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RESEARCH ARTICLE

The weakening pricing power of major brand over private label grocery products: evidence from a Dutch retailer

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Abstract

The primary objective of this research is to investigate and quantify how consumers' preference on name brand essential products has changed during the COVID period and beyond as characterized by their marginal willingness to pay for such brands over private labels. Based on existing theories, it is hypothesized that consumers' preference on name brand essential products has been weakened, and there is a shift of preference from name brand products to private label products either before the pandemic, during the COVID-19 pandemic and after the pandemic in the years of 2021 and 2022. We use sales data from a Dutch grocery chain to conduct empirical data analysis using a proposed discrete choice model on several essential product categories. The analysis supports the conjectural shift of preference from name brand products to private label products, which indicates unique growth opportunities and pricing power for private label products in the post-COVID era. These insights provide valuable theoretical and practical implications for retail business practitioners and name brand manufacturers, particularly in inventory planning and pricing strategy of both name brand products and private label products.

Keywords Private label · Store brand · Name brand · Price premium · Marginal willingness to pay · Discrete choice model

Introduction

Private label (or private brand) products cover a full spectrum of consumer packaged goods (CPG) and have been a worldwide phenomenon even before the COVID-19 pandemic (Cuneo et al. 2015). According to Biscotti (2020), the philosophy of private labels is evident, and the reasoning is crystal clear to retailers: A retailer need not spend costly resources in attempting to compete with popular brands when the retailer itself can be the brand, i.e., with the name of the retailer on the packaging. As far as the US retail market is concerned, private label goods have already accounted for as much as 80% of the store shelves of Trader Joe's as early as 2018 (Tyler and Taylor 2018). Costco's Kirkland signature brand attained $39 billion in sales in Costco's 2019 fiscal year, which accounted for 30% of its total revenue (Tarlton 2020). Moreover, according to Target (2020), Target initialized and grew its assortment to 8 private brands in 2019, including Good & Gather, Target's largest private brand. These three examples are specific cases in the retail industry manifesting the thriving growth and expansion of private labels before the COVID-19 pandemic.

The outbreak of COVID-19 in the fourth quarter of 2019 (WHO 2020) had shaken the world in an unusual way since the great influenza pandemic of 1918 (Morens and Fauci 2007). Early in the pandemic, due to herd behavior such as panic buying and pantry loading (Chua et al. 2021), many CPG brands disappeared from store shelves, among which is the most popularly stockpiled toilet paper products (see, e.g., Engstrom et al. (2021), Leung et al. (2021)). Therefore, some consumers were forced to buy private label products because of the unavailability of their preferred brands, and have continued to do so even when product supplies became stable, leaving tremendous room for private label products to keep growing. In addition, the fact that the unit prices of private label products are generally less expensive than those of the corresponding name brand products contributed as well since financially constrained consumers impacted by the pandemic have to tighten their belts. According to

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Begley and McOuat (2021), the dual advantages of better availability and lower pricing made private label products appreciably more enticing to consumers after the initial COVID-induced panic buying.

The shifting toward private label products is advantageous to retailers as well because private brands are typically more lucrative and cost-effective for retailers as compared to name brands Begley and McOuat (2021). Moreover, private brands with high quality and more reasonable prices can attract and retain devoted shoppers—a vigorous driving force in consumer loyalty to a retailer. The above brief description of the two benefits helps to explain why more and more retailers spent non-trivial amount of efforts in launching their own initiatives to build and promote their private labels even when popular CPG brands are stably back on the shelves at the time of this writing at the beginning of 2023 when the effect of the pandemic is more predictable as compared to the situation in early 2020.

The above discussion motivates this research, whose objective is to empirically investigate the shift in consumers' brand preference of grocery products from name brands to private labels. With retail sales data on 14 product categories of a supermarket chain in the Netherlands, we intend to answer the following three questions for each of the product category via the help of canonical discrete choice models (Train 2009): (1) Did consumers switch to private labels prior to the pandemic? (2) For product categories in which consumers did not yet switch to private labels, were consumers switching to private labels when COVID-19 became stable? (3) Would the trend of shifting to private labels persist into the post-COVID era? All are critical questions for which insights from analyzing retail sales data will not only help to confirm (or refute) the reported consumers' shopping behavior of private labels in the literature, but also bear important managerial meaning to retail merchandising practitioners allowing further optimization of its pricing strategies and supply planning practices.

With canonical discrete choice models, the focus is on how to quantitatively measure a consumer's preference of a brand. Assuming there are two competing brands: brand A and brand B for the same product, and further designating brand B as the baseline brand, we employ the concept of marginal willingness to pay (MWTP) (Train 2009; Park and Koo 2016) of brand A to fulfill the task. MWTP is a metric to gauge the price premium of a brand compared to the baseline brand. In other words, if the MWTP of brand A is above 0, it indicates consumers are willing to spend extra money to purchase brand A over the baseline brand (brand B), i.e., consumers prefer brand A and associate it with more value. More technical details will be presented in "Data, variables and the proposed modeling algorithm" section. In summary, through empirical analyses, we have identified 8 out of the 14 product categories, for which name brands could not charge a price premium even before the pandemic. For the rest of the 6 product categories, although name brands could still charge a price premium, their ability of doing so dwindled during the pandemic.

The rest of the paper is organized as follows. In "Literature review and hypotheses development" section, we provide some theoretical background and develop pertinent hypotheses based on our literature review. The data, variables, and the proposed modeling algorithm are detailed in "Data, variables and the proposed modeling algorithm" section. The analysis results are presented in "Analyses and results" section. We conclude with some remarks and describe future research work in "Discussion and concluding remarks" section.

Literature review and hypotheses development

Brand preference is an established routine for shoppers that is built over time with brand reputation, functionality, quality, advertisement, etc. It is the main factor why a name brand product can charge a premium price when competing with less well-established brands. The effect of brand preference on consumers' purchase intentions and choices have been studied by many researchers, for example Jara and Cliquet (2012) focused on retail brand equity attempting to understand where the retail brand value stems from and how to measure it, and Chang and Liu (2009) studied the impact of brand equity on brand preference and consumers' purchase intentions in the service industries. The authors then presented a structural equation model and have empirically confirmed the impact of brand equity on customers' brand preference and purchase intentions. In addition, Khenfer and Cuny (2020) investigated an interesting topic on how the pronunciation of brand names affects consumers' brand preference when consumers experience service failure. Throughout different experimental studies, the authors showed that consumers prefer brand names containing plosives (i.e., "b," "d," "p," and "t") as a compensation for a loss of perceived control inherent to service failure.

Among all the relevant literature, we have identified the following two articles that are closely aligned to our research. Kim et al. (2020) utilized a mixed logit model, a specific model belonging to the broad discrete choice model family (Train 2009) to analyze consumers' brand loyalty and interest for smartphones in South Korea. Throughout the empirical analysis on the stated preference, the authors concluded that Samsung has the highest interest and Apple has the highest brand loyalty among all the cellphone brands considered in the article. Another relevant article is about modeling brand preference evolution using discrete choice models, where Lachaab et al. (2006) quantified consumers' brand shifting with hierarchical Bayesian state space models of discrete choice. A nice feature of such a general Bayesian state space model is that it can capture unobserved heterogeneity and temporal variability in brand preferences. The authors then applied the developed model to a scanner dataset containing household brand choices over an eight-year period. Their analysis indicated that brand preferences exhibit significant variation over the time-span of the data.

As introduced in "Introduction" section, a private label product is different from a name brand product in various ways and has its unique features such as (1) better shelf availability, (2) lower unit price and (3) better profitability for the retailer. The research on consumers' choice of private label products dates back to over half a century ago. Collins-Dodd and Lindley (2003) studied how store image and store impression influence consumers' attitudes toward the store's own brand products using regression models. Baltas et al. (1997) employed a nested multinomial logit model (MNL) to study consumer choice under situations where name brands and private labels competed directly for the consumers' patronage. The authors applied the proposed model to panel data on a frequently bought food product and concluded that consumers' attachment to private labels, once switched is high since if the leading name brand cut price by 10%, it drew 4.74% sales quantity from other name branded competitors but only 2.77% from the private labels. In a more specific paper that concerned US consumers' behavior, Boyle and Lathrop (2013) investigated the value of private labels to consumers using both subjective evaluation on survey responses and objective measures of price and quality for private labels and national brands in the US. The authors have concluded that the quality gap that determined the "quality premium" of name brands had largely vanished.

In addition, consumer motivations for private label grocery purchases were examined by McNeill and Wyeth (2011), where the authors used shoppers' data in New Zealand. Through analysis, the authors suggested that product category was the most important factor in determining choice between a private label and a branded good. Zhuang et al. (2009) studied consumer choice of private label or national brand for the case of organic and non-organic milk using the discrete choice model. A bunch of different factors affecting choice have been identified, among which the authors found that when the national brand price increases, non-organic buyers were more likely to buy private label milk. Admittedly, there is extensive literature about consumers' choice of private brand or name brands for various products and/or product categories, and we are merely able to review articles that are are more pertinent to our research objectives. It is also intriguing to note that for the majority of the papers reviewed so far, the discrete choice model(Train 2009) is a common preference, which is also the model we will use in this research.

Private label products kept growing during the COVID-19 pandemic (Biscotti 2020) because of better shelf availability and lower unit prices, which were extremely important in the early stages of COVID-19. Needless to say, COVID-19 have profound impact on consumers' shopping behaviors, and studies about this are plentiful in the literature. Diallo and Kaswengi (2016) employed dynamic choice models to assess how marketing policy and consumer characteristics affect the choices of private brands across 4 different product categories during specific crisis periods. The authors empirically confirmed that product price has a positive effect on private labels in times of crisis. Omar et al. (2021) carefully investigated how psychological factors such as uncertainty, perceptions of severity affected the panic buying behavior of consumers using empirical data from Malaysia. The pandemic's impact on consumers' e-commerce shopping behavior was studied by Guthrie et al. (2021), and the authors made important observation on how consumers utilized e-commerce online shopping platform to react to and adjust to periods of environmentally imposed constraints, such as the COVID-19 pandemic.

Moreover, Chen and Lim (2023) studied how the pandemic impacted Dutch consumers' price sensitivity to life essential products, and the authors confirmed via empirical analysis that consumers were indeed less price sensitive to life necessities during the COVID-19 pandemic. Zuokas et al. (2022) analyzed 150 product categories using the data of a supermarket chain in the Netherlands and showed that there was a large but brief growth at 30.6% in excess sales associated with panic buying across most product categories within a two-week period using time series forecasting techniques. In addition, with time series clustering, the authors also projected that product categories used for cooking, baking or meal preparation in general will have elevated sales even after the pandemic. Furthermore, Lim et al. (2023) made observation via quantitative analyses that the COVID-19 pandemic boosted online shopping at the expense of in-store sales. The authors also concluded that the pandemic not only drove consumers to stock-up on shelf-storable fruits, but also triggered a demand shift towards organic poultry and beef products over conventional ones that is trending towards a new normalcy.

When the COVID-19 pandemic became more stable, some of the consumers who previously had to purchase private label goods as a result of their preferred brand products being out of stock due to panic buying (Chua et al. 2021) stayed with private labels because private label products satisfied their needs (Gielens et al. 2021) and met their expectations (Nuru 2020). Financial consideration was also one of the factors driving shoppers to private labels as they become economically impacted by the pandemic (Zheng et al. 2021). Doering (2022) reported that private labels were becoming more appealing to shoppers amid a sweeping increase in food prices when the pandemic became more stable. Similarly, according to a survey by McKinsey (Begley and McOuat 2021), nearly 40% of US consumers had tried private label products since the onset of COVID-19, and much of the switching behavior was because of availability issues as we had already mentioned before. Although there are extensive papers and online articles qualitatively discussing the growth of private labels in the literature, as far as we know, there is a gap in the literature on the quantification of the shift (if any) from major brands to private labels during the COVID-19 pandemic and also whether the shift is temporary or sustained. Aided by the discrete choice models, our research closes this gap by statistically examining and confirming that there was indeed a shift to private label products. In particular, we aim to test the following three hypotheses:

1. Hypothesis 1: For highly substitutable products, the shift from major brands to private labels occurred even before the COVID-19 pandemic.
2. Hypothesis 2: For non-highly substitutable products, there was a shift from major brands to private labels during the COVID-19 pandemic.
3. Hypothesis 3: For non-highly substitutable products, the shift to private labels persists into the post COVID-19 period.

There are still two issues that require further discussions. First, we are not aware of a standard definition of highly substitutable products. In this paper, we therefore regard products as highly substitutable as long as the product meet either of the following conditions depending on the product category: (1) For food products, it does not involve taste, for which consumers would likely have their preferred flavor and/or brand that have been established over time (Yamada et al. 2014); or (2) For household products, the switching cost is zero (El-Manstrly 2016), i.e., it did not require any further learning process to switch from one product to another. Second, the concept of brand shifting is abstract. We propose to concretely quantify it by estimating the ability for a name brand product to charge a price premium compared to the private label product, which is modeled by a discrete choice model. More details about the product categories and the way we measure price premium will be presented in "Data, variables and the proposed modeling algorithm" section.

Last but not least, with all the literature that has been reviewed, our originality can be concisely summarized in the following three perspectives. First, we treat store brand as the independent variable instead of dependent variable in the proposed regression model, and consumers' brand preference is quantified by the average price premium, explicitly measured by the MWTP. Second, sustainability has been taken into account when constructing hypotheses as we aim to investigate the long term effect, and it tends to evaluate if the trend in shift from major brands to private labels carries into the post-pandemic era or not. Third, the proposed measurement can apparently indicate if the gap in consumers' brand preference becomes narrow or wide, which can be used to provide important managerial recommendations to supply chain and pricing practitioners in the retail and CPG industries.

Data, variables, and the proposed modeling algorithm

We first review some important technical details before the proposed model is presented. The theory of random utility explains how a consumer makes a decision when facing J different alternatives. In particular, the utility for the consumer picking the jth alternative is modeled as a linear function as follows:

$$U_j = V_j + \epsilon_j, \tag{1}$$

where V_j is the deterministic term and is often framed as a linear combination of p product features,

$$V_j = \beta_{j0} + \sum_{k=1}^{p} \beta_{jk} x_{jk} \tag{2}$$

and ϵ_j is the stochastic term, which is usually assumed to follow a parametric distribution for the ease of statistical inference. In other words, ϵ_j is the systematic error that the model is unable to explain. With the proposed equations (1) and (2), the choice probability (Train 2009) for the jth product is given as follows.

$$P_j = \frac{\exp(V_j)}{\sum_{t=1}^{J} \exp(V_t)}. \tag{3}$$

In plain language, the larger the utility is, the higher the probability that the product will be chosen by the consumer. The contribution of each product feature to its utility is modeled as a linear function in equation (2). In addition, working under the above discrete choice model, an estimate of MWTP for the kth ($k = 1, \ldots, p$) feature can then be computed as

$$\mathrm{MWTP}_k = -\frac{\delta U_j / \delta x_k}{\delta U_j / \delta x_{\mathrm{price}}} = -\frac{\beta_k}{\beta_{\mathrm{price}}}, \tag{4}$$

where MWTP is the indicative amount of money customers are willing to pay for a particular feature of the product. Please note that when estimating MWTP, unit price (the price for a unit quantity of measurement) must be included in the model as one of the k product features as equation (4) involves β_{price}. In the scenario of brand comparison, we further define price premium (PP) of brand A versus a baseline brand as $-\frac{\beta_A}{\beta_{\text{price}}}$, in which β_A is the coefficient of the binary brand indicator variable x_A such that

$$x_A = \begin{cases} 1 \text{ if the product is brand A,} \\ 0 \text{ if the product is the baseline brand.} \end{cases} \quad (5)$$

Now, with all the important concepts reviewed, we propose a model that quantifies unit price of $m + 1$ brands for a given product category. In addition, two confounding factors, seasonality and inflation, are included in the model. The model is same as Equation (1) and

$$V_j = \beta_0 + \beta_p x_{jp} + \eta_k x_{jk} + \beta_{\text{seasonality}} x_{\text{seasonality}} + \beta_{\text{inflation}} x_{\text{inflation}}, \quad (6)$$

and the stochastic term $\epsilon_j \sim N(0, \sigma^2)$. Note that x_{jp} is the unit price of product j, and x_{jk} is a binary indicator variable such that x_{jk} is 1 if the jth product is brand k, and 0 otherwise, and the possible range of k is from 1 to m. The proposed model introduces the m name brands, while leaves out the private label brand that is treated as the baseline brand. The unit price has already taken the packaging size into consideration.

In addition, the calculation of seasonality and inflation is at the aggregated product category level, i.e., regardless of product and brand, seasonality is computed by comparing the sales volume of a given period, e.g., week i to the average sales volume of all periods in consideration for all products. Inflation is computed by comparing the unit price of a given period to its baseline, which is a rolling average of its S adjacent periods, and S is one of 4, 8, 12, 24. The best S is determined by the log-likelihood value, a metric of model fitting under the paradigm of maximum likelihood estimation (MLE) (Casella and Berger 2001).

It is also plausible to have one composite metric by defining the concept of average price premium (APP) of the m name brands to the private label as

$$\text{APP} = \sum_{k=1}^{m} \left(-\frac{\eta_k}{\beta_\text{p}}\right) w_k, \quad (7)$$

where the weighting factor is each brand's total volume, i.e., $w_k = \frac{\text{total vol}_k}{\sum_{k=1}^{m} \text{total vol}_k}$.

We use the sales transaction data from a Dutch grocery chain to conduct empirical analyses to test the three hypotheses. In total, we have considered 14 product categories that contain multiple products within each category that may differ not just in brand but also in package sizes. This is also the reason why unit price is utilized in the proposed model in equation (6). The 14 product categories are presented below.

- Food and beverage: (1) raw chicken, (2) raw beef, (3) fresh fruit, (4) fresh salad vegetable, (5) baguette bread, (6) spreadable cheese, (7) milk, (8) extruded snacks, (9) Earl Grey tea.
- Household products: (10) toilet paper, (11) dishwasher pods, (12) fabric softeners, (13) shampoo, (14) toothpaste.

The 14 selected product categories cover a full scope of life necessities (Kelly et al. 2012), ranging from basic food and drink, such as raw beef and milk to household chemicals such as shampoo and toothpaste. The specification of these product categories is a result of both the research interests and the availability of the retail data, which can well cast a comprehensive picture of how consumers' brand preference has shifted. In addition, the grocery chain carries quite a few private label products in these categories that are named after the grocery chain.

Before any model is fitted, results on exploratory data analysis are presented in Table 1 for the whole year of 2019, i.e, from December 30, 2018 to December 28, 2019—a total 52 weeks. In Table 1, g stands for gram, ml stands for milliliter. The fourth column (unit price) is computed as sales amount/total sales volume. In addition, the fifth column (No. of Brands) includes the private label brand, for example, for raw chicken, it includes 2 name brand products and 1 private label brand from the retail chain rendering 3 in the fifth column. For the last column (No. of Stores), the number of stores will be counted as long as it carries at least one product for the product category.

From Table 1, it is obvious that the selected 14 product categories make up both some large categories, for example the raw chicken category has about € 98 million sales and some small categories such as earl grey tea category with less than € 1.5 million sales in 2019. The purpose is to consider as much diverse product categories as possible, for which consumers could exhibit distinct preference over brands.

Following the core idea of Chen and Lim (2023), we specify three non-overlapping periods: (1) the pre-COVID period, which is from December 30, 2018 to December 28, 2019; (2) the COVID period, which is from July 5, 2020 to July 3, 2021; (3) the post-COVID period, which is from July 5, 2021 to March, 13, 2022 to investigate the change of consumers' brand preferences. To be clear, the COVID pandemic was still in effect during the last period, but we so name it because COVID vaccines became generally available in the period and consumers' shopping behavior gradually shifted to a new normal with the help of the vaccines. Furthermore, the determination of the above three time intervals is a combination of scientific evidence and availability of data: Since the available data are from a Dutch retailer, the COVID period is defined to align with

Table 1 Exploratory data analysis of the 14 categories from a major Dutch retail chain

Category	Sales amount	Total sales volume	Unit price	No. of brands	No. of products	No. of stores
Raw chicken	€ 98,393,564	10,223,900,649 (g)	€ 0.00962	3	118	632
Raw beef	€ 96,757,163	13,900,913,261 (g)	€ 0.00696	4	116	631
Fresh fruit	€ 92,745,591	16,757,141,659 (g)	€ 0.00553	4	46	632
Fresh salad vegetable	€ 5,562,625	735,864,685 (g)	€ 0.00756	3	42	632
Baguette bread	€ 13,204,953	3,988,114,370 (g)	€ 0.00331	3	23	631
Spreadable cheese	€ 19,851,516	2,167,154,080 (g)	€ 0.00916	5	44	631
Toilet paper	€ 35,111,667	104,908,196 (roll)	€ 0.33469	4	33	632
Dishwasher pods	€ 9,653,926	82,244,388 (pod)	€ 0.11738	4	45	632
Milk	€ 56,248,796	61,818,237,100 (ml)	€ 0.00091	3	29	632
Earl grey tea	€ 1,407,822	27,076,840 (bag)	€ 0.05199	4	10	631
Extruded snacks	€ 25,847,716	2,609,130,122 (g)	€ 0.00991	4	46	632
Fabric softeners	€ 5,490,566	1,745,215,190 (ml)	€ 0.00315	4	62	632
Shampoo	€ 5,204,249	608,085,150 (ml)	€ 0.00856	5	44	631
Toothpaste	€ 8,884,537	266,184,700 (g)	€ 0.03338	4	63	632

the Dutch government's announcement that supermarket and restaurants could reopen from June 1, 2020 (Medicalxpress 2020) after a lock-down period. In other words, the period of COVID-induced panic buying is not included from the COVID period in the analysis to get a much clearer picture of consumers' grocery purchasing behavior in the period.

For each of the 14 product categories, we first fit the proposed model with the private label brand as the baseline that is not included in the model for the whole year of 2019. If the estimated APP is less than 0, it stops as it indicates that even before the pandemic, the p major brands was not able to charge a price premium. Nevertheless, if APP is greater than 0, we will then fit the same model for the COVID period and the post-COVID period, and then compare the APP of pre-COVID with that of the COVID period as well as the post-COVID period. The proposed algorithm is encapsulated in Algorithm 1, which is more succinct than the above verbal description.

Analyses and results

Following the logic of Algorithm 1, we have identified 8 out of the 14 product categories with negative APP in the pre-COVID period. The remaining 6 categories have a positive APP in the pre-COVID period, so the same model is fitted with the data in the COVID period and the post-COVID period. The results for all the 14 product categories are reported in Tables 2 and 3, respectively. In total, 26 separate models have been fitted. The detailed modeling results are presented in the Appendix in a separate document.

From Table 2, it is apparent that all of the 8 categories that had a negative APP in the pre-COVID period are highly substitutable, for instance raw chicken, raw beef and salad vegetable, for which further culinary processes such as roasting, boiling, and seasoning are entailed to have the food ready-to-serve. Therefore, it is understandable that consumers did not show a strong brand preference of name brands

Algorithm 1 The proposed modeling algorithm

procedure PP MODELING
  For each product category
  Fit the proposed model for the pre-COVID period and compute the average PP (PP_{prior})
  if the average PP <0 **then**
    Break (Hypothesis 1 is supported)
  else
    Fit the proposed model for the COVID period and post-COVID period and compute the average PP for the two periods: PP_{COVID} and PP_{post}
    if $PP_{\text{COVID}} < PP_{\text{prior}}$ **then**
      Hypothesis 2 is supported
    if $PP_{\text{post}} < PP_{\text{COVID}}$ **then**
      Hypothesis 3 is supported
    Stop

Table 2 The 8 categories have already shifted to private label in the pre-COVID period

	APP Pre-COVID
Raw chicken (1 g)	€ -0.00483
Raw beef (1 g)	€ -0.00226
Fresh fruit (1 g)	€ -0.00167
Raw salad vegetable (1 g)	€ -0.00578
Baguette bread (1 g)	€ -0.00210
Spreadable cheese (1 g)	€ -0.00367
Toilet paper (1 roll)	€ -0.11966
Dishwasher pods (1 pac)	€ -0.06610

for these raw ingredients. The same reasoning also applies to bread, cheese as well as "raw" household products such as toilet paper and dishwasher pods. For all the 8 categories in Table 2, consumers had already shifted to the private labels even before the COVID-19 pandemic, supporting Hypothesis 1.

The numbers reported in Table 3 are visualized in Fig. 1 using bar charts. From both Fig. 1 and Table 3, we can safely conclude that for all of the remaining 6 product categories, the APP of the COVID period is less than that of the pre-COVID period suggesting that compared to the private labels, the name brands can still charge an overall price premium but their ability to do so weakened in the COVID period. Moreover, the trend persists into the post-COVID period as all of the 6 numbers are lower for the post-COVID period as compared to those of the COVID period. In other words, both Hypothesis 2 and Hypothesis 3 are firmly supported by the empirical examination of the 6 product categories.

In addition, it is also observed that no matter if it is milk, Earl Grey tea, snacks, shampoo, or toothpaste, the product categories have characteristics involving flavor, taste or scent, which are different from most of the raw product categories reported in Table 2. This may be the reason why name brands can still charge an overall price premium compared to the private labels. However, the COVID pandemic has gradually "exhausted" consumers' preference of name brands, and focused more on the product functionality itself

Table 4 Market share of the private label for the 6 categories that consumers were shifting to private label

	Pre-COVID (%)	COVID (%)	Post-COVID (%)
Milk	83.27	84.49	84.77
Earl grey tea	18.14	22.81	32.54
Extruded snacks	3.84	7.96	9.57
Fabric softeners	29.81	35.03	39.92
Shampoo	23.99	24.84	25.82
Toothpaste	4.58	5.57	6.54

Table 5 Actual price premium of the 6 categories that consumers were shifting to private label

	Pre-COVID	COVID	Post-COVID
Milk (1 ml)	€ 0.00030	€ 0.00022	€ 0.00025
Earl grey tea (1 bag)	€ 0.02130	€ 0.02762	€ 0.04061
Extruded snacks (1 g)	€ 0.00185	€ 0.00442	€ 0.00515
Fabric softeners (1 ml)	€ 0.00139	€ 0.00353	€ 0.00566
Shampoo (1 ml)	€ 0.00839	€ 0.00864	€ 0.00918
Toothpaste (1 g)	€ 0.02710	€ 0.02956	€ 0.02837

to fulfill the need. It is therefore not very surprising that the name brand products are steadily losing their edge in charging a price premium over their private label counterparts.

Moreover, for the 6 product categories for which name brands' pricing power has been weakened, we also report the market share of the associated private labels in Table 4 and the actual unit price premium between name brands and private labels in Table 5 as calculated from the available data for each period. From Table 4, it is clear that the private labels' market share kept increasing for all the 6 product categories, although the absolute market share varies from one category to the another.

The actual price premium reported in Table 5 offers some sensible explanations for the root cause of private labels' increasing market share: If one compares the actual price premium in Table 5 to the theoretical numbers in Table 3, it is apparent that with merely a few exceptions, the majority of the actual price premium is larger than the theoretical numbers. For example, the actual price premium for milk in

Table 3 The 6 categories that consumers were shifting to private label

	APP pre-COVID	APP COVID	APP post-COVID
Milk (1 ml)	€ 0.00058	€ 0.00037	€ 0.00018
Earl grey tea (1 bag)	€ 0.04135	€ 0.02284	€ 0.02098
Extruded snacks (1 g)	€ 0.00298	€ 0.00163	€ 0.00138
Fabric softeners (1 ml)	€ 0.00203	€ 0.00143	€ 0.00124
Shampoo (1 ml)	€ 0.00626	€ 0.00532	€ 0.00399
Toothpaste (1 g)	€ 0.01259	€ 0.00853	€ 0.00668

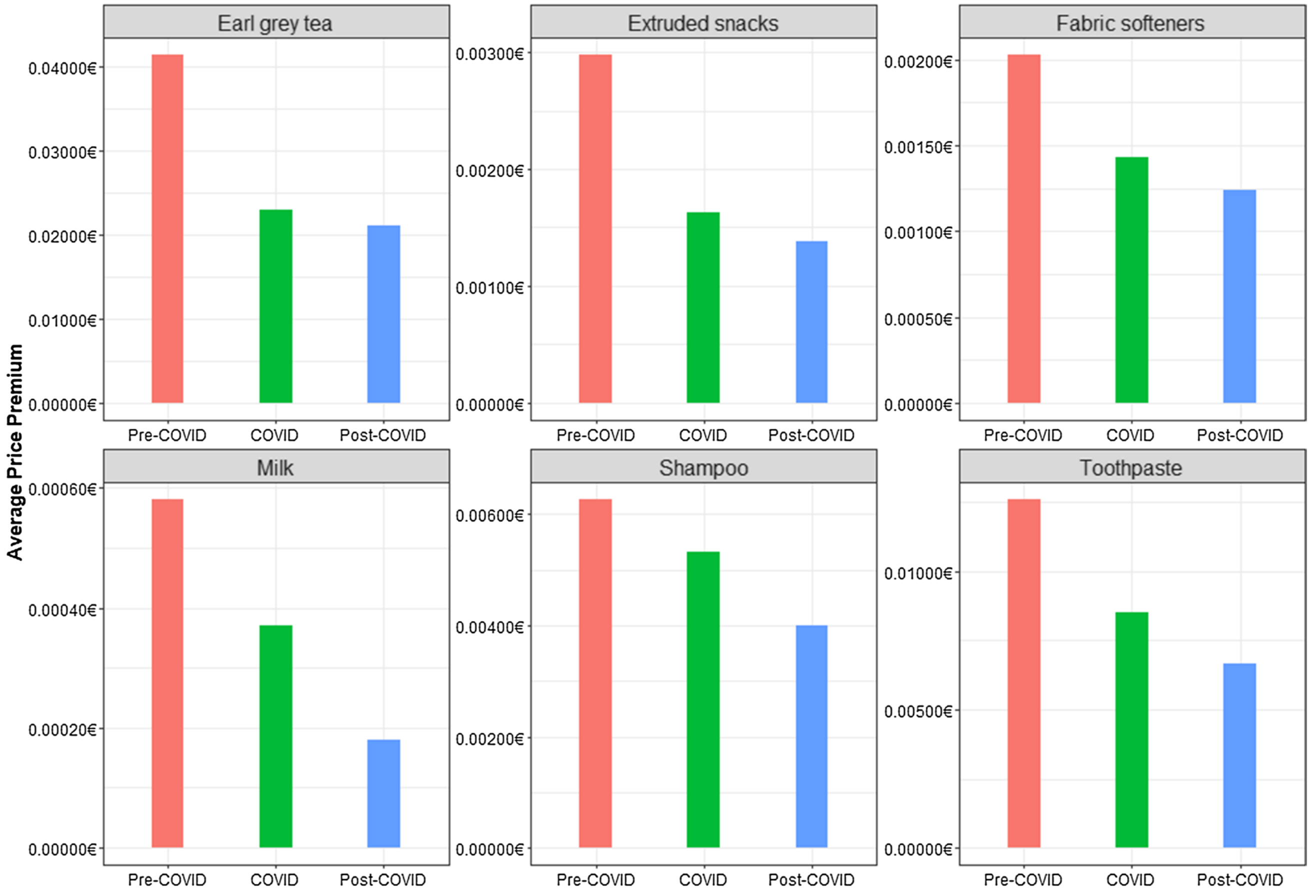

Fig. 1 Visualization of the 6 product categories that consumers were shifting from major brands to private label

the post-COVID period is 0.00025 versus 0.00018 as suggested in Table 5. In other words, if one treats the numbers in Table 3 as the recommended price premium, any number that is greater than it will be perceived as unfair pricing leading to a decrease of its market share. In fact, the theoretical price premiums in Table 3 constitute a fair pricing strategy, for which a lower price premium leads to potentially missed revenue, while a higher price premium would possibly result in a loss in market share.

Discussion and concluding remarks

The primary objective of this study is to explore how consumers' brand preference had been impacted by the COVID-19 pandemic. Three hypotheses have been developed and validated via empirical analyses of data from a Dutch retailer: (1) For highly substitutable products, the shift from major brands to private labels had occurred even before the COVID-19 pandemic; (2) For non-highly substitutable products, there was a shift from name brands to private label during the COVID-19 pandemic. (3) For non-highly substitutable products, the shift to private labels persists in the post COVID-19 period. The concept of brand shift is abstract, so we have explicitly quantified it using the metric of price premium of a brand compared to the baseline. Through the proposed modeling algorithm via a discrete choice model, we have identified 8 out of the 14 product categories that support Hypothesis 1, and the remaining 6 product categories confirmed Hypothesis 2 and Hypothesis 3 as evidenced from actual transaction data of a grocery chain in the Netherlands. Through this research, we not only demonstrated the usefulness of the proposed modeling algorithm, but also derived a number of valuable theoretical and managerial contributions discussed below.

First, the 14 product categories were analyzed separately to allow inference of consumers' brand preference in each category before and during the COVID-19 pandemic, which ensured flexibility of the possible structural difference across categories. For highly substitutable products, consumers had already switched to the private label products, while for non-highly substitutable products, the major brands could still charge a price premium, but their ability to so had weakened.

Second, in terms of data, unlike existing research literature that employs data collected from questionnaires to study consumers' perception of COVID-19 and its impact on the retail industry, the transaction data analyzed in this paper were directly collected from the Dutch grocery chain, which permits the estimation of the price premium for each of the brand at product category level. Unlike surveys collected from the consumer's side, the sales data provide an important perspective and a different view from the retailer's end. The modeling and data analysis can then be straightforwardly applied by retail and CPG supply chain and pricing practitioners in real-world business scenarios to make critical managerial decisions.

Third, we selected three non-overlapping time intervals in the research: (1) the pre-COVID period, (2) the COVID period, and (3) the post-COVID period to explore the impact of the pandemic on price premium of the brands considered for each of the product categories. As the effect of COVID on consumers' panic buying is non-trivial from the literature review in "Literature review and hypotheses development" section, the COVID panic hoarding period is not included in the research to reduce its impact on the analysis.

In addition, the research also provided important managerial insights. Among the different product categories, the name brands need to adjust its sales and promotion strategies accordingly for all the 6 categories that have been analyzed, which showed practically smaller APP's as compared to private labels during the COVID period and continue to trend down in recent months. For example, the name brands need to have more and stronger marketing efforts in order to retain consumers that could switch to private labels. At the very least, any CPG company needs to carefully watch for the possible further change in consumers' brand preference for important product categories, particularly its brand's pricing premium over private labels, and act swiftly when a considerable pattern is recognized through similar analysis. Similarly, grocery retailers should consider decreasing the discount of its private label products over their name brand counterparts and adjust demand forecasts in their supply chain systems accordingly.

Last but not the least, the APP values reported in Table 3 can actually be treated as a theoretical values for fair pricing. It would provide imperative insights on fair pricing, if retail practitioners could compare their actual price premium with the theoretical number and adjust accordingly. Based on the APP, it would also supply an important way for optimal price recommendation, which constitutes one of the future work that motivated by this study. Furthermore, admittedly a limitation of this research is that the current analysis was only performed on Dutch retail data, but the methodology employed in this paper is a general one, and it can be applied on data from the same or different product categories of other retailers in the different parts of the world when data become available. As the COVID-19 pandemic is not completely over with new variants, it is interesting to observe if the insights from this research form a "new normal" consumer behavior towards brand preference into 2023 and beyond or merely a temporary reaction to the health crisis. This will also constitute an interesting future research project following this article.

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Data availability The data that support the findings of this study are available from the corresponding author, HC, upon reasonable request.

Declarations

Conflict of interest The authors have no conflict of interest to declare.

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