Graphical Abstract

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Highlights

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- Private label market share increases as average wage and the number of stores increase.
- The average wage enhances the negative effect of the number of brands, weakens the negative effect of the private label price, weakens the positive effect of national brand price.
- The number of stores enhances the positive effect of the SKU proliferation of private label, enhances the negative effects of the number of brands , and enhances the negative effect of the private label price.

The Moderating Effect of Average Wage and Number of Stores on Private Label Market Share: A Hierarchical Linear Model Analysis

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ABSTRACT

Existing research on private label market share is primarily in the context of the Western market. The Chinese market context research is scarce, although private labels are developing rapidly in the past several years. This study investigates how the average wage and number of stores affect the Chinese market's private label market share. More importantly, this paper examines the moderating effect of the average wage and the number of stores on the relationship between the private label market share and product assortment as well as the relationship between the private label market share and pricing. Data collected from a Chinese supply chain dyad is analyzed to study category management using hierarchical linear models. The results reveal that the average wage and the number of stores positively affect the private label market share. Furthermore, the average wage enhances the negative effect of the number of brands, weakens the negative effect of the private label price, weakens the positive effect of national brand price. Meanwhile, the number of stores enhances the positive effect of the SKU proliferation of private label, enhances the negative effects of the number of brands , and enhances the negative effect of the private label price. This study contributes to category management. Furthermore, the findings will be valuable to domestic and international grocery marketers and retailers operating private labels in China.

1. Introduction

The private label (PL) is the exclusive brand for which the retailer is responsible. Retailers develop their private label to compete with others and enhance their private label market share (Bontems et al., 1999). Existing researches mainly focus on private label market share. Hoch and Banerji (1993) demonstrate that the private label performs better in high-margin product categories, and the private label also has a good market share when competing with less well-advertised manufacturer brands. Rubio and Yagüe (2009) reveal that strategies and structural performance factors influence the private label market share. Rubio et al. (2017) claim that the economic recession in Europe, more specifically in Spain, has helped promote private label products. Steenkamp and Geyskens (2014) use a data set covering 23 countries to examine the factors that influence private label market share.

The significant growth of private label has encouraged extensive research of the European market and North American, while studies on emerging markets like China are limited. In China, many retailers, like Lianhua, Yonghui, Carrefour China, have been developing private label since the 1990s. Although the present weighted average share is not high, the growth of private label is remarkable. From 2017 to 2019, private label have grown by 26% in China, well ahead of the growth of fast-moving consumer goods (FMCG), which is 11% [1]. Currently, the proportion of private label SKUs by the Hema Fresh X member store is more than 40% [2]. In our research, the retailer started introducing the private label in 1996. The average market share has exceeded 41% in some product categories. The Chinese market is an emerging market, and hence the context and the driving force behind it are worth exploring. However, to the best of our knowledge, this is the first research on private label market share in the context of China by using large-scale data.

Category management is a process for managing entire product categories as business units, which involve decisions such as product assortment, pricing, and shelf-space allocation to each product (Kurtuluş and Toktay, 2011). Usually, retailers decide which brands and SKUs to include in the category, how to price each product, and where each brand is on the shelf. Simonson (1999) demonstrates that the retailer's product assortment affects customers' preferences and purchase decisions. Sethuraman and Cole (1997) investigate how private label market share is affected by the specific characteristics of a product category. Pauwels and Srinivasan (2004) show that the introduction of the private label rarely yields category expansion and does not create store traffic, however consumers can benefit from enlarged product assortment. The proliferation of items, the total number of brands in a category, affect the private label market share negatively (Hoch and Banerji, 1993; Dhar and Hoch, 1997).

Meanwhile, product pricing is another essential factor in category management. Dhar et al. (2001) reveal that retailers can get more than their market share by charging lower product prices. Erdem and Swait (2004) demonstrate that if the price of private label is high, price-sensitive consumers will reduce their purchase of private label. Soberman and

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[1]White Paper of China private label Daymon in 2020

[2]Sina Finance and Economics News

Parker (2006) show that when both the manufacturer and the retailer have market power if the retailer introduces a quality-equivalent private label, it can lead to higher average category prices. Ferreira et al. (2015) obtain cross-product effects by studying the impact of category average prices and show that increasing the category average prices will negatively affect products' sales.

Previous researches demonstrate that the macroeconomic factor has a significant impact on the private label market share. Ma et al. (2011) show that macroeconomic conditions change consumers' attitudes, shopping behavior, and consumption. Lamey et al. (2007) manifest that due to low prices and the reduced disposable income of households, retailers are more likely to increase their private label market share when the economy is suffering and shrinks. Analyses by Gil-Cordero et al. (2016) show that macroeconomic indices, such as GDP, positively impact private label market share.

The above discussion studies the macro-environment and category level separately. However, few studies have probed interaction influences between them on private label market share. Meanwhile, which factors affect consumers' choice of private label in the Chinese market and how these factors affect the change of private label market share remain unanswered. This paper studies the private label market shares and examines the impact of two-level factors on private label market share. In particular, this paper will answer the following questions. 1) how category level factors, product assortment and pricing to drive customers to purchase private label? 2) how the macro context variables, including average wage and number of stores, moderate the relationship between the private label market share and the category level factors. This paper conceptualizes category level factors' dimensions using a hierarchical linear model and examines how these dimensions influence customers to purchase private label. More importantly, this study examines the moderating effect of the average wage and the number of stores on the relationship between the private label market share and product assortment as well as the relationship between the private label market share and product pricing in China's grocery market.

This study has both academic and practical significance. In terms of its academic importance, although current literature demonstrates that product introduction negatively affects the choice of the private label, and increasing the average category prices will negatively affect the sales of private label products. However, existing research on the private label market share is primarily in the context of the European market and the North American market (Hoch and Banerji, 1993; Rubio and Yagüe, 2009; Steenkamp and Geyskens, 2014; Rubio et al., 2017). To the best of our knowledge, this is the first research on private label market share in the context of China by using large-scale data. Our study fills the gap and extends the private label literature. We conceptualize and operationalize the influence factors of private label market share in China, which deepens the understanding of category level factors' influence. This operationalization of product assortment and product pricing contributes to a better understanding of category management. Besides providing the theoretical contributions, our paper provides several practical implications for domestic and international retailers and marketers who operate the hypermarket and supermarket in China.

We organize the rest of the paper as follows. Section 2 provides a theoretical background and hypotheses. We layout the econometric model and describes our estimation method in Section 3. Section 4 gives the results and discussions. Finally, Section 5 shows our conclusions, managerial implications, and possible research limitations.

2. Theoretical background and hypotheses

2.1. Macro context effect

Generally, economic recessions divert demand for national brand (NB) to lower-priced private label (Lamey et al., 2012). Some of the macroeconomic indices are significant predictors of customer choice and PL market share in the retail chains (Gil-Cordero et al., 2016; Dubé et al., 2018). Lamey et al. (2007) maintain that a 1% decline in real per capita GDP leads to a permanent increase in the PL market share at an annual growth rate of 1.22%. Lamey et al. (2012) reconfirm that there is one countercyclical phenomenon in the PL market share by time-series analysis. Rubio et al. (2017) show that the economic recession in Europe cause purchasing power decline, which decrease people's ability to pay for NB products while promoting the use of PL products. However, other studies pose different concepts. Gil-Cordero et al. (2016) demonstrate that GDP positively influences the volume of PL and purchase choice, which then indirectly, positively impacts PL market share.

GDP is calculated by the sum of national income, national output, and national expenditure. Glynn and Chen (2009) demonstrates that consumers are less prone to buying PL when they have more household income. Dubé et al. (2018) demonstrate that household income negatively affects PL market shares. However, Mandhachitara et al. (2007) conduct identify shopper surveys between the U.S and Thailand to test possible retail grocery shopping differences and demonstrate that the low-income customers are not willing to buy the PL products. Shukla et al. (2013) demonstrate the attractiveness of deals for high-income customers and find that the consumers with high income also show a stronger positive relationship between general deal proneness and attitude towards PL products.

The influence of income on the willingness to buy PL does not coincide with each other. Existing research on private label market share is primarily in the North American or European market while ignoring the Chinese market, which is emerging and has excellent prospects. The effect of income on PL is not studied. In this paper, we examine the income effect on the PL market share in China. We use the data[3] on the average wage of employed staff and worker

[3] The data comes from the Chinese City Statistical Yearbook-2016 and National Bureau of Statistics of China

(AWESW) of 13 cities in China to measure the effect of income on the PL market share, and then we hypothesize:

H1a. Average wage of employed staff and worker of the city has a positive effect on PL market share.

The number of stores that each retailer operates in a particular market determines the market size of the chain. It represents the potential for a retailer to benefit from economies of scale (Dhar and Hoch, 1997). "Most retailers in China operated with the "back margin" model, i.e. charging listing fees on suppliers for selling their products in the stores. Therefore, the more stores they open and the more brands they have in their stores, the more fees or profits they can have. With the fast growing economy, there was no need or incentive to develop private labels" (Moerman, 2016). The number of stores negatively affect the private label market share.

However, the greater the number of hypermarkets in a city, the more familiar the consumer is with its corporate brand. Meanwhile, a higher number of hypermarket stores make risk-averse consumers more likely to purchase known brand products because familiar brands almost eliminate the risk the risk of buying products of low quality, and the brand is already known to be reliable and trusted (Lee et al., 2016). Dhar and Hoch (1997) demonstrate that retailers are eager to increase the number of their stores, and the actual number of stores positively affects the private label market share. Thus we hypothesize:

H1b. The number of store in a city has a positive effect on PL market share.

2.2. Category level effect

Hoch and Banerji (1993) show that customers usually buy products that they are familiar with, and the present category structure mainly determines their choice. Ailawadi and Harlam (2004) point that many retailers provide unique PL products to meet the requirements of both price-conscious and quality-oriented consumers. Dhar and Hoch (1997) show that SKU proliferation provides critical predictors of customer purchase choice for a PL. Gielens (2012) demonstrates that as PL products increasingly operate through multi-quality, multi-tier portfolios, PL products have gained significant market share. In this research, we use the SKU proliferation of PL (SKURPL) and the number of brands (NumBRA) in the category as the independent variables to predict the PL market share. The SKU proliferation of PL is calculated as the number of PL SKUs divided by the total number of SKUs in the category.

The more products displayed on the shelves, the greater the opportunity perceived and purchased by the customers (Hoch and Banerji, 1993). For the SKU proliferation of PL (SKURPL), the higher the SKU proliferation of PL, the more likely the PL be found and purchased by the customers. If consumers' average salary is high, then the customers' range of products will be expanded. So the income will enhance the positive relationship between SKU proliferation of PL in the category (SKURPL) and PL market share. Thus we hypothesize:

H2a. Average wage of employed staff and worker (AWESW) enhance the positive relationship between SKU proliferation of PL in the category (SKURPL) and PL market share.

The number of brands in the category is critical to the PL market share. Dacin and Smith (1994) use two laboratory experiments and a survey to demonstrate that an increasing number of products has positive effects on evaluations when quality variance among extensions is low. Sayman and Raju (2004) find that higher amount of PL in other categories can increase the PL market share in the target category. Kumar (2007) demonstrates that if there are no strong leading brands, there will be fierce price competition in the markets where manufacturers' brands are concentrated. Furthermore, Hoch and Banerji (1993) believe that with an increasing number of NBs, the competitiveness of the NB manufacturer is weak in specific market segments so that retailers may gain more significant market share through their PL products.

However, some studies hold the opposite view, believing that the higher the number of manufacturers NBs, the lower the share of PL (Narasimhan and Wilcox, 1998). Achieving a leading brand position among manufacturers means that each brand's sales are decreasing, thus reducing the pressure on NB to cut prices, which may harm the PL market share (Messinger and Narasimhan, 1995). Meanwhile, Simmons and Meredith (1983) indicate that if there are more types of products with higher supply and higher investment, there is a lower market share of PL. Sethuraman and Gielens (2014) conduct a meta-analysis on 54 individual and aggregate market studies and demonstrate that a higher number of national brands has a substantially adverse effect on the PL market share.

As stated above, the number of brands in a category has different effects on the PL market share so that the interaction effect may exist between the variables. The more the number of brands in one category, the greater the manufacturers' market power and the higher channel bargaining power, which will inhibit the development of PL (Cotterill et al., 2000). When the customer's average income is high, they choose the high quality and appropriate products. Therefore, the income will increase the negative effect of the number of brands on the PL market share. Thus, we hypothesize:

H2b. Average wage of employed staff and worker (AWESW) enhance the negative relationship between number of brands in the category (NumBRA) and PL market share.

It is difficult for small retailers to control products' quality on their own and bargain with their suppliers in China. The higher the number of stores, is the more profit the retailer can get from the economies of scale (Dhar and Hoch, 1997). Furthermore, when there are more stores, the customers have more opportunities to choose the merchandise they want. Therefore, increasing the number of PL SKUs in a category will allow consumers to choose and purchase more. Meanwhile, the number of stores magnifies the negative impact of increasing the number of national brands in a category on the PL market share. Thus, we hypothesize:

H3a. The number of stores (NSTORE) enhance the positive relationship between SKU proliferation of PL in the category (SKURPL) and PL market share.

H3b. The number of stores (NSTORE) enhance the negative relationship between number of brands in the category (NumBRA) and PL market share.

Soberman and Parker (2006) show that when both the manufacturer and the retailer have market power, a quality-equivalent PL that introduced by retailers can lead to higher average category prices. Ferreira et al. (2015) obtain cross-product effects by studying the impact of category average prices and show that increasing the category average prices will negatively affect the sales of products. In this paper, we use the average NB price of the category (NBPrice) and the average PL price of the category (PLPrice) as the predictors to verify the PL market share trend.

Previous studies demonstrate that the price of a brand (PL or NB) negatively affect their market share (Raju et al., 1995; Sayman et al., 2002). That is, there is a negative relationship between demand and price in economic models. The higher the NB price or the lower the PL price, the stronger the customer's willingness to purchase the PL is. If the price of PL is high, price-sensitive consumers will reduce their purchase of PL (Erdem and Swait, 2004). If a consumer's income is high, they will not care so much about the price increase of PL products: in this way, the income will weaken the negative effect of PL prices on demand; similarly, if the consumers' income is high, they may purchase high quality, high price products. Thus, if consumers are willing to pay a higher price to obtain a (perceived) better quality product, then NB products may be the first choice for them. If this is the case, increasing the income should also weaken the positive effect of NB prices on PL demand. Thus, we hypothesize:

H4a Average wage of employed staff and worker (AWESW) weaken the negative relationship between average PL price of the category (PLPrice) and PL market share.

H4b Average wage of employed staff and worker (AWESW) weaken the positive relationship between average NB price of the category (NBPrice) and PL market share.

The greater the number of stores that a supermarket brand has in a city is, the higher the corporate brand awareness will be, and the more consumers can enter the store and purchase products (Pae et al., 2002). Meanwhile, customers have more choices to go shopping. If the private label price increases, the customers will reduce much more purchase. It is the same as the national brand price. If the national brand price increases, many more customers will turn to buy a private label. Thus, we hypothesize:

H5a The number of stores (NSTORE) enhance the negative relationship between average PL price of the category (PLPrice) and PL market share.

H5b The number of stores (NSTORE) enhance the positive relationship between average NB price of the category (NBPrice) and PL market share.

2.3. The proposed conceptual model

Based on the background introduction and preceding hypotheses, a conceptual model is proposed and will be tested empirically. The conceptual model is shown as follows in Fig.1.

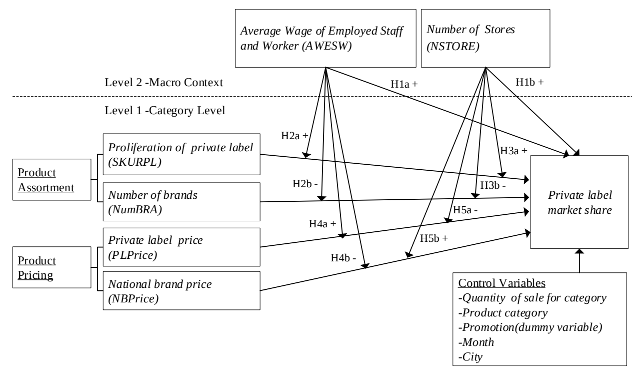


Figure 1: Conceptual model of private label market share

3. Research Methodology

To examine the PL market share at the category level, we collected data from one of the largest hypermarket chains of 44 off-line stores within six popular product categories (i.e., roll toilet paper, flat toilet paper, wet wipes, baby wipes, vinegar and sesame oil) including PL products and NB products. The supermarket chain had 2015 annual sales of \$4.37 Bn.

3.1. Description of Data

We select 55 fast-moving products and more than 153,000 observations and the data set includes all point of sale (POS) record over the period of January 2015 through December 2015. Each product category has multiple brands, each brand has multiple products (SKUs) in different specifications, and a unique SKU number identifies each product.

Table 1 shows the distribution of all products, brands, and observations for all product categories. For example, the product categories with the highest number of products are baby wipes and flat toilet paper; they have 16 and 13 products, respectively. To better understand the relationship between product category, brand and product, we present the products in a sample product category (i.e., roll toilet paper) at a sample store in Table 2. The store carries four brands of roll toilet paper products, including PL and NB, such as Jhui, Nepia, Vinda, and Mind act upon mind (Maum); specifically, Jhui has one product, Nepia has three products, Vinda has three products, and Maum has one product.

Table 3 presents the definitions of variables in our model as well as their observations, means, standard deviations,

Table 1
Distribution of products, brands and product categories.

Product Category	Category Name	Products Number	Brands Number	Obs.
1	Toilet paper	13	3	112552
2	Roll toilet paper	8	4	650
3	Wipes	5	4	5054
4	Baby wipes	16	5	9221
5	Vinegar	4	4	19172
6	Sesame oil	9	5	5019
Total		55	25	151668

Table 2
Examples of substitute products for roll toilet paper.

Brand	Product name	Spec
Jhui	Double laminated roll toilet paper	10 volume
Nepia	Extra long roll toilet paper	10 volume
Nepia	Roll toilet paper	20 volume
Nepia	Velvet roll toilet paper	4 volume
Vinda	Blue classic toilet paper	10 volume
Vinda	Double-layer toilet paper	10 volume
Vinda	Three-layer roll paper	10 volume
Maum	Preferred upgraded three-layer web	10 volume

minima, and maxima. Table 4 demonstrates the correlation matrix for the variables.

3.2. Model Development

Usually, we use single-level statistical models to estimate coefficient and effect, such as the ordinary linear regression or analysis of variance (ANOVA). However, when dealing with multi-level data, standard deviation is often biased, and the parameter estimates are inconsistent. As shown in Fig.1, we construct one model with two-level variables. The statistical analysis model to analyze the multi-level data is hierarchical linear model (HLMs) (Raudenbush and Bryk, 2002), also known as a random coefficient regression model (Curran, 2003; Aguinis et al., 2013). HLMs can not only correctly process hierarchical data through parameter estimation, but also analyze the effects of microscopic and macroscopic variables, and cross-level interaction. Raudenbush and Bryk (2002) demonstrate that HLMs provide a consistent modeling framework for multi-level data with linear structural models and non-normal distribution errors. HLMs can be used to resolve bias issues and enhance the precision of estimates over non-hierarchical methods and this allows us to model variability across contexts. Hence, we use HLMs in this study to estimate the PL market share.

We calculate PL market share as the ratio of total sales for the PL to total sales for the category over one year and is expressed in percentage terms (see Sebri and Zaccour, 2017). The measure is as follows:

$$\text{PL market share (\%)} = \frac{\text{Private label sales for category}}{\text{Total retail sales for the category}}$$

For the linear model, in respect of the residuals, we assume a normal distribution. Thus, in this paper, we utilize a logit transformation of PL market shares (PLShare) as the dependent variable (see Dhar and Hoch, 1997), and locate the independent variables in two levels. We adopt the average wage of employed staff and worker (AWESW) and the number of store (NSTORE) in a city as the macro context variables. The SKU proliferation of PL (SKURPL), the number of brands of the category (NumBRA), the average category price of PL (PLPrice) and the average category price of NB (NBPrice) are computed as the main predictor in our model.

Some marketing research involves hierarchical data structures in which a lower-level unit nests within a higher-level group (Steenkamp and Geyskens, 2014). PL market share is not only influenced by the characteristics of their category, but also by store context. In some of the literature, the hypothesis accepted as more probable is that the PL achieves a higher market share in categories with a higher price elasticity of demand (Connor and Peterson, 1992; Raju et al., 1995) and that these products are primarily purchased by price-sensitive consumers (Hoch, 1996; Erdem and Swait, 2004). In this paper, we add the control variables, including purchase quantity of the category (QSale), different category (Dept1-Dept6), promotion information of the product (Promotion), month of the deal (Month1-Month12) and the city of the store located (Cityid1-Cityid13).

We seek to decrease collinearity of the intercept and slope estimation and to provide higher accuracy of estimate for HLM analysis. We regard the grand mean and group mean as the center to adjust variables at the two level, respectively (Hofmann and Gavin, 1998; Aguinis et al., 2013). Hence, equation (1) for the level 1 model is as follows:

$$\begin{aligned} PLShare_{ij} =& \beta_{0j} + \beta_{1j}(PLPrice_{ij} - \overline{PLPrice_{.j}}) \\ &+ \beta_{2j}(NBPrice_{ij} - \overline{NBPrice_{.j}}) \\ &+ \beta_{3j}(SKURPL_{ij} - \overline{SKURPL_{.j}}) \\ &+ \beta_{4j}(NumBRA_{ij} - \overline{NumBRA_{.j}}) \\ &+ \beta_{5j}(QSale_{ij} - \overline{QSale_{.j}}) + \beta_{6j} Promotion_{ij} \\ &+ \sum_{N=7}^{12} \sum_{K=1}^{6} \beta_{Nj} DeptK_{ij} + \sum_{N=13}^{24} \sum_{K=1}^{12} \beta_{Nj} MonthK_{ij} \\ &+ \sum_{N=25}^{37} \sum_{K=1}^{13} \beta_{Nj} Cityid_{ij} + \beta_{38j} Resid\_SKU_{ij} \\ &+ \beta_{39j} Resid\_Num_{ij} + \beta_{40j} Resid\_PL_{ij} \\ &+ \beta_{41j} Resid\_NB_{ij} + \varepsilon_{ij} \end{aligned} \tag{1}$$

Where β_{0j} is the intercept; β_{ij} (i=1,...41;j=1,...44) represent the slopes estimated for each store; and ε_{ij} indicates the residual at the level 1. The equations (2) for the level-2

Table 3
Descriptive statistics

VarName	Definition	Obs	Mean	SD	Min	Max
PLShare†	PL products market share in the category for year	151668	-0.64	1.36	-4.59	7.86
NSTORE	Corporate brand awareness, measured by the number of stores in the city	151668	21.65	17.73	1	39
AWESW‡	Average wage of employed staff and worker of the city (¥)	151668	82.14	19.82	51.35	100.97
SKURPL	Number of PL SKU divided by total number of SKU in category	151668	0.53	0.14	0.03	1
NumBRA	Total number of brands in the category	151668	2.74	0.81	1	5
PLPrice*	Average PL products price of category (¥)	151668	5.41	3.45	1.08	22.56
NBPrice*	Average NB products price of category (¥)	151668	9.55	4.91	0.45	37.04
QSale‡	Quantity of sale for the category	151668	16.70	15.04	0.006	50.92
Deptid	Category in the each hypermarket	151668	2.68	1.24	1	6
Promotion	The product are promotion, dummy variable	151668	0.05	0.22	0	1
Cityid	City ID for each hypermarket located	151668	4.75	4.71	1	18
Month	The month of sales record	151668	6.18	3.53	1	12

† Logit transformation form. ‡ Units are in thousand. * Product sales price divided by their spec, then multiply the common spec in the category.

Table 4
Correlations matrix of variables

	PLShare	NSTORE	AWESW	SKURPL	NumBRA	PLPrice	NBPrice	QSale	Deptid	Promotion	Cityid	Month
PLShare	1											
NSTORE	0.50*	1										
AWESW	0.50*	0.96*	1									
SKURPL	0.70*	0.40*	0.41*	1								
NumBRA	-0.22*	0.00*	-0.03*	-0.61*	1							
PLPrice	-0.26*	-0.19*	-0.18*	-0.37*	0.40*	1						
NBPrice	-0.12*	0.11*	0.10*	-0.17*	0.35*	0.78*	1					
QSale	0.05*	0.46*	0.42*	0.38*	-0.16*	-0.26*	-0.05*	1				
Deptid	-0.01*	-0.21*	-0.21*	-0.62*	0.65*	0.36*	0.14*	-0.54*	1			
Promotion	-0.01*	0.03*	0.01*	0.03*	-0.01*	0.03*	0.03*	0.06*	-0.06*	1		
Cityid	-0.34*	-0.81*	-0.86*	-0.32*	-0.04*	0.14*	-0.09*	-0.40*	0.20*	-0.03*	1	
Month	0.24*	0.34*	0.32*	0.20*	-0.05*	-0.29*	0.01*	0.19*	-0.08*	-0.00	-0.16*	1

* $p < 0.05$.

model are as follows:

$$\begin{aligned}
\beta_{0j} =&\gamma_{00} + \gamma_{01}(NSTORE_j - \overline{NSTORE_{.}}) \\
&+ \gamma_{02}(AWESW_j - \overline{AWESW_{.}}) + \mu_{0j} \\
\beta_{1j} =&\gamma_{10} + \gamma_{11}(NSTORE_j - \overline{NSTORE_{.}}) \\
&+ \gamma_{12}(AWESW_j - \overline{AWESW_{.}}) + \mu_{1j} \\
\beta_{2j} =&\gamma_{20} + \gamma_{21}(NSTORE_j - \overline{NSTORE_{.}}) \\
&+ \gamma_{22}(AWESW_j - \overline{AWESW_{.}}) + \mu_{2j} \\
\beta_{3j} =&\gamma_{30} + \gamma_{31}(NSTORE_j - \overline{NSTORE_{.}}) \\
&+ \gamma_{32}(AWESW_j - \overline{AWESW_{.}}) \\
\beta_{4j} =&\gamma_{40} + \gamma_{41}(NSTORE_j - \overline{NSTORE_{.}}) \\
&+ \gamma_{42}(AWESW_j - \overline{AWESW_{.}}) \\
\beta_{5j} =&\gamma_{50}; \beta_{6j} = \gamma_{60}; \beta_{7j} = \gamma_{70}; \beta_{8j} = \gamma_{80}; \\
\beta_{9j} =&\gamma_{90}; ...; \beta_{40j} = \gamma_{400}; \beta_{41j} = \gamma_{410}
\end{aligned} \tag{2}$$

Where NSTORE_j and AWESW_j represents the jth level 2 variables, j=1, … , 44; γ_{00}, γ_{10} ,γ_{20},γ_{30} and γ_{40} denote the respective level 2 intercept terms; γ_{0j} is the coefficient that indicates the effect of NSTORE_j and AWESW_j on the within store represented by β_{0j}; γ_{1j}, γ_{2j}, γ_{3j} and γ_{4j} are the slopes that relate NSTORE_j and AWESW_j to the slope terms β_{1j},β_{2j}, β_{3j} and β_{4j} in the level 1 model; and μ_{0j},μ_{1j} and μ_{2j} indicate level 2 residuals. By replacing the algebraic symbols with the corresponding variables, we substitute the equations (2) into equation (1) and get the equation (3), then use the equation (3) to test our hypotheses:

$$\begin{aligned}
PLShare_{ij} =& \gamma_{00} + \gamma_{01}(NSTORE_j - \overline{NSTORE_{.}}) \\
&+ \gamma_{02}(AWESW_j - \overline{AWESW_{.}}) + \mu_{0j} + \varepsilon_{ij} \\
&+ \gamma_{10}(PLPrice_{ij} - \overline{PLPrice_{.j}}) + \mu_{1j}(PLPrice_{ij} - \overline{PLPrice_{.j}}) \\
&+ \gamma_{11}(NSTORE_j - \overline{NSTORE_{.}})(PLPrice_{ij} - \overline{PLPrice_{.j}}) \\
&+ \gamma_{12}(AWESW_j - \overline{AWESW_{.}})(PLPrice_{ij} - \overline{PLPrice_{.j}}) \\
&+ \gamma_{20}(NBPrice_{ij} - \overline{NBPrice_{.j}}) + \mu_{2j}(NBPrice_{ij} - \overline{NBPrice_{.j}}) \\
&+ \gamma_{21}(NSTORE_j - \overline{NSTORE_{.}})(NBPrice_{ij} - \overline{NBPrice_{.j}}) \\
&+ \gamma_{22}(AWESW_j - \overline{AWESW_{.}})(NBPrice_{ij} - \overline{NBPrice_{.j}}) \\
&+ \gamma_{30}(SKURPL_{ij} - \overline{SKURPL_{.j}}) \\
&+ \gamma_{31}(NSTORE_j - \overline{NSTORE_{.}})(SKURPL_{ij} - \overline{SKURPL_{.j}}) \\
&+ \gamma_{32}(AWESW_j - \overline{AWESW_{.}})(SKURPL_{ij} - \overline{SKURPL_{.j}}) \\
&+ \gamma_{40}(NumBRA_{ij} - \overline{NumBRA_{.j}}) \\
&+ \gamma_{41}(NSTORE_j - \overline{NSTORE_{.}})(NumBRA_{ij} - \overline{NumBRA_{.j}}) \\
&+ \gamma_{42}(AWESW_j - \overline{AWESW_{.}})(NumBRA_{ij} - \overline{NumBRA_{.j}}) \\
&+ \gamma_{50}(QSale_{ij} - \overline{QSale_{.j}}) + \gamma_{60}Promotion_{ij} \\
&+ \sum_{N=7}^{12}\sum_{K=1}^{6}\gamma_{N0}DeptK_{ij} + \sum_{N=13}^{24}\sum_{K=1}^{12}\gamma_{N0}MonthK_{ij} \\
&+ \sum_{N=25}^{37}\sum_{K=1}^{13}\gamma_{N0}Cityid_{ij} + \gamma_{380}Resid_SKU_{ij} \\
&+ \gamma_{390}Resid_Num_{ij} + \gamma_{400}Resid_PL_{ij} + \gamma_{410}Resid_NB_{ij}
\end{aligned} \tag{3}$$

The level-1 model is a linear model regressing PL market share outcomes on several category level variables and control variables. The interpretation can be put in this way: the change of PL market shares with one unit of increase in the explanatory variable. The level-2 model is a linear regression model which assumes a normally distributed error term μ_0. The effects of the regressors (including the intercept, PL-Price, NBPrice) in both models are treated as random. The intercept β_0 is a random coefficient which is associated with the store, such as the variation in PL market share μ_0.

Table 5
ANOVA results for PL market share

Fixed Effect	Coefficient	Std. Err.	P-value	
Mean of PL market share† ,γ_{00}	-1.144	0.108	0.000	
Random Effect	Std. Var.	Std. Err.	95% Conf. Interval	
Between, μ_{0j}	0.515	0.110	0.339	0.782
Within, ϵ_{ij}	1.075	0.004	1.068	1.083
Random Effect	Reliability			
Intercept, β_0	0.99			

† Logit transformation form.

4. Analysis and results

4.1. Intra-class Correlation Coefficients

In order to make sure that there is significant macro context variability in the category level variables and the HLMs is adequate and suitable for our research, we examine the intra-class correlation coefficients, ICC_1 and ICC_2, which must be large enough (Aguinis et al., 2013). We formulate the equations for HLMs as follows. First, the null model begins with specifying the following relationship.

Null model (Level 1):

$$\text{PLShare}_{ij} = \beta_{0j} + \varepsilon_{ij} \tag{4}$$

Null model (Level 2):

$$\beta_{0j} = \gamma_{00} + \mu_{0j} \tag{5}$$

Null model (Mixed):

$$\text{PLShare}_{ij} = \gamma_{00} + \mu_{0j} + \varepsilon_{ij} \tag{6}$$

Substituting equation (5) in equation (4), equation (6) can be obtained, then use equation (6) to analyze and compute ICC_1 and ICC_2. While ICC_1 compares the between store variance to the within store variance to indicate the portion of the variance in individual responses that are accounted for by the between store difference, it ranges from 0 to 1. ICC_2 reveals the reliability of the mean of a level 2 variable (see Shrout and Fleiss, 1979; Bliese, 2000). Peugh (2010) demonstrate that the cutoff point of ICC_1 is from 0.05 to 0.20 in social research studies. Mathieu et al. (2012) demonstrate that the ICC_1 reported in studies range from 0.15 to 0.30. Meanwhile, ICC_2 is greater than 0.70 indicates good reliability of group-mean (LeBreton and Senter, 2008).

Using the values of the Table 5, $ICC_1 = 0.515/(0.515 + 1.075) = 0.324$ indicating an appreciable degree of nesting in the data, and $ICC_2 = 0.99$. Thus $ICC_1 = 0.324$ indicate that differences across level 2 account for about 32.4% of the total variance in PL market share.

4.2. Endogeneity

Since the SKU proliferation of PL and number of brands are subject to managerial decisions, and the PL price and NB price of the category are also related to the omitted marketing mixed variables, these variables are not assumed to be exogenous. Including any one of these four variables as a predictor can lead to a correlation between these variables and the error term (i.e., endogeneity), and biased parameter estimates. Thus, we use instrumental variable and control function approach to deal with the endogeneity issue (Petrin and Train, 2010).

To ensure the applicability of the instrumental variable (IV) regression and the effectiveness of the tool, we use several statistical tests. First, we perform the Durbin-Wu-Hausman test to assess whether a suspicious variable is endogenous. Second, following Song and Chintagunta (2006), we choose the wholesale price as an instrumental variable to solve the endogeneity problem of the PL price and NB price. Third, as for the SKU proliferation of PL and number of brands, we choose the Hausman style variables from other markets as the instrumental variable, respectively (Rossi, 2014; Rutz and Watson, 2019). For example, we use the SKU proliferation of PL and the number of brands in another store as the targeted store's instrumental variables in the same city, which are related to the original store's SKU proliferation of PL and the number of brands, but are not related to the customer's choice in the targeted store. Furthermore, we also check how well the selected instrumental variables predict endogeneity, and we find that the F-statistics for the first stage is higher than 10 (Stock et al., 2002). According to Petrin and Train (2010), the control function approach as follows:

Step 1: Run linear regression of PL price, NB price, SKU proliferation of PL, and the number of brands on their IV and predict their residuals.

Step 2: Plug in all the predicted residuals into HLMs and use maximum likelihood estimation (MLE) to estimate the parameters.

As our model involves cross-level predictors and the dependent variable is at the lower category level, we utilize maximum likelihood to estimate the hypotheses using Stata.

4.3. Results

Table 6 demonstrates the estimate results. Because the models belong to the nested model, we can appraise whether the model fit improves by comparing the deviance statistic (-2 log likelihood) between these models. According to our

Table 6
Hierarchical linear model results for PL market share

	Model 1	Model 2	Model 3	Model 4
AWESW		0.318*	0.406**	0.397**
NSTORE		0.543***	0.342*	0.458**
SKURPL	0.844***	0.844***	0.717***	0.717***
NumBRA	−0.054***	−0.054***	−0.158***	−0.158***
PLPrice	−0.034	−0.034	−0.100***	−0.111***
NBPrice	0.043*	0.043*	0.020	−0.041
AW#SKURPL			−0.005	−0.006
AW#NumBRA			−0.096***	−0.096***
NS#SKURPL			0.103***	0.103***
NS#NumBRA			−0.049***	−0.048***
AW#PLPrice				0.177***
AW#NBPrice				−0.154**
NS#PLPrice				−0.181***
NS#NBPrice				0.085
QSale	−0.141***	−0.141***	−0.197***	−0.197***
Promotion=1	0.003***	0.003***	0.001*	0.001*
Month=2	−0.002***	−0.002***	−0.001*	−0.001*
Month=3	0.000	0.000	−0.000	−0.000
Month=4	0.005***	0.005***	−0.001*	−0.001*
Month=5	−0.001	−0.001	0.000	0.000
Month=6	−0.001	−0.001	0.001*	0.001*
Month=7	0.000	0.000	−0.001	−0.001
Month=8	−0.001	−0.001	−0.000	−0.000
Month=9	0.001	0.001	−0.000	−0.000
Month=10	−0.001	−0.001	0.001	0.001
Month=11	−0.009***	−0.009***	0.001	0.001
Month=12	−0.010***	−0.010***	0.000	0.000
Cityid=2	−0.184***			
Cityid=3	−0.221***			
Cityid=4	−0.258***			
Cityid=5	−0.249***			
Cityid=6	−0.463***			
Cityid=7	−0.178***			
Cityid=8	−0.351***			
Cityid=9	−0.301***			
Cityid=10	−0.233***			
Cityid=11	−0.141***			
Cityid=12	−0.066*			
Cityid=13	−0.192***			
Deptid=2	0.041***	0.041***	0.026***	0.026***
Deptid=3	0.015***	0.015***	0.040***	0.040***
Deptid=4	0.266***	0.267***	0.236***	0.236***
Deptid=5	0.648***	0.648***	0.509***	0.509***
Deptid=6	0.317***	0.317***	0.259***	0.259***
Resid_SKU	−0.017***	−0.017***	0.056***	0.056***
Resid_Num	0.002	0.002	0.009***	0.009***
Resid_PLP	0.061***	0.061***	0.050***	0.050***
Resid_NBP	0.023***	0.023***	0.008***	0.008***
Obs.	147698	147698	147698	147698
AIC	−36171	−36151	−104325	−104349
BIC	−35716	−35795	−103929	−103913
Dev	18131.6	18111.5	52202.7	52218.4
△dev	–	−20.1	34091	15.7

Standardized beta coefficients
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

research hypotheses, we examine random coefficient models by LT test and compare the Akiake information criterion (AIC) and Bayesian information criterion (BIC) to select the appropriate model.

4.3.1. Main effects

We demonstrate the parameter estimates for the final model in Table 6. The Model 2 shows that AWESW of the city is found as statistically significant ($\beta = 0.318$, $p < 0.05$). Accordingly, H1a is supported and has a significant positive effect on PL market share. Meanwhile, the PL market share increase as the number of stores increase in a category ($\beta = 0.543$, $p < 0.001$), therefore leads to an initial strong support for H1b. The higher the number of stores is, the higher the market share of PL will be.

For the category level variables, SKU proliferation of PL in the product category (SKURPL) has a positive effect on PL market share ($\beta = 0.844$, $p < 0.001$). The higher the ratio of the PL SKUs is, the more opportunity is perceived and thus purchased by customers and the higher the PL market share will be. Meanwhile, the number of brands in the category (NumBRA) has a negative effect on the PL market share ($\beta = -0.054$, $p < 0.001$). The larger the number of brands is, the lower the PL market share will be in the category. Finally, we estimate a positive effect of the NB price (NBPrice) on PL market shares ($\beta = 0.043$, $p < 0.05$). However, our analysis in Model 2 does not reveal that the PL price of the category (PLPrice) has a significant negative effect on the PL market share ($\beta = -0.034, n.s.$), but when we consider the moderating effect, the Model 4 reveals that the PL has a significant negative effect on the PL market share($\beta = -0.111$, $p < 0.001$).

4.3.2. Moderating effect

Another primary purpose of this study is to check whether average wage and the number of stores moderate the relationship between the category level variables and PL shares. LR test is used to confirm whether there is a significant difference between the models. Model 1 in Table 6 is the random coefficient model only with the category variables and control variables. Model 1 in Table 6 shows that there is a significant difference between the different cities. Thus, base on Model 1, we add the macro context variables in Model 2. In order to avoid the collinearity and test the store variable effect on the PL market share, we replace the cityid with the average wage and the number of stores in the following models. Meanwhile, in Model 3 and Model 4, we add the interaction variables to test expected hypothesis. The results of the LR test are significant, and AIC and BIC demonstrate that there is a significant difference between the models in Table 6.

Model 4 demonstrate that the effects of category price, such as PL price and NB price, on PL market share depend on average wage and the number of stores. Meanwhile, the effects of product introduction, such as proliferation of PL and number of brands, on PL market share are also moderated by the average wage and number of stores. The significant moderating effects are further investigated and illustrated graphically in Fig.2 and Fig.3. The figures show the observed relationships between explanatory variables and PLShare (Logit transformation form) (Dhar and Hoch, 1997), all other things equal, with three values of moderator variable: medium, high, and low, represented by the mean value of moderator variable and one standard deviation above and below the mean.

Moderating product assortment

The results of Model 3 in Table 6 show that the moderating effect of AWESW on the relationship between the proliferation of PL and PL market share is negative and not significant ($\beta = -0.005, n.s.$). That is, the hypothesis H2a is not supported.

Meanwhile, the moderating effect of AWESW on the relationship between the number of brands and PL market share is negative and significant ($\beta = -0.096$, $p < 0.001$). That is the AWESW strengthen the negative relationship between the number of brands and PL market share, providing support for H2b. The Fig.2(a) shows that there is a significant moderating effect. When the AWESW is low, the PL market share change a little as the number of brands (NumBRA) increases. On the other hand, when the AWESW is high, the PL market share decreases sharply as the number of brands increases.

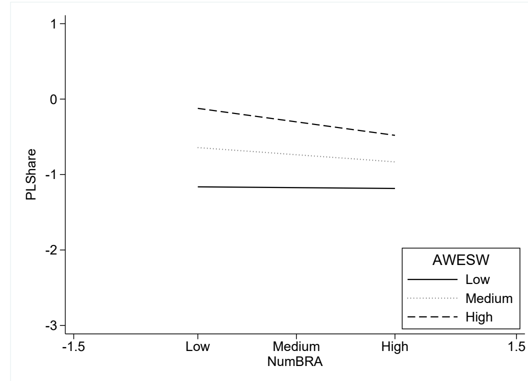
The results of Model 3 in Table 6 demonstrate that there is a significant moderating effect between number of stores and the the proliferation of PL within a category ($\beta = 0.103$, $p < 0.001$). That is, the number of stores enhance the positive relationship between the proliferation of PL in the category and the PL market share, providing support for H3a. The Fig.2(b) demonstrates that when the number of stores is at a low level, PL market share increases as the the proliferation of PL (SKURPL) increases, which accords with our predictions. When number of stores is at a high level, PL market share increases with the increases in proliferation of PL , and there is also significant moderating effect at a significance level of 0.001.

Likewise, the Model 3 in the Table 6 shows that there is a significant moderating effect ($\beta = -0.049$, $p < 0.001$) between number of stores and the number of brands in the category. The Fig.2(c) demonstrates that when the number of stores is low, increasing the number of brands causes a lower PL market share. However, if the number of stores is at a high level, the PL market share decreases much more than that the number of stores is at a low level. The number of stores enhances the negative relationship between the number of brands and PL market share, providing support for H3b.

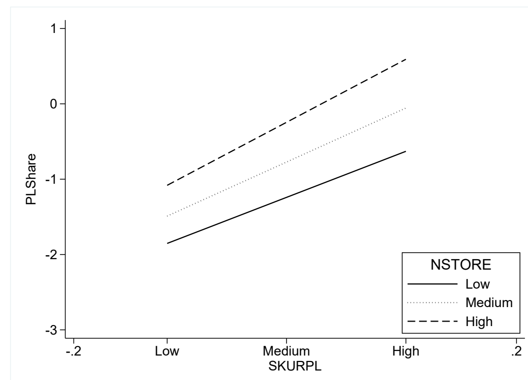
Moderating product pricing

The results of Model 4 in Table 6 show that the moderating effect of AWESW on the relationship between the PL price and PL market share is positive and significant ($\beta = 0.177$, $p < 0.001$). That is, the AWESW weaken the negative relationship between average PL price of the category (PLPrice) and PL market share, providing support for H4a. The Fig.3(a) demonstrates that when AWESW is low, PL market share decreases as the PL price increases. On the other hand, when the AWESW is high, the PL market share increases as the PL price increases.

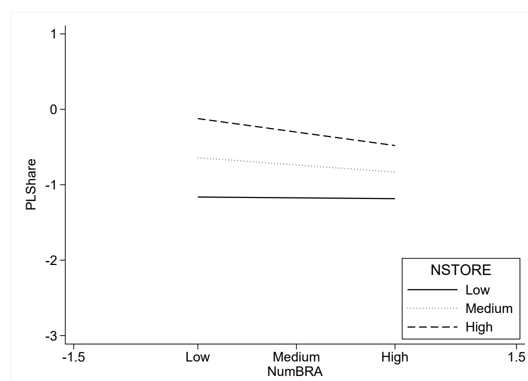
Meanwhile, the moderating effect of AWESW on the relationship between the NB price of category and PL market share is negative and significant ($\beta = -0.154$, $p < 0.01$). That is, the AWESW weaken the positive relationship between average NB price of the category (NBPrice) and PL market share, providing support for H4b. The Fig.3(b) shows that when the AWESW is low, the PL market share increase as the NB price increases. On the other hand, when the AWESW is high, the PL market share decreases as the NB price increases. These findings imply that affluent consumers



(a)



(b)



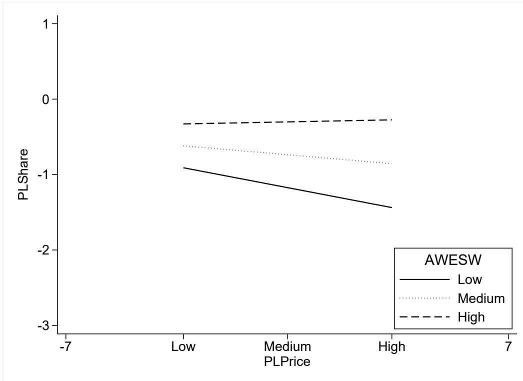
(c)

Figure 2: Moderating effect of macro context variables on the relationship between product and private label market share

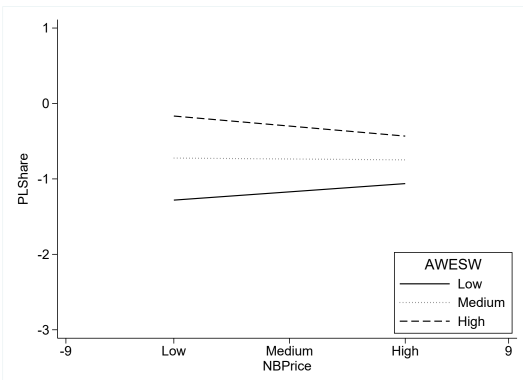
may focus on the perceived quality of the product and are not sensitive to the price of the product.

In Table 6, we can also find that there is a significant moderating effect between the number of stores and the PL price within a category ($\beta = -0.181$, $p < 0.001$), which providing support for H5a. Likewise, the Table 6 shows that there is not a significant moderating effect between number of stores and the NB price for the category ($\beta = 0.085$, *n.a.*). The H5b is not supported.

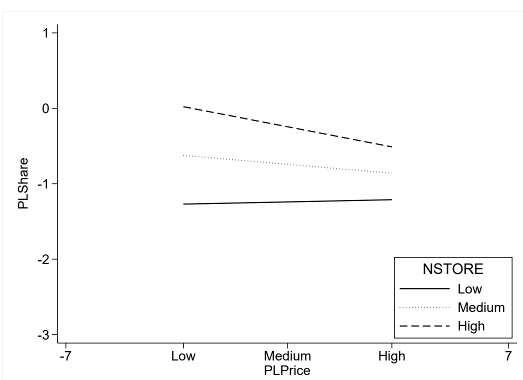
Meanwhile, if the interaction term is significant, then even if the main effect variable is not significant, it should



(a)



(b)



(c)

Figure 3: Moderating effect of macro context variables on the relationship between price and private label market share

be placed in the regression model (Franzese and Kam, 2009; James et al., 2013). In other words, interaction makes sense with main effect, and our HLMs should include the variables of NBPrice, even if it is not significant in the Model 4.

4.3.3. The effects of control variables

Table 6 shows the results of the parameter estimates and the significance level for these variables. We find that the promotion has a positive effect on the PL market share ($\beta = 0.001$, $p < 0.05$). Meanwhile, we find that the categories with larger product sales have a smaller market share of PL ($\beta = -0.197$, $p < 0.001$). The reason is that large sales do not indicate high margins in that category; Products with great sales performances may have high cost and low return, which cannot motivate retail managers to introduce and develop PL products within the category. The introduction of PL has not been vigorously promoted, and the market share of PL is small within the category. Furthermore, according to the traditional concept and economic theory, consumers with lower incomes are expected to prefer PL because of their lower prices, and consumers who buy plenty of products are more likely to purchase economical alternatives, which save a lot of money (Baltas, 1997; Jung et al., 2016). However, it can be argued that consumers with lower incomes may be willing to pay a higher price premium for NB to avoid possible product failures (Mandhachitara et al., 2007). In order to avoid the failure of the PL products, customers are willing to purchase a small number of PL products when they are shopping.

4.4. Discussion

Each of the research findings with its respective hypotheses is present. Hypotheses H1a-H5b represented the estimated result of the influence factor, as shown in Table 6, and the moderating effect plot presented in Fig.2 and Fig.3. All the Hypotheses 1a-5b except for H2a and H5b are supported in this study.

As showed in Table 6, H1a is supported. The private label market share is higher when the average wage is higher in the city. Our research finding is aligned with the ideas of Shukla et al. (2013) and Mandhachitara et al. (2007). The regional economy's diversity is a universal problem in all countries' economic development, especially in China. There is a massive difference in the city size and different economic development levels in China's different regions. Retailers who are willing to develop private label and profit from them usually locate their stores in the areas with relatively high average wage levels. There are some small brands in the store in areas with relatively low average wage levels. The introduction of a private label is relatively new in China. Private labels have no advantage of low prices when facing competition from small brands. Thus, retailers have low incentives to introduce private labels in cities where the customers' average wage is low.

Table 6 demonstrates that the number of stores in a city positively affects private label market share. That is, cities with more hypermarket stores have a larger market share of private label. The finding aligns with the previous literature (Dhar and Hoch, 1997). H1b is supported.

H2a-H5b tests the moderating effect. H2a is not supported. Usually, retailers post the private label signage on the shelves in the hypermarket. The shelf display effect caused by the proliferation of private label attracts consumers' attention. Meanwhile, the private label's introduction causes the wholesale prices of national brand to increase, and then the national brand price increase and enlarge the price gap (Gabrielsen and Sørgard, 2007). However, consumers with higher income ignore the impact of the above mentioned.

The reason is that with the rapid growth of personal income, consumers in China have become increasingly mature. Consumers pay much more attention to commodities' quality and consumption experience when making purchasing decisions, which reduces the positive effect of the PL's SKU proliferation. Another reason is that consumers in higher-income have more ability and are more willing to try new brand products in China. Although the private label signages attract the customers' attention, if the retailers fix the number of brands in the category and increase only the SKUs, high-income customers will show little interest in purchasing the private label brand.

H2b is supported. That is, the average wage enhances the negative effect of the number of brands. A high level of the average wage stands for the customer's ability to purchase good service and high-quality products. Customers usually perceive the national brand as a high-quality and useful service in China. Therefore, when customers purchase commodities, the probability that they choose the national brands increases.

H3a is supported. Our findings show that the number of stores enhances the positive effect of the SKU proliferation of PL and enhances the negative impact of the number of brands. Increasing the number of stores, the customers have more opportunities to choose the merchandise. Meanwhile, the more stores the retailer opens, the more consumers learn about the product through the corporate brand. "In some cases, brand awareness alone is sufficient to result in more favorable consumer response, for example, in low-involvement decision settings where consumers are willing to base their choices merely on familiar brands" (Keller, 2013). When consumers are not familiar with the corporate brand, they will believe that the brand and products are untrustworthy. They may think that the risk is too high to consume the PL product and change their original purchase choice for PL. However, if consumers are familiar with the corporate brand, they will repeatedly purchase the brand products (Pae et al., 2002) and tend to buy private label.

H3b is supported. Most manufacturers have a dominant position in specific categories and have absolute pricing power. When the manufacturer introduces a new national brand product, private label are less likely to enter the category successfully (Srinivasan et al., 2004). The number of stores mainly stands for the retailer's power to develop its product category. The more stores retailers open, the more brands they have in their stores. More brands are introduced, which negatively affects the market share of private label. Thus, the number of stores enhances the negative relationship between the number of brands and private label.

H4a is supported. Consumers with higher incomes have more ability and are more willing to try new brand products. If a consumer's income is high, they will not care so much about the increase of PL price. That will weaken the negative effect of the private label price. H4b is supported. Our findings indicate that the average wage weakens the positive relationship between the national brand price and private label market share. When consumers' income is low, it is feasible to expand private label market share by raising the national brand price. However, if the consumers' income is high, increasing the national brand price can decrease private label market share. That is to say, in the low-income region, the main reason that consumers buy commodity is the lower price. If the price is low, consumers are willing to choose them. However, if the income is high, consumers pay more attention to the quality of the product. Many consumers associate high price with high quality when they perceive more significant variance among brands (Yang et al., 2019). Even if national brands' price rises, it will not affect consumers' perception and purchase of the national brands. As a result, income weakens the positive effect of the national brand price.

Table 6 demonstrates that the number of stores enhances the negative effect of the private label price. When the number of stores is at a high level, the retailer could introduce some small brands because they can get more slotting fees and profit from the new brand manufacturer. Private label have no advantage of low prices when facing competition from the small brands. If the private label price increase, customers will abandon the private label. Another reason is that the higher the number of stores is, the more profit the retailer can get from the economies of scale (Dhar and Hoch, 1997). One of the advantages of economies of scale is that retailers can obtain strong bargaining power and lower wholesale prices from manufacturers. The lower NB price attracts the customers to come back choose the NB product (Abril and Sanchez, 2016). In this way, the advantage of the price gap between the private label and national brand is reduced. Thus, the number of stores enhances the negative relationship between private label price and private label market share. H5a is supported.

Furthermore, customers are better off with an increase in the number of stores. It is easy for customers to compare the national brand prices in different stores. In this case, the price gap between the private label and national brand will be more easily perceived by the customers if the national brand price increases (Arce-Urriza and Cebollada, 2012). Thus, consumers are more inclined to choose a private label. That is, the number of stores enhances the positive effect of the national brand price. However, it is not significant. H5b is not supported. The possible reason is that the target product categories in our study are the daily necessities. Their price elasticity and cross-price elasticity is low, and the price difference is not significant. Besides, in China, there are many small supermarkets and convenience stores around residential areas. Consumers do not need to go to hypermarket for shopping in large quantities, and they only spend little time and traffic cost to buy what they want whenever they need them, which will mitigate the moderating effect of the number of stores.

5. Conclusion

5.1. Theoretical contributions

In terms of the theoretical importance, the present research on the private label market share is primarily in the context of the Western market (Hoch and Banerji, 1993; Rubio and Yagüe, 2009; Steenkamp and Geyskens, 2014; Rubio et al., 2017). The Chinese market is an emerging market. There is an extensive market prospect for private label in China. In this paper, the sales data collected from a large Chinese supply chain dyad. The private label market share is analyzed using hierarchical linear models. To our best knowledge, this paper is the first to uses daily sales data to study the private label market share in China.

This paper study the moderating effects of the average wage and the number of stores on the private label market share. We reach the conclusion that the private label market share is higher when the average wage is higher in the city. This finding is aligned with the ideas of Shukla et al. (2013) and Mandhachitara et al. (2007). There is a huge difference in city size and economic development levels among different areas in China. Retailers who are willing to develop private label locate their stores in areas with relatively high average wage levels. Meanwhile, the number of stores has a positive effect on the private label market share. The number of stores that each retailer operates in a particular market determines the market size of the chain; it represents the potential for a retailer to benefit from economies of scale (Dhar and Hoch, 1997).

For the category-level variables, the SKU proliferation of PL in the category positively has a significant effect on the PL share. The higher the PL SKUs ratio, the more opportunity is perceived and thus purchased by customers. Meanwhile, the number of brands in the category harms the PL market share. The larger the number of brands is, the lower the PL market share will be. Finally, we estimate a positive effect of the national brand price on PL market shares. The higher the national brand price is, the more opportunity for PL is purchased by customers.

We examine the moderating effect of average wage on the relationship between the private label market share and product assortment as well as pricing. Our finding shows that the average wage enhances the number of brands' negative effects. The average wage enhances the negative relationship between the average PL price and private label market share and weakens the positive relationship between the average NB price and private label market share.

We examine the moderating effect of the number of stores on the relationship between the private label market share and product assortment as well as pricing. Our findings show that the number of stores enhances the positive effect of the SKU proliferation of PL and enhances the number of brands' negative effects. Meanwhile, the findings show that the number of stores enhances the PL price's negative effect.

Our study extends the private label literature by conceptualizing and operationalizing the influence factor of private label market share in China, which deepens the understanding of the product assortment and pricing. The operationalization of product assortment, pricing, moderating effect of the average wage and the number of stores contributes to a better understanding of category management.

5.2. Practical implications

Besides the theoretical contributions, our paper provides several practical implications for domestic and international retailers and marketers who operate the hypermarket and supermarket in China.

The average wage has a significant influence on the private label market share. Hence, retailers willing to develop private label should locate their stores in areas with relatively high average wage levels. The number of stores has a significant positive influence on the private label market share. That is, more stores in the supply chain mean that the private label could develop nicely.

According to the moderating effect of macro context variables, retailers can fix or reduce the number of brands when they locate the stores in the area where the average wage is high. Furthermore, the average wage moderates the relationship between the national brand price and the private label market share. When the average wage is high, retailers should not increase the national brand's price to enhance the price gap between the private label and national brand price. They can use this price strategy when they locate the stores where the average wage is low. The above method will help develop the private label and increase the private label market share. Meanwhile, when the average wage is low, decreasing the private label price is significant to increase the private label market share. However, when the average wage is high, decreasing the PL price is not a good idea to increase the private label market share.

Finally, the number of stores enhances the positive effect of the SKU proliferation of PL. When the number of stores is high, the private label market share increase as the SKUs of PL increase. The number of stores enhances the number of brands' negative effects on the private label market share. When the number of stores is high, reducing the number of brands in the category can help retailers develop the private label. Meanwhile, the number of stores moderate the negative relationship between the private label price and private label market share. To get a high market share of private label, the retailer should not increase the private label price, especially when the number of stores is high.

5.3. Limitations and future research

Our study has some limitations. We collect data consisting of store information, product characteristics, sales unit, and sales price for each transaction. Although the data set involves 44 retail stores, it comes from one company's supply chain dyad. This is one of our research limitations. Meanwhile, to examine the factors influencing private label market share, we select the categories with higher sales volume. The categories that have a smaller proportion of private label are not included in this study. This is another limitation of our research. In future research, we suggest collecting more categories to investigate the factors influencing private label market share.

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Declaration of competing interest

None

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