household Income	.116***	.116***	.006	.020
Retail Characteristics						
θ_{16}	DRUGSTORE	Drug Stores	.024	.090**	.131***	.061
θ_{17}	FOODSTORE	Food Stores	.142***	.109***	.020	.040

Notes: PE = Promotion Elasticity. Dependent variables are trimmed at the 1 % and 99 % levels (hence number of observations in the above model is 2557, reduced from 2610. Because outliers vary across outcome variables, a slightly non-overlapping set of observations is used). Winsorizing and retaining all 2610 observations rather than trimming results in virtually identical results. Variable are weighted by the inverse of their standard errors. Covariates are standardized.
* $p < .05$, ** $p < .01$, *** $p < .001$.

categories and markets. For this analysis, we collected or compiled 17 relevant influencing category and market variables from four data sources – retail scanner data (RMS), household scanner data (HMS), American Community Survey (ACS), and a purpose-designed survey using Prolific. Most of these variables have been identified as potential determinants of promotional effects or elasticities in early studies – e.g., Bell et al. (1999), Narasimhan et al. (1996), Nijs et al. (2001), and Ailawadi et al. (2006). Table W6 in the Web Appendix lists these 17 variables, their operationalizations, data sources, as well as presents descriptive statistics.

We regress the promotion elasticity for each category (c) and market (m) on these 17 variables, as shown in the following equation.

$$\begin{aligned} PE_{cm} = {} & \alpha + \theta_1 PENETR_{cm} + \theta_2 FREQ_{cm} + \theta_3 SOB_{cm} + \theta_4 PROMOFREQ_{cm} + \theta_5 PROMODEPTH_{cm} + \theta_6 BCONC_{cm} + \theta_7 RCONC_{cm} \\ & + \theta_8 NBRANDS_{cm} + \theta_9 NSTORES_{cm} + \theta_{10} IMPULSE_c + \theta_{11} STOCKPILE_c + \theta_{12} CATSALES_{cm} + \theta_{13} SBSHARE_{cm} + \theta_{14} HHAGE_m \\ & + \theta_{15} HHINC_m + \theta_{16} DRUGSTORE_m + \theta_{17} FOODSTORE_m + \vartheta_{cm} \end{aligned} \tag{3}$$

We estimate the model in (Eq. 3) for each of the four product types: LP-NB, HP-NB, LP-SB, and HP-SB so we can look for commonalities in influencing variables across the product types, highlight, and explain differences. To account for the uncertainty in the dependent variables' estimates, we estimate (Eq. 3) with weights equal to the inverse standard errors of the estimates (e.g., Datta et al., 2022; van Heerde et al., 2013). We use heteroskedasticity-robust standard errors to assess significance. The results from the estimation of (Eq. 3) for the four types of products are in Table 6. We standardize variables such that the parameters can be interpreted as a variable's change of one standard deviation.[7]

The intercept term (α) measures the average value of promotion elasticity (when all covariates are at their mean) is negative for all four types of products, consistent with our expectations and economic theory. In line with Table 4, NBs generally have a higher elasticity than SBs. Of key interest are the parameters of the moderators: if parameters for the same moderators differ substantially across the four sample products, they may result in situations where SBs are as elastic as NBs.

We are most likely to find these cases if moderators' parameters go in opposite directions for NBs and SBs. In our sample, this is the case for stockpilability, impulse categories, and SB share. We find that particularly categories low in stockpilability, low in impulse purchases, and low in SB share account for smaller differences in promotion elasticities across brand types. Rather than discussing all moderators (most of which have a consistent effect across product types or are of limited economic significance), we focus on estimates with opposite directions for NBs and SBs as they have the greatest managerial relevance.

We find the parameters for "impulse purchase" to be negative and significant for NBs ($\theta_{10}^{LP-NB} = -.203$, $p < .001$; $\theta_{10}^{HP-NB} = -.092$, $p < .001$) but positive for low-priced SBs ($\theta_{10}^{LP-SB} = .110$, $p < .001$). That is, in more impulse-driven categories (e.g., soft drinks or potato chips), the price elasticity is higher for NBs but even lower for SBs. Conversely, in less impulse-driven categories (e.g., dog food or liquid bleach), the promotion elasticities for NBs and SBs get closer to one another. Why might this be the case? NBs traditionally have an advantage over SBs in that they are often on top of mind and thus enjoy greater mental availability (Ailawadi et al., 2001; Dickson & Sawyer, 1990; Hakala et al., 2012). In categories that are less impulse driven, consumers are more likely to plan purchases ahead, such that the top-of-mind advantage in the shopping aisle fades. Consequently, the promotion elasticity will be more comparable between NBs and SBs (Gupta, 1988; Slotegraaf & Pauwels, 2008).

Next, we find that stockpilability has a negative effect for NBs ($\theta_{11}^{LP-NB} = -.176$, $p < .001$; $\theta_{11}^{HP-NB} = -.039$, $p > .05$) but a positive effect for SBs ($\theta_{12}^{LP-SB} = .148$, $p < .001$; $\theta_{11}^{HP-SB} = .045$, $p > .05$). Thus, in categories with higher stockpilability (e.g., paper towels or batteries), NBs realize even greater promotion elasticities than SBs. This is in line with NB-based findings by Narasimhan et al. (1996) and Sun (2005), which report greater promotional effectiveness with higher stockpilability. If categories have less stockpilability (e.g., fresh cakes or orange juice), however, the difference in promotion elasticities gets reduced. This is in line with the fact that households are typically constrained in their ability to stockpile products (e.g., spoilage or space constraints), even when faced with an attractive price promotion. Thus, NBs' general advantage fades. What is more, products low on stockpilability often have an experiential component or are store-prepared (e.g., fresh cakes or fresh-squeezed orange juice), where retailers have an advantage and consumers' perceived value of SBs increases, resulting in greater promotional effectiveness and a narrowing gap with NBs.

Finally, we document a negative effect of a category-market pair's SB share on NB promotion elasticity ($\theta_{13}^{LP-NB} = -.208$, $p < .001$; $\theta_{13}^{HP-NB} = -.254$, $p < .001$) but a positive effect on SB promotion elasticity ($\theta_{13}^{LP-SB} = .117$, $p < .001$; $\theta_{13}^{HP-SB} = .201$, $p < .001$). One possible explanation for this finding is that higher SB share implies a larger pool of SB consumers that NBs can draw from; hence its promotion elasticity is higher or more negative. On the other hand, SB price promotions are less elastic in categories and markets with larger SB share than with smaller SB share. An explanation for this finding could be that higher SB share reflects greater SB strength. In categories or markets with such strong SBs, consumers are loyal to their SBs, do not buy them for their low price, and are not as influenced by their promotions. Hence, promotions are less elastic for SBs when their share is higher.

What are the economic consequences of these effects? On average, low-priced SB's promotional effectiveness is −2.317 compared to −3.399 of a high-priced NB. In categories with a SB share, stockpilability, and impulse purchase level at one standard deviation below the mean (such as orange juice in several markets), the promotion elasticities are almost identical to one another (LP-SB: −2.317

[7] The bivariate absolute correlations among the covariates are all below .70 with the highest correlations being .68 (PL share and brand concentration), −.67 (share of drug stores and share of food stores), and .62 (impulse purchase and penetration). In an additional analysis, we drop brand concentration, the share of drug stores, impulse purchase, and penetration as covariates to assess whether they affect the focal insights. The results are highly comparable.

−.117 −.148 −.110 = −2.692; HP-NB: −3.399 + .254 + .039 + .092 = −3.014).

5.5. Supplemental analysis: effect of price promotion on category sales

Our comprehensive empirical analysis pertained to incremental product sales lift from price promotions. In particular, we investigate whether price promotions by higher-priced products result in greater own product sales lift than price promotions by lower-priced products, and how this depends on the brand type. While greater sales lift for the promoted product is attractive for the product itself, it may come at the expense of other products offered in the same category. It is therefore also of interest to the retailer to assess whether retail price promotions increase category sales. To assess the effect of product price promotions on category sales, we estimate Eq. (4) akin to Eq. (1). We aggregate the data from the product-store-week level to the category-store-week level. All variables are also aggregated to the category level, using a product's (volume sales-based) market share within a store in the previous quarter (e.g., Datta et al., 2017), and denoted by a "ʻ".[8] Consequently, CATSALES is the sum of volume sales across all products in the category. We then estimate, again at the category-market level:

$$
\begin{aligned}
CATSALES_{cst} = {} & \underbrace{\beta'_1 PROMO'_{cst}}_{\text{promotion effect of mid-priced NBs}} + \underbrace{\beta'_2 SB'_c \times PROMO'_{cst}}_{\text{promotion effect difference for mid-priced SBs}} + \\
& \underbrace{\beta_3^{H'} HIGHPRICE'_{cst} \times PROMO'_{cst}}_{\text{promotion effect difference for high-priced NBs}} + \underbrace{\beta_3^{L'} LOWPRICE'_{cst} \times PROMO'_{cst}}_{\text{promotion effect difference for low-priced NBs}} + \\
& \underbrace{\beta_4^{H'} SB'_c \times HIGHPRICE'_{cst} \times PROMO'_{cst}}_{\text{promotion effect difference for high-priced SBs}} + \underbrace{\beta_4^{L'} SB'_c \times LOWPRICE'_{cst} \times PROMO'_{cst}}_{\text{promotion effect difference for low-priced SBs}} + \\
& \underbrace{\sum_{l=1}^{4} \beta'_{4+l} PROMO'_{cs(t-l)} + \beta'_{8+l} PROMO'_{cs(t+l)}}_{\text{intertemporal effects (lag\&lead)}} + \\
& \underbrace{\gamma'_1 PRICE'_{cst} + \gamma'_2 SB'_c \times PRICE'_{cst} + \gamma'_3 FEATURE'_{cst} + \gamma'_4 WSCOMPROMO'_{cst} + \gamma'_5 ORCOMPROMO'_{cst}}_{\text{control variables}} + \\
& \underbrace{\alpha'_{c,s} + \alpha'_t}_{\text{fixed effects}} + \varepsilon_{cst},
\end{aligned}
\tag{4}
$$

Table W7 of the Web Appendix provides the average parameter estimates (in bold) from (Eq. 4) and contrasts it with the product-level estimates of the focal model; we derive heteroskedasticity and autocorrelation consistent (HAC) standard errors. All focal parameter estimates (β'_1-β'_5) and relevant control variables (γ'_1-γ'_5) are directionally identical to the focal (product-level) parameter but smaller in magnitude. That is, all insights extend from the product- to the category-level but are less pronounced due to within-category switching included by price promotions.

6. Conclusion

This research is motivated by our desire to empirically test whether higher-priced products yield greater price promotional sales lift than lower-price products, as has been traditionally believed, and to assess the role of brand type (NB vs. SB). We develop three empirical models – first, for estimating product sales lift in the form of promotional price elasticity; second, to explore heterogeneity in the promotion elasticities; and third, to estimate incremental category sales due to price promotion.

The focal model is estimated using a comprehensive dataset with a total of nearly 700 million observations comprising 30 grocery categories in 100 markets, covering over 4000 brands and 60,000 products. This extensive data set on grocery products across 2500+ category-market pairs allows us to ascertain how the ability of price promotions to increase product-level sales depends on the brand type, the product's price level, and the interaction of the two.

In a second, exploratory, analysis, we investigate heterogeneity in the 2500+ promotional price elasticities across categories and markets obtained from the focal model. In the third analysis, we assess the category sales implications aggregating the data to the category-store-week level. Together, these three models provide numerous results, which help retail managers make informed price promotion decisions. The key empirical results and their corresponding managerial implications are presented in Table 7.

6.1. Future research

Our empirical findings raise a host of intriguing questions that can be deemed as starting points for future theoretical investigations. In particular, the following questions are germane:

[8] In doing so, we drop the within-store competitive promotion measure, which is not defined at the category level, and the control function terms because category-level price, feature, and promotion decisions are less likely to be endogenous than product-level decisions and replace product-store by category-store fixed effects. SB_c represents the (market-share-weighted) average of SB products within a category.

Table 7
Key empirical results and their corresponding managerial implications.

#	Key empirical results	Implication
1	Role of Brand Type. The average promotional price elasticity for mid-priced NB products is -3.466 and -2.400 for SB products at the same price level.	On average, a 1 % price discount for NBs, increases the promoted product's sales by 3.5 %, while SBs' sales only increase by 2.4 %. This difference is sizeable given that prior meta-analyses found no difference between SBs' and NBs' price elasticity (Bijmolt et al., 2005) though their focus was not to disentangle price and brand type. Ceteris paribus, NBs should be promoted more often than SBs.
2	Role of Price Level. The average promotion elasticity for high-priced products is greater than the promotional price elasticity for low-priced products, but only for SBs (−2.561 vs. −2.387). For NBs, the promotional price elasticity is lower, but the effect is of lower economic magnitude (−3.409 vs. -−3.517).	A product's price level plays less of a role in product's promotion elasticity than previously assumed. Yet, small differences exist and, on average, one should promote LP-NB over HP-NB and HP-SB over LP-SB for greater product sales lift.
3	Variation across Markets and Categories. Promotional price elasticity varies predictably across markets and categories, with the (economically) strongest factors being a category's share-of-budget (higher elasticities), purchase frequency (lower elasticities), SB share (effect depends on brand type), and purchase impulsivity (effect depends on brand type).	Price promotions for the same product can be expected to yield substantially different results across different markets and retailers. Similarly, the promotional sales lift varies drastically across categories. The randomness in variation can be drastically reduced using the 17 factors in the heterogeneity analysis. Managers should avoid one-size-fits-all price promotion strategies. Instead, they should tailor price promotions to category and market characteristics: For example, deep discounts work better in markets with older households or lower income levels.
4	Role of Brand Type and Price Level in Variation across Markets and Categories. Generally, price promotion elasticity varies similarly across markets and category for SBs, NBs, and high- and low-priced products. However, for SB share, purchase impulsivity, and stockpilability the effect depends drastically on the brand type.	NB promotions work better than SB promotions in markets and categories with a higher SB share as compared to markets with a low SB share. Similarly, in categories with a higher level of impulse purchase rate and higher levels of stockpilability, NB promotions have a greater advantage over SB promotions than in categories with lower levels of impulse purchase rate and stockpilability. Conversely, in categories with a low SB share, and high levels of impulse purchase rates and stockpilability, high-priced SBs may be as effective as NBs.
	A product's price level has less of an influence.	Retailers can use promotions on higher-priced SBs to directly compete with NBs and strengthen retailers' bargaining power.
5	Category Sales Implications. Directionally, all focal effects generalize from the product to the category level, i.e., promotions increase sales for all products, but mostly for low-priced NBs, followed by high-priced NBs, high-priced SBs, and least for low-priced SBs.	The smaller elasticities highlight that at least a portion of the promotional sales lift is driven by across-product switching within the same category and store. But because the elasticity is still positive, sales increase at the category level, either due to primary demand or store switching.

- We find lower-priced NBs to have a greater promotional price elasticity than higher-priced NBs, and advanced two reasons for that: their ability to attract store switchers and ability to charge prices below the impulse purchase threshold. Pinpointing the exact mechanism is a fruitful area for further research.
- Why is, despite reducing the quality gap, the promotional sales lift of NBs greater than that of SBs? Is it because of their (NBs) higher brand awareness, perceived quality, or trade support? SBs are typically unique to a given retail chain, while NBs are widely available, which may further drive differences. Recently, manufacturers have started to embrace offering exclusive products (Grey & Gielens, 2025), available only at a given retailer, which narrows the intrinsic differences of SBs and NBs further and allows an apples-to-apples comparison.
- Why are incremental category sales higher for lower-priced than for higher-priced products, contradicting the inference from asymmetric price-tier effects? Is it because of neighborhood price effects proposed by Sethuraman et al. (1999), the price-quality positioning explanation proposed by Bronnenberg and Wathieu (1996), the segmentation reason of Ailawadi et al. (2001), or other reasons?

On the empirical front, because we are able to compile a large number of promotion elasticities, we investigated some category and market characteristics that may potentially influence such promotional price elasticities. However, this heterogeneity analysis is primarily exploratory with the 17 potential influencing variables selected based on availability in four datasets and drawn from four prior studies. A second major research avenue is to go beyond our exploratory analysis and identify the product, brand, category, market, and retailer drivers of product sales lift and incremental category sales due to price promotions, both theoretically and empirically. In summary, we hope the insights from our empirical research inspire more work on price promotions as a core and influential marketing tactic.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jretai.2026.01.001.

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