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Distribution effectiveness through full- and self-service channels under economic fluctuations in an emerging market

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Abstract

Retail distribution is one of the major challenges in emerging economies. These economies are volatile and filled with inefficiencies, and the representativeness of unstructured retail increases the complexity of distribution systems for consumer packaged-goods companies.

We analyze 644 brands to extend the existing literature by modeling the retail distribution and market share in an emerging market according to the type of retail channel (full- and self-service channels), moderated by economic fluctuations and the market position of a brand (high- and low-share brands). Our model controls for endogeneity using instrumental variables (IVs) and accommodates heterogeneity across brands and categories by means of a fixed-effects robust regression. Our study highlights that the relationship between distribution and market share exhibits greater convexity in the self-service channel than in the full-service channel. Further, we contribute to the existing research in distribution effectiveness in emerging markets by showing the convex effect of distribution on market share could vary when the economy changes. Distribution gains are more effective in the self-service channel than in the full-service channel in times of economic decline. Also, the results indicate the higher degree of convexity in the relationship between distribution and market share for the self-service channel compared with the full-service channel is increased further for high-share brands than for low-share brands.

Keywords: Emerging markets; Distribution; Economic changes; Market share; Consumer packaged goods; Channel formats.

Introduction

Retail distribution is critical for product manufacturers to make products accessible and reach their customers (Sharma, Kumar, and Cosguner 2019). Past research supports the idea that retail distribution is important given its high elasticity in generating sales impulses in both developed and emerging markets (Ataman, van Heerde, and Mela 2010; Venkatesan et al. 2015). As reported by Euromonitor, store-based retailing is largely relevant for retail distribution in different markets, such as the U.S., India, and Brazil, where it accounts for approximately 78%, 94%, and 88% of total retail sales, respectively.[2]

Consumer packaged-goods (CPG) companies in emerging markets manage retail distribution through large chain self-service (SS) stores (e.g., Walmart, Carrefour) and traditional full-service (TF) stores formed by independent small owner-managed mom-and-pop stores (Roberts, Kayande, and Srivastava 2015; Venkatesan et al. 2015). Particularly, TF stores are smaller and carry less inventory, and the owner often makes the decisions, whereas SS stores rely on professionalized buy-

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[2] Euromonitor International Reports (2020), "Retailing in the US," "Retailing in India," and "Retailing in Brazil."

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0022-4359/

ing centers and large product assortment due to the larger store size (Sharma et al. 2019; Venkatesan et al. 2015).

The prevalence of both TF and SS channels adds to the difficulties in dealing with market inefficiencies in a more economically volatile environment than in developed economies (Narasimhan, Srinivasan, and Sudhir 2015; Sheth 2011). Russia, Brazil, Argentina, and other Latin American countries, for example, have faced frequent and rapid gross domestic product (GDP) fluctuations.[3,4,5] Given the marketing budgetary constraints in times of economic changes (Dekimpe and Deleersnyder 2018), retail distribution decisions can be more complicated in a volatile emerging-market environment for different reasons. First, distribution costs represent a considerable percentage of CPGs' total sales in comparison with developed markets, because of the underdeveloped logistics system (Sharma et al. 2019). Furthermore, manufacturers need to distribute their products to a large number of mom-and-pop stores that operate in these markets (Venkatesan et al. 2015), which can increase distribution costs even further. For example, whereas in the U.S., TF stores represent approximately 50% of the total number of grocery stores, in Brazil, they represent more than 97%, with almost 450,000 stores.[6] Second, retailers' stocking decisions generally prioritize products with wide consumer preference and higher rates of inventory turnover (Farris and Ailawadi 1992); however, consumer tastes, preference, and price sensitivity can shift during economic changes (Katona 1979; Dekimpe and Deleersnyder 2018; Kamakura and Du 2012; Lamey et al. 2012). To overcome these challenges, CPG manufacturers need to understand whether their results in terms of growth or reduction in distribution enhance market-share performance during changes in the economy.

The extant literature on the distribution–market-share relationship describes it as an increasing and convex curve (Reibstein and Farris 1995; Wilbur and Farris 2014). Thus, an inflection point exists at which market-share growth is more accentuated as a function of distribution (Wilbur and Farris 2014). The convexity curve helps companies assess whether their products are under-distributed or over-distributed, to optimize distribution decisions and efforts given that retail distribution is not directly controlled by CPG manufacturers (Ailawadi 2001; Farris and Ailawadi 1992). Prior studies in this research stream have supported the notion of the "double jeopardy" phenomenon whereby high-share brands tend to sell more per point of retail distribution than low-share brands (Reibstein and Farris 1995; Wilbur and Farris 2014). This phenomenon can be attributed to weak preference for low-share brands and retailer assortment strategies (Wilbur and Farris 2014). Low-share brands have small penetration rates, lower repeated purchase rates, and limited distribution because retailers often prioritize brands with strong consumer preference (Ailawadi and Farris 2020; Wilbur and Farris 2014).

With regard to analyzing the relationship between distribution and market share, we extend prior literature on distribution effectiveness in emerging markets. Kumar, Sunder, and Sharma (2015) and Venkatesan et al. (2015) examine the impact of distribution on sales in the emerging market. Although Venkatesan et al. (2015) also investigate the moderating role of SS versus TF channels, both prior studies focus on distribution elasticities and not the convex relationship between market share and distribution. We also extend the literature by showing the critical role of economic declines and market-share position in moderating the relationship between distribution and market share.

Motivated by these gaps, in this study, we extend the existing literature by examining the convex relationship between distribution and market share in the SS and TF channels and how economic changes and market-share position in an emerging market can moderate the distribution–market-share relationship.

Research questions

The proposed research questions are outlined below:

(A) Does the distribution–market-share relationship differ across TF and SS channels?
(B) Does the effect of retail distribution on market share vary with economic changes?
(C) How do distribution effects based on different channel formats vary between high-share and low-share brands?

To investigate our research questions, we use monthly brand-level distribution and market-share data from store audits conducted by a large global market research firm spanning from January 2013 to December 2015 for 644 brands through SS and TF stores in six distinct categories (i.e., beer, cookies and biscuits, laundry detergent, instant coffee, shampoo, ready-to-drink juice) across two main market regions in southeast Brazil that represent approximately 37% of total grocery sales in the country.[7] The data refer to a favorable context for our research, due to the rapid short-term economic change (i.e., GDP fluctuations) during the data-collection period as well as for the satisfactory mix of large (SS) and traditional retailers (TF) in Brazil. For example, whereas TF stores in the U.S. represent 11% of total sales from store-based retailing and 97% in emerging markets such as India,

[3] We refer to economic fluctuations and economic changes interchangeably in the manuscript.

[4] *Financial Times* (2016), "Russian GDP contracted 3.7% in 2015." (accessed July 28, 2019) [available at https://www.ft.com/content/81b0b40f-e1d2-35cf-8b52-02d6e245daf5].

[5] Deloitte Insights (2018), "Volatility in emerging economies: Is contagion too harsh a word?" (accessed November 6, 2019) [available at https://www2.deloitte.com/us/en/insights/economy/volatility-in-emerging-markets-fears-of-contagion.html].

[6] Euromonitor International Reports (2020), "Retailing in the US" and "Retailing in Brazil."

[7] Nielsen. Mudanças no mercado brasileiro. In: Seminário Nielsen Tendências. São Paulo, 2010.

this retail format represents 41% in Brazil, and the SS stores account for almost all of the remaining difference.[8]

According to our research design, we employ an econometric model to examine the distribution–market-share relationship across TF and SS retail formats and to assess the effect of distribution on market share during monthly GDP fluctuation. We then split the data into two groups (high- and low-share brands) and reconduct the analysis to find brand-position differences in the distribution–market-share relationship across retail formats. We contribute to the literature by revealing that the degree of convexity of the market share in retail distribution changes across TF and SS channels. Brands achieve more market-share gains per point of distribution in the self-service than in the full-service channels. Additionally, we show that the convex effect of distribution on market share vary with the economic changes. Finally, although both high-share brands and low-share brands can generate better returns from distribution in the SS channel than in the TF channel, these higher returns in the SS channel are further increased for high-share brands than for the low-share brands. Therefore, managers should consider the type of retail channel, changes in the economy, and the brand market-share position before making investments in retail distribution or trying to negotiate with retailers to stock their brands to target specific market-share outcomes in an emerging market, especially the TF channel, where distribution is overall less effective.

In the following section, we provide the conceptual background and hypotheses. Then, we describe the data and model framework and present the results from the model estimation. We conclude by discussing the managerial implications and provide some limitations of our own research to motivate future work.

Related Literature

Our research falls into the intersection of three areas: distribution effectiveness, distribution in emerging markets, and economic fluctuation. This section provides an overview of these different streams of marketing literature to describe how we contribute to prior studies.

Distribution effectiveness

Prior studies in the distribution-effectiveness literature have analyzed the effectiveness of multiple retail channels for manufacturer sales and profitability (Kumar, Sunder, and Sharma 2015; Venkatesan et al. 2015). Studies in this stream have emphasized the relationship between distribution and market share (Farris, Olver, and de Kluyver 1989; Reibstein and Farris 1995; Wilbur and Farris 2014). Overall, these studies empirically described this relationship as increasing and convex. Thus, after a certain point, the market-share gains from retail distribution accelerate and brands can expect a higher market share per distribution point. This evidence can help managers analyze whether their products are under-distributed and whether they should invest in efforts to try to increase distribution because of the high sales that can be achieved per distribution point (Ailawadi and Farris 2020). By doing so, managers can propose realistic market-share objectives given a certain distribution that can be achieved, and best allocate efforts and resources for their consumer brands between marketing push and pull depending on the position of the product in the convexity curve (Farris, Olver, and de Kluyver 1989; Wilbur and Farris 2014).

Based on the convexity curve of the relationship between distribution and market share, previous studies show the double-jeopardy phenomenon whereby “high-share brands tend to sell more per point of retail distribution than small-share brands” (Wilbur and Farris 2014, p. 154). The low-share brands usually have small penetration and repeat purchase rates (Ehrenberg 1988; Reibstein and Farris 1995). One explanation for double jeopardy is that low-share brands do not achieve broad distribution, because retailers prioritize brands with strong consumer preference, making finding and buying harder for the few customers who prefer them, and repeated purchase rates for lower-share brands suffer (Farley 1964; Reibstein and Farris 1995; Wilbur and Farris 2014). Most existing studies in the distribution–market-share research stream are carried out in developed markets, in which economies tend to be less volatile, a considerable level of retail concentration exists, and large retailers dominate.

Distribution in emerging markets

In emerging markets, manufacturers should optimize their distribution efforts and resources by carefully trying to distribute their products through many stores in each retail channel (Sharma et al. 2019) in the presence of high economic volatility (Aguiar and Gopinath 2007; Narasimhan et al. 2015). Primarily since 2015, the marketing literature has started to investigate the impact of distribution strategies on sales and market share in these markets (Kumar et al. 2015; Sharma et al. 2019; Venkatesan et al. 2015). These studies empirically uncover the importance and challenges of distributing a brand through different retail formats, such as SS and TF stores (Kumar et al. 2015; Venkatesan et al. 2015). The different characteristics such as ownership, management styles, store, and assortment sizes between these channels can cause a difference in the marketing-mix effectiveness (Venkatesan et al. 2015). Further, although SS stores account for a larger portion of retail sales, the TF stores also represent a significant share of retail sales in emerging markets (Diaz, Lacayo, and Salcedo 2007; Kumar et al. 2015; Venkatesan et al. 2015).

Given a selected channel strategy in a multichannel context, manufacturers need to decide how to govern their relationships with channel intermediaries from formal contractual obligations to verbal agreements (Heide and John 1988; Watson et al. 2015). Channel-governance strategies consider the notion of power and coercion, incentives, monitoring, and relational governance to describe how channel partners initiate,

[8] Euromonitor International Reports (2020), “Retailing in the US,” “Retailing in India,” and “Retailing in Brazil.”

maintain, and end their exchanges (Heide 1994). When defining governance strategies to sell their products through each channel, CPG manufacturers should consider the substantial heterogeneity that exists in management styles across stores. For example, the management of SS stores relies on more formal, embedded processes, contracts, and a professional buying center during the relationship with suppliers. By contrast, TF stores rely on more informal agreements with suppliers, and the owner is often the one who leads the relationship with them (Venkatesan et al. 2015). Between a transactional and a relational exchange, CPG manufacturers in emerging markets must develop different governance strategies to manage their relationship with these different channels.

Economic fluctuation

Emerging markets are also characterized by large temporal variations in economic and sociopolitical conditions (Narasimhan et al. 2015). Economic fluctuations can severely affect the performance of firms (Burns and Mitchell, 1946; Srinivasan, Rangaswamy, and Lilien 2005). Recession, in particular, is defined as the period between a peak and a trough, based on the location of peaks and troughs from economic indicators (Dekimpe and Deleersnyder 2018). Such volatility can be observed through different aggregate economic series, such as GDP, real income, employment, and consumer confidence (Hunneman, Verhoef, and Sloot 2015; Ou et al. 2014; Stock and Watson 1999). For example, between 2014 and 2015, GDP in Brazil declined by 3.8%.[9] Other emerging markets besides Brazil have also experienced rapid changes and strong economic fluctuations.[10,11] Developed countries have faced recessions as well, but they are less susceptible to shocks and have greater recovery power than emerging markets.

Since the 2000s, the number of marketing studies on economic changes has grown rapidly (Dekimpe and Deleersnyder 2018). The main findings from empirical research in this stream have almost exclusively focused on price, advertising, and innovation (Deleersnyder et al. 2009; Kashmiri and Mahajan 2014; Ou et al., 2014; Peers, van Heerde, and Dekimpe 2017; Srinivasan et al. 2005; van Heerde et al. 2013). According to previous studies, during economic contractions, consumers spend more time browsing products, because they shop around more and distribute their purchases differently across stores (Dekimpe and Deleersnyder 2018; Hunneman et al. 2015; van Heerde, Helsen, and Dekimpe 2007), to improve the price-quality ratio and reduce the perceived risks associated with purchases as they compare options (Ou et al. 2014). Hence, a wide distribution can be beneficial during economic changes. However, empirical research about distribution in the context of economic fluctuations is scarce (Dekimpe and Deleersnyder 2018).

Table 1 is a snapshot of the prior literature in the area of distribution effectiveness and our contributions to the marketing literature. Thus, we add to the existing literature by addressing the distribution–market-share relationship across channel formats with different forms of governance, and how distribution effects can be moderated by economic fluctuations and market-share position in an emerging market.

Research Framework and Hypotheses

In this study, our first objective is to examine how the relationship pattern between retail distribution and market share (i.e., the degree of convexity) is moderated by the retail-channel format and the negative change in the gross domestic product. The second objective is to compare how the moderation of the distribution-share relationship by the retail-channel format may differ or be further moderated by the market-share position of a brand (low vs. high market share). As such, Fig. 1 shows the conceptual framework.

Hypotheses

We expect the relationship between distribution and market share to differ between SS and TF channels. Stores in the SS channel belong to corporate retail groups (chains) rather than independent owners, which can result in more similar assortment strategies for each store in the chain (Venkatesan et al. 2015). In terms of relational governance, this channel format also relies on more formal governance strategies with CPG manufacturers, by establishing formal contracts rather than verbal agreements that are prevalent in the supplier-retailer relationship in the TF channel with the less professionalized independent stores (Heide and John 1988; Venkatesan et al. 2015; Watson et al. 2015). Once the relationship is established between CPGs and corporate retailers in the SS channel, distributing products through a large network of retail stores that are relevant to the specific category by selling to—and through—more stores within the same chain as fewer transactional costs and relationship risks arise (Heide 1994) is less complicated than in the TF channel. As such, products that are widely distributed can have higher penetration and repurchase rates (Wilbur and Farris 2014). Hence, sales per point of retail distribution can be higher for the SS channel format. Thus,

> *H_1: The degree of convexity in the relationship between distribution and market share is higher in the SS channel than in the TF channel.*

Brands, in general, are expected to reduce marketing spending during tough economic times (Dekimpe and Deleersnyder 2018) in addition to the high distribution costs in emerging markets (Sharma et al. 2019), which

[9] *Financial Times* (2016). “Brazil’s GDP shrinks 3.8%.” Retrieved from: https://www.ft.com/content/57a3a1e8-e13e-11e5-8d9b-e88a2a889797 (accessed July 28, 2019).

[10] *Financial Times* (2016). “Russian GDP contracted 3.7% in 2015.” Retrieved from https://www.ft.com/content/81b0b40f-e1d2-35cf-8b52-02d6e245daf5 (accessed July 28, 2019).

[11] The Conference Board (2018), “Global Consumer Confidence: Q2 2018 results,” available at<https://www.nielsen.com/content/dam/nielsenglobal/ru/docs/TCB-Global-Consumer-Confidence-Report-Q2-2018.pdf>, September 5, 2018 (accessed March 6, 2019).

Table 1
Related literature with focus on distribution effectiveness and positioning of the current study.

	Multichannel Distribution	Distribution–Market-Share Relationship	Double Jeopardy	Emerging-Market Setting	Economic Fluctuations
Farris, Olver, and de Kluyver (1989)	No	Yes	No	No	No
Reibstein and Farris (1995)	No	Yes	Yes	No	No
Bronnenberg, Mahajan, and Vanhonacker (2000)	No	Yes	No	No	No
Ataman, van Heerde, and Mela (2010)	No	No	No	No	No
Wilbur and Farris (2014)	No	Yes	Yes	No	No
Kumar et al. (2015)	Yes	No	No	Yes	No
Shah, Kumar, and Zhao (2015)	No	No	No	Yes	No
Venkatesan et al. (2015)	Yes	No	No	Yes	No
Sharma et al. (2019)	Yes	Yes	No	Yes	No
This study	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

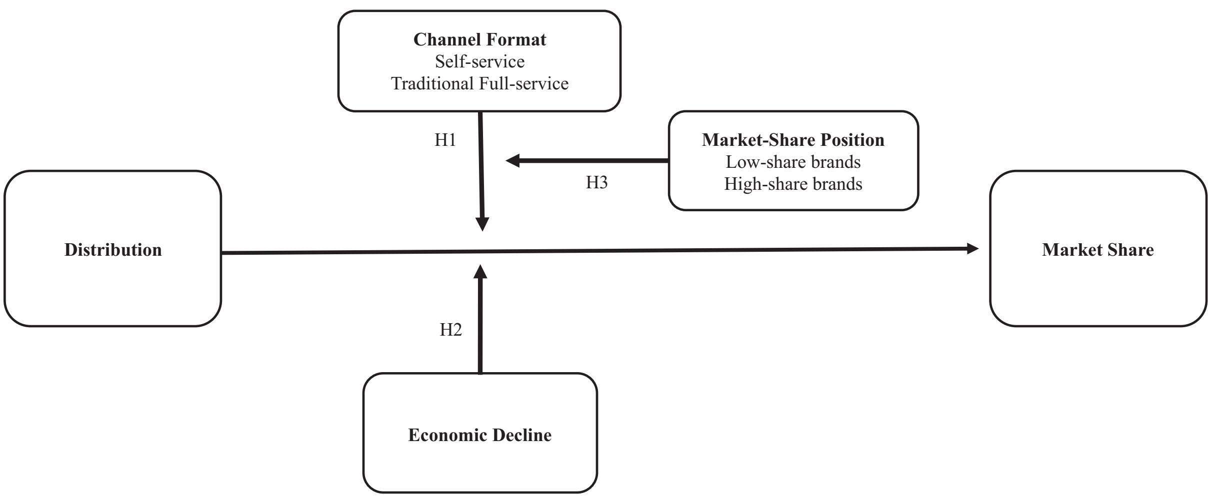

Fig. 1. Research framework.

can lower their ability to be stocked by more retailers, consequently reducing brand penetration and repurchase rates (Wilbur and Farris 2014). Furthermore, consumer preferences shift in times of economic volatility (Kamakura and Du 2012; Lamey et al. 2012), which can affect brand loyalty and market-share performance. For example, consumers are more willing to consider different products that improve their price-quality ratio when the economy contracts (Dekimpe and Deleersnyder 2018; Kashmiri and Mahajan 2014; Lamey et al. 2012; Ou et al. 2014). With more product switching and less search loyalty as the economy contracts, in conjunction with higher distribution obstacles that can affect the ability to widely distribute a brand across both TF and SS stores, the effect of the distribution on market share can decrease as the economy weakens. Thus:

H_2: The degree of convexity in the relationship between distribution and market share decreases in both the SS channel and the TF channel as the economy weakens.

Furthermore, in our study, we analyze how the effect of different channel formats on the distribution–market-share relationship could vary according to the market position of a brand, which allows us to account for the double-jeopardy problem that low-share brands face. Previous studies indicate the effect of retail distribution on market share tends to be larger for higher-share brands (Wilbur and Farris 2014). Retailers can give priority to high-share brands that consumers prefer (e.g., buy more per point of sales) to low-share brands (Ailawadi and Farris 2020). In general, SS stores have more professional management than TF stores. Thus, in selecting assortments, these retailers may respond more to data on sales velocities than do less professionally managed TF retail stores (Venkatesan et al. 2015). Hence, low-share brands could have more difficulty penetrating a more professionalized SS store, and even when they succeed, these brands face more in-store competition with high-share brands that enjoy greater consumer preference. Thus:

H_3: The higher degree of convexity in the relationship between distribution and market share for the SS channel compared with the TF channel is increased further for high-share brands than for low-share brands.

Data Description

For this study, we use data from retail audits conducted by a large global market research firm. The data contain information on 644 brands in six different categories (beer, cookies and biscuits, laundry detergent, ready-to-drink juice, instant coffee, and shampoo) for three years (from January 2013 to

Table 2
Descriptive statistics for the analyzed categories.

	Revenue (0.000 US$)	Num. Manufacturer	Num. Brands	Brand market share (basis points)		Brand %PCV SS (basis points)		Brand %PCV TF (basis points)		Relative price	
				Mean	SD	Mean	SD	Mean	SD	Mean	SD
Category											
Beer	23,944.27	7	83	1.58	4.57	54.63	29.24	20.48	24.42	127.89	59.42
Cookies and biscuit	5555.69	24	224	0.67	0.95	49.71	27.68	17.00	17.66	130.76	81.81
Laundry detergent	2641.23	10	67	2.61	6.34	58.06	29.75	23.61	25.26	132.85	97.62
Instant coffee	2328.47	7	27	4.91	8.25	56.71	29.34	17.56	20.62	105.42	26.62
Ready-to-drink juice	2261.93	32	67	1.97	4.21	41.10	29.67	16.32	19.68	119.77	54.30
Shampoo	684.66	18	176	1.04	1.01	62.60	25.90	36.21	25.87	112.93	54.64

December 2015) across SS and TF stores. These data encompass two designated market areas in Brazil. Both regions are in the state of São Paulo, the most economically developed in the country, and where monthly GDP data are available. The first region is the state metropolitan area, including the capital and its surroundings. The second refers to the state interior.

Our research analyzes a weighted measure reflecting the quality of distribution (i.e., distribution of the brand through the most important retail stores for a specific category, %PCV[12]). According to Reibstein and Farris (1995), it is a measure of product-category volume, calculated as the percentage of category sales made by the stores that stock the product. We include categories from all product classes analyzed by previous research on marketing-mix effectiveness over economic fluctuations (van Heerde et al. 2013): food (cookies and biscuits), beverages (fruit juice, instant coffee, and beer), household care (laundry detergent), and personal care (shampoo) (see Table 2).

The data cover a predominantly recessionary period including some months of positive economic fluctuation (see Fig. 2), with a general decrease of more than 12 percentage points by the end of the series. During the three years under analysis, Brazil experienced relevant events, such as (a) the start of the "Carwash Operation" to investigate a nationwide corruption scandal in March 2014, (b) the FIFA World Cup, which occurred in the country between June and July 2014, and (c) the reelection of then-President Dilma Rousseff in October 2014 from the left-wing Workers' Party, which followed (d) the unveiling of a large corruption scheme in the county's largest oil company, Petrobras, with serious implications for the governing party. These events led to changes in the country's GDP, which we use to account for the economic fluctuations in the market, following previous research (Dekimpe and Deleersnyder 2018).

[12] As stated by Farris, Olver, and de Kluyver (1989), given S stores that carry brand b's product category, we define $\%PCV_b$ as $\%PCV_b = \sum_{s=1}^{S}(d_{b,s}PC_s)$, where PC_s is store s's share of all sales in the product category, and $d_{b,s} = 0$ if brand b is not present in store s, and 1 otherwise.

Descriptive analysis

Table 2 shows the descriptive statistics for each category we analyze. The beer category has the highest revenue among the analyzed categories but the lowest number of CPG manufacturers (the same number as instant coffee). By contrast, the ready-to-drink juice has the highest number of manufacturers—more than four times the number of beer manufacturers—and a lower revenue than the other analyzed categories, except shampoo. The cookies and biscuit and shampoo categories have a relatively large number of different brands, whereas instant coffee has a smaller brand diversity. The instant-coffee category is the most concentrated in the data, with an average of 4.91 market share per brand, whereas the cookies and biscuits are less concentrated, with an average of 0.67 points of market share. The shampoo category has more points of distribution in the SS and TF stores. The laundry-detergent category has the higher average relative prices, but with a far higher dispersion.

Table 3 provides the operationalization and summary for these data, including the analyzed regions, retail formats, and variables. We highlight similar patterns for the %PCV measures across the two regions and channels. For example, we observe that, on average, brands are distributed through SS stores that represent 55.36% of the category sales in the metropolitan region (and 50.93% in the state interior). The average %PCV is different for SS and TF retail formats.

We also provide model-free evidence of the distribution–market-share relationship for each category in Figs. 3A and 3B. The plots suggest an increasing and convex relationship for the brands from our dataset in both channel formats.

Model Development

Our model addresses the primary objective to assess (a) the effects of distribution in two different retail formats on brand market share and (b) the effects of the interactions between distribution and economic changes. Additionally, our model controls for endogeneity using IVs and accommodates heterogeneity across brands and categories by means of a fixed-effects robust regression. It also accounts for seasonality and

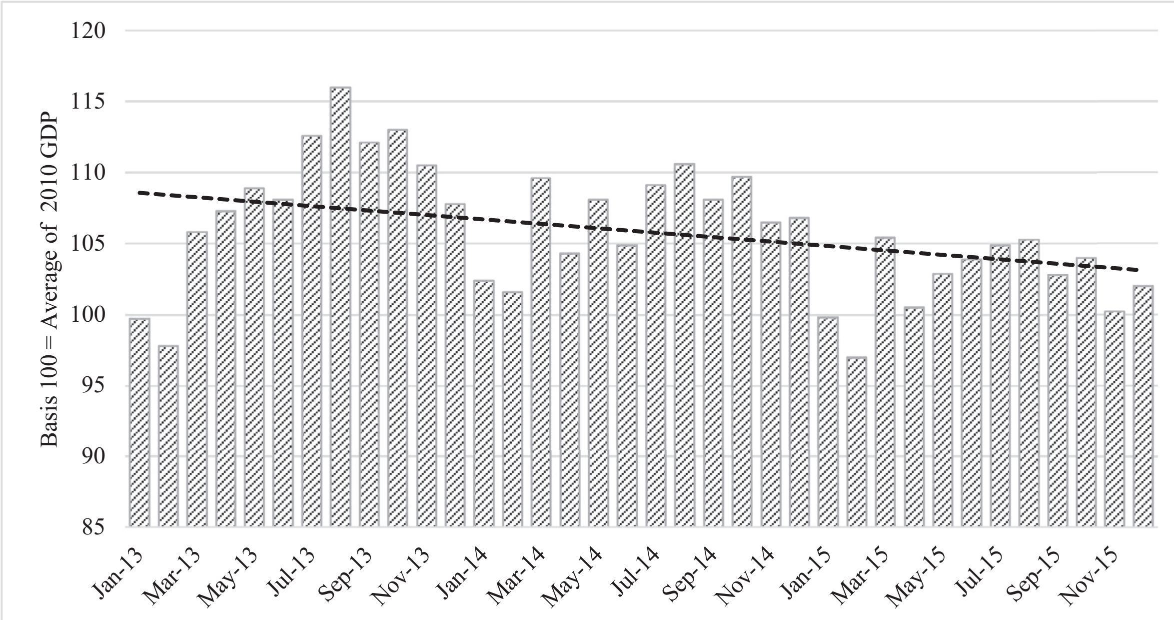

Fig. 2. Gross domestic product – Sao Paulo State.

Table 3
Variable operationalization and descriptive statistics.

Variable	Name	Description	Mean	SD
Market areas				
SS weighted distribution in region *ri*	$SS\%PCV_{ri}$	The percentage share of category sales made by stores that stock at least one SKU of the brand, compared with all stores in the relevant market, and adjusted for out-of-stock situations	55.36	29.64
SS weighted distribution in region *r*	$\mathrm{SS\%PCV_r}$		50.93	27.60
TF weighted distribution in region *ri*	$TF\%PCV_{ri}$		25.31	24.51
TF weighted distribution in region *r*	$\mathrm{TF\%PCV_r}$		17.19	19.37
Distribution market share				
Brand market share	*Share*	Volume sales of a brand to the total volume sales in the category in a month	1.34	3.52
Low-share brand	*Low-share*	The below-median volume share brands in the category in a month	0.21	0.28
High-share brand	*High-share*	The above-median brands in the category in a month	2.46	4.71
Total weighted distribution (SS)	*Total SS%PCV*	The sum of the weighted distribution of all brands for each category in the SS channel	3855.86	2006.15
Total weighted distribution (TF)	*Total TF%PCV*	The sum of the weighted distribution of all brands for each category in the TF channel	4423.05	2094.39
Economy				
Gross domestic product	*GDP*	Gross domestic product (GDP) is the sum of all final goods and services produced by the analyzed region (basis 100 = average of 2010)	105.8	4.49
Relative price for brand b in region r	$Price_{r,b}$	Brand price to consumers divided by the average price to consumers in the relevant category	124.79	71.58
Herfindahl-Hirschman Index	$HHI_{r,b}$	A market-concentration metric derived by adding the squares of the individual market shares of all the players in a market	0.062	0.062

serial correlation. Then, a model split into low- and high-share brands captures potential differences caused by market position in the effects of distribution in the two different retail formats on market share.

The model development has two stages. First, the endogeneity of distribution and price (included as a control variable) is controlled by means of IVs for weighted distribution (%PCV) in both SS and TF channels and relative price. In the second stage, we use the IVs obtained in the previous regression to assess the market-share elasticity due to the level of distribution by retail format (i.e., SS and TF channels) and its moderating effects, while accounting for the impact of time-variant fluctuation changes in the market.

Accounting for distribution endogeneity

Extant literature on marketing-mix modeling uses instruments to account for endogeneity problems Ataman et al. 2010; Kumar et al. 2015; Sharma et al. 2019;

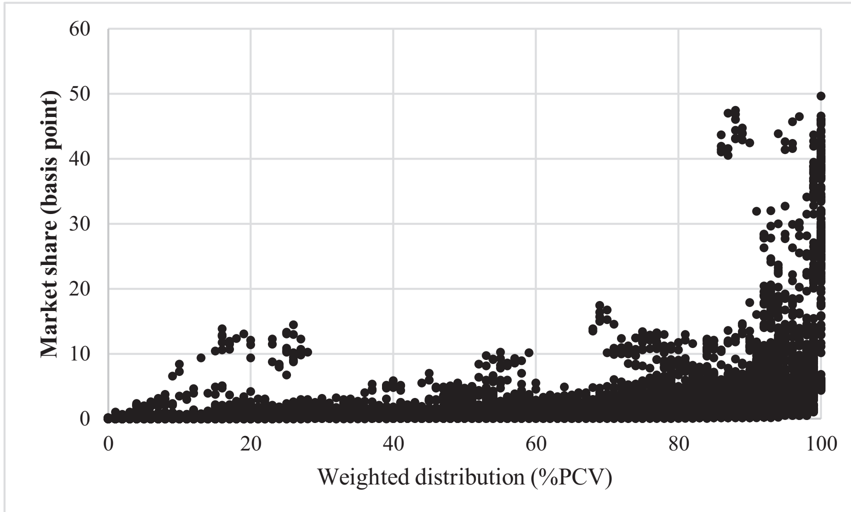

Fig. 3A. Weighted distribution and market share for self-service retail format (all brands in the data).

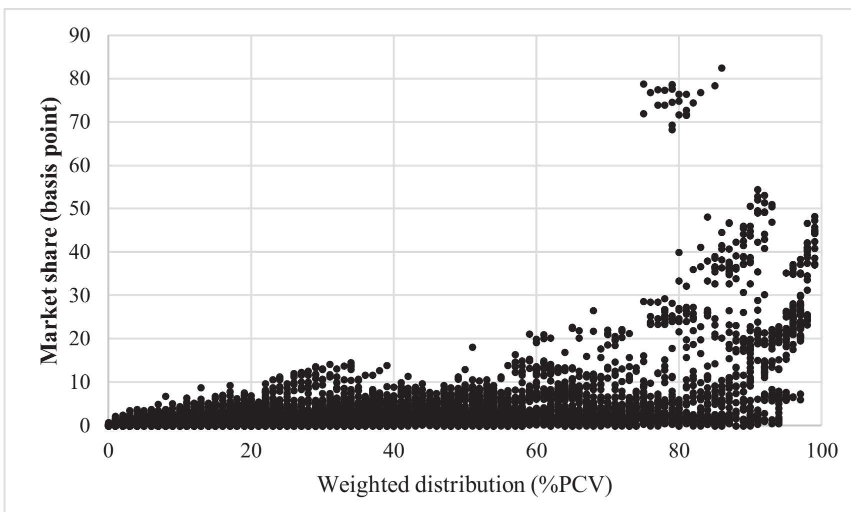

Fig. 3B. Weighted distribution and market share for traditional full-service retail format (all brands in the data).

van Heerde et al. 2013). Endogeneity can be manifested as a feedback effect of the marketing-mix variables (Hunneman et al. 2015; Kumar et al. 2015; Venkatesan et al. 2015), and prior studies identify instruments to account for such an issue (Sharma et al. 2019). Without a treatment for endogeneity, the model could contain an error term correlated with the main explanatory variable and produce biased estimates (Rossi 2014; Rutz and Watson 2019). We control for the endogeneity bias by means of instruments for distribution and price, based on the similarity of brand distribution between the two analyzed regions under study (see Table 3). We select the two most similar and geographically closest regions in the dataset considering their distribution characteristics, retail structures, and competitive dynamics for the relationship between CPG manufacturers and retailers in comparison with other options. Eqs. (1)–((3) specify, respectively, the use of brand weighted distribution and relative price from a region to estimate the value of the brand performance for the other region:

$$SS\ Distribution = SS\%PCV_{r,b,t} = \gamma_0 + \gamma_1 \times SS\%PCV_{ri,b,t} + \varepsilon_{r,b,t}, \tag{1}$$

$$TF\ Distribution = TF\%PCV_{r,b,t} = \gamma_0 + \gamma_1 \times TF\%PCV_{ri,b,t} + \varepsilon_{r,b,t}, \tag{2}$$

$$Price_{r,b,t} = \gamma_0 + \gamma_1 \times Price_{ri,b,t} + \varepsilon_{r,b,t}, \tag{3}$$

where $SS\%PCV_{r,b,\ t}$ is the estimated weighted distribution for brand b in month t for SS retail in region r, and $SS\%PCV_{ri,b,\ t}$ is the instrumental weighted-distribution metric by brand b in month t for the retail format c in region ri (which is different than r). $Price_{r,b,t}$ is the estimated relative price for brand b in month t in region r, and $Price_{ri,b,t}$ is the instrumental relative price metric by brand b in month t in region ri. We control for trend and time-variant effects with time fixed effects, assigning a dummy for each month; $\varepsilon_{r,b,\ t}$ is the error term. For the TF channel, the same rationale can be used for $TF\%PCV_{r,b,\ t}$ in Eq. (2). We also control for brand fixed effects. The F-statistics for all first-stage regressions are significantly greater than 10. The R^2 measures range between 0.57 and 0.80 for TF and SS retail formats, respectively.

We conduct specific tests to assess the validity and robustness of the instruments. First, we applied the Sargan-Hausman Test[13] to verify if the unique errors are correlated with the regressors, for all equations. The evidence from this test supports the use of fixed effects to capture category brand-specific characteristic. Second, based on the Wald test, we estimate a robust model with heteroskedasticity-consistent standard errors.[14] We also conduct the Wooldridge test for autocorrelation[15] to check if the size of standard errors of the coefficients could influence the R^2. Finally, we analyze whether the error term and the instruments could be correlated, which allows us to verify that error dependency was not an issue in our instrument (Dinner, Van Heerde, and Neslin 2014; Kumar et al. 2015; Hunneman et al. 2015; Lamey et al. 2012). The appendix (Tables A1 and A2) shows the estimates for the IVs used in the first stage of the model.

Assessing economic fluctuations in recessions

In previous studies, the use of quarterly GDP data led researchers to perform interpolation to estimate monthly data (Pauwels et al. 2004; van Heerde et al. 2013). To assess the economic fluctuations in this study, we use monthly data for the GDP of the state of São Paulo, provided by Fundação SEADE, a well-reputed public research institute in the state.[16] To calculate the magnitudes of the positive and negative fluctuations, we define the following terms:

$$Economic\ fluctuation_t = \Delta GDP_t = \Delta GDP_{t-1\to t} = GDP_t - GDP_{t-1}, \tag{4}$$

where

Δ is the first-difference operator (denoted by $\Delta X_t = \Delta X_{t-1\to t} = X_t - X_{t-1}$). It captures short-term changes in the economy considering both increases and decreases.

Fig. 2 presents the expansions and contractions in the economy between 2013 and 2015. In this period, Brazil (and the state of São Paulo) left a time of economic growth and fell into an intense economic decline. We consider an increase in the ΔGDP_t a positive economic fluctuation and a decrease in the ΔGDP_t a negative economic fluctuation.

Model for assessing the market share and distribution relationship per channel format and its moderation by economic fluctuation

We specify an autoregressive model for market share and adopt the parsimonious error-correction specification (Fok et al. 2006; Pauwels, Srinivasan, and Franses 2007; van Heerde et al. 2007; van Heerde, Srinivasan, and Dekimpe 2010; van Heerde et al. 2013) with a lagged first difference to control for the long-term effect of marketing-mix effectiveness on the market share. We employ the augmented Dickey-Fuller test for the dependent variable (i.e., market share) and conclude the unit root is not a concern. The results support the rejection of the null hypothesis of the unit root; therefore, the series is stationary.

In the second stage (Eq. 5), we use time-invariant characteristics and heteroscedasticity as controls, as we did in the first stage, and estimate the equation with stacked regions. We also control for relative price as an instrument, market-share concentration (by means of the Herfindahl-Hirchman Index [HHI]),[17] brand-specific trends, and time fixed effects. Following Kumar et al. (2015) and van Heerde et al. (2013), we consider the cross effect of competitors on the effects of the distribution and market share as a control by means of the total distribution of the competitors, that is, considering all competitors except the brand, separated by channel type.

Because the interpretation of convex relations can be challenging, we first build a model with distribution having a linear main effect on market share (Model 1), and subsequently, add the non-linear quadratic terms of the distribution variables (Model 2) to account for convexity. The equation for Model 1 is specified as follows:

$$\begin{aligned}
&\Delta lnMarket\ share_{r,b,t} \\
&= \beta_0 + \beta_1 \times \Delta lnMarket\ share_{r,b,t-1} - \beta_2 \times \Delta GDP_t + \beta_3 \\
&\quad \times \Delta ln\widehat{SS\%PCV}_{r,b,t} + \beta_4 \times\ \Delta ln\widehat{TF\%PCV}_{r,b,t} - \Delta GDP_t \\
&\quad \times \left[\beta_5 \times\ \Delta ln\widehat{SS\%PCV}_{r,b,t} + \beta_6 \times\ \Delta ln\widehat{TF\%PCV}_{r,b,t}\right] \\
&\quad + \beta_7 \times \Delta ln\widehat{Price}_{r,b,t} + \beta_8 \times\ \Delta HHI_{r,b,t} + \beta_9 \\
&\quad \times \Delta SS\%PCVcomp_{r,b,t} + \beta_{10} \times\ \Delta TF\%PCVcomp_{r,b,t} + e_{r,b,t},
\end{aligned} \tag{5}$$

where

[13] The Hausman test conducted confronts fixed effects and random effects checking if the differences in coefficients are not systematic. The test does not confirm the null hypothesis, which states that all instruments are uncorrelated with the error term. These results show strong evidence of time-invariant characteristics that may affect predictions. So, we employ fixed effects in the regression for %PCV.

[14] The Wald test checks the null hypotheses of $\sigma_i^2=\sigma^2$ for all i. Rejecting the null hypothesis implies in heteroskedasticity and the model needs control with robust standard errors estimators.

[15] Autocorrelation between the dependent variable in previous periods and the explanatory variable in the current period may also result in endogeneity bias (Rossi 2014; Rutz and Watson 2019). We tested for serial autocorrelation in the distribution results from both SS and TF stores in both regions and did not find evidence of autocorrelation.

[16] SEADE (2020), Produto Interno Bruto (GDP) – Mensal, (accessed July 21, 2020), [http://catalogo.governoaberto.sp.gov.br/dataset/757-produto-interno-bruto-pib-mensal].

[17] The HHI is a dispersion metric calculated using the total sum of the quadratic values of brands' market shares. A low index indicates a competitive market, and a high index indicates a few brands constitute a significative market share in the category (Reibstein and Farris 1995).

ln indicates the natural logarithm of the respective term[18];

$\Delta lnMarket\ share_{r,b,t}$ is the first difference in market share for brand b between months $t-1$ and t *in region* r;

$\Delta lnMarket\ share_{r,b,t-1}$ is the lagged first difference in market share for brand b between months $t-2$ and $t-1$ *in region* r, which we use to control for the persistence of the marketing-mix effects on the market share;

ΔGDP_t is the component for economic fluctuation in month t. The signs of its terms are inverted in the equation because the study is focused on the effects of negative economic fluctuations;

$\Delta ln\widehat{SS\%PCV}_{r,b,t}$ is the first difference in the weighted-distribution instrument for SS stores for brand b between months $t-1$ to t in region r;

$\Delta ln\widehat{TF\%PCV}_{r,b,t}$ is the first difference in the weighted-distribution instrument for TF stores for brand b between months $t-1$ and t in region r;

$\Delta ln\widehat{Price}_{r,b,t}$ is the effect of the relative price instrument between months $t-1$ and t, to control for the effect of pricing and for its endogeneity;

$\Delta HHI_{r,b,t}$ controls for the level of market-share concentration in region r for the product category of brand b between months $t-1$ and t;

$\Delta SS\%PCV comp_{r,b,t}$ is a control for the cross effect of competitors of brand b distribution between months $t-1$ and t in SS stores;

$\Delta TF\%PCV comp_{r,b,t}$ is a control for the cross effect of the competitors of brand b distribution between months $t-1$ and t in TF stores;

$e_{r,b,t}$ is the error term for brand b in month t.

To explore the convex relationship according to Wilbur and Farris (2014) when distribution has a non-linear effect, we specify Model 2 to account for the squared terms (%PCV). Thus, whereas Model 1 estimates the linear relationship between distribution and market share, Model 2 estimates the distribution-share convexity as Eq. (6) expands Eq. (5) by adding the squared terms for the SS and TF channels and for the interactions between economic fluctuation and these variables as well:

$$\begin{aligned}
&\Delta lnMarket\ share_{r,b,t}\\
&= \beta_0 + \beta_1 \times \Delta lnMarket\ share_{r,b,t-1} - \beta_2 \times \ \Delta GDP_t\\
&\quad + \beta_3 \times \ \Delta ln\widehat{SS\%PCV}_{r,b,t} + \beta_4 \times \Delta ln\widehat{TF\%PCV}_{r,b,t}\\
&\quad - \Delta GDP_t\left[\beta_5 \times \ \Delta ln\widehat{SS\%PCV}_{r,b,t} + \beta_6 \times \ \Delta ln\widehat{TF\%PCV}_{r,b,t}\right]\\
&\quad + \beta_7 \times \ \Delta ln\widehat{Price}_{r,b,t} + \beta_{12} \times \ \Delta ln\widehat{TF\%PCV}^2_{r,b,t}\\
&\quad - \Delta GDP_t\left[\beta_{13} \times \Delta ln\widehat{SS\%PCV}^2_{r,b,t} + \beta_{14} \times \Delta ln\widehat{TF\%PCV}^2_{r,b,t}\right] + e_{r,b,t}. \qquad (6)
\end{aligned}$$

The coefficients of the first differences in the distribution terms (β_3 to β_6) capture the velocity of the distribution–market-share convexity for the respective channel type, whereas the coefficients of the squares of these terms (β_{11} to β_{14}) assess the acceleration of such convexity for the respective channel type. In practical terms, the velocity coefficients quantify the rate at which market-share gains occur due to increases in distribution, and the acceleration coefficients measure the rate of change on such velocity as distribution increases. Therefore, Model 2 assumes the velocity of gains on market share due to distribution may change along distribution increments and can become substantially higher as a certain point of distribution is achieved, thus capturing the idea of convexity.

Model extension for assessing the moderation effects of market-share position

We conduct a further analysis for the brands with low market share and brands with high market share. Like van Heerde et al. (2013), we adopt the median split within each category separately to avoid confounding the brand and category characteristics. We classify "low-share brands" as those with market share below the median, and "high-share brands" as those with market share equal to or above the median value; this classification can change over time for some brands in the dataset. Thus, we can compare the magnitude of the distribution effects for the different types of brands in each period.

In summary, we analyze the patterns for the distribution–market-share relationship with data from two different regions, considering two types of channels during economic fluctuations in a recession, while accounting for endogeneity and controlling for product categories, brands and time effects, price, and competition. We also test for differences between high-share and low-share brands.

We compare the convexity coefficients of the different channel formats by standardizing their differences and testing these difference nullities as described by Gelman and Stern (2006) for coefficients in the same regression models with large samples. The tests for differences in the effects between low-share and high-share brands follow the comparison of coefficients of different regression models with large samples (Clogg, Petkova, and Haritou 1995).[19]

Results

In this section, we first present the results of the relationship between the distribution (%PCV) through different retail

[18] The second stage considers several brands from different manufacturers over the categories. Therefore, the efforts and costs necessary to increase its market share or distribution are different. The use of logarithmic transformation helps compare the distribution–market-share relationship in a more equitable and clearer situation. In addition, the literature presents a convex and growing relationship, which can create a bias due to the high extremity. The application of the transformation can reduce this effect.

[19] The tests consist of dividing the difference between the coefficients by its standard errors and testing its significance in terms of nullity. The standard error is calculated as the square root of the variance of the difference. When the coefficients are estimated in the same model, the variance of their difference considers the variances of both coefficients and their covariance. When they are estimated by means of different models, the covariance of the coefficients is not available, but it is assumed to be equal to zero, due the robustness of the model controls and estimations. Even for the comparison of coefficients in the same model, in which the covariance between the coefficients is available, such covariance is practically equal to zero and does do not substantively affect the calculation of the variance of the difference between coefficients.

Table 4
Estimation results.

	All brands		Low-share brands		High-share brands	
	Model 1 Coef. (S.D.)	Model 2 Coef. (S.D.)	Model 1 Coef. (S.D.)	Model 2 Coef. (S.D.)	Model 1 Coef. (S.D.)	Model 2 Coef. (S.D.)
$\Delta lnMarket\ share_{r,b,t-1}$ (β_1)	−0.13 (0.021)***	-0.13 (0.020)***	−0.18 (0.020)***	−0.17 (0.020)***	−0.12 (0.024)***	−0.12 (0.024)***
ΔGDP_t (β_2)	0.074 (0.021)***	0.054 (0.020)***	n.s	-0.040 (0.019)**	0.14 (0.031)***	0.13 (0.031)***
$\Delta ln\widehat{SS\%PCV}_{r,b,t}$ (β_3)	0.22 (0.013)***	0.27 (0.014)***	0.13 (0.012)***	0.17 (0.015)***	0.39 (0.021)***	0.37 (0.019)***
$\Delta ln\widehat{TF\%PCV}_{r,b,t}$ (β_4)	0.088 (0.0088)***	0.084 (0.0084)***	0.060 (0.0070)***	0.066 (0.0086)***	0.097 (0.012)***	0.090 (0.013)***
$\Delta GDP_t \times \Delta ln\widehat{SS\%PCV}_{r,b,t}$ (β_5)	0.0074 (0.0024)***	0.0080 (0.0027)***	0.0038 (0.0023)*	0.0060 (0.0030)**	n.s.	n.s.
$\Delta GDP_t \times \Delta ln\widehat{TF\%PCV}_{r,b,t}$ (β_6)	n.s.	-0.0034 (0.0019)***	n.s.	n.s.	n.s.	-0.0052 (0.0031)*
$\Delta ln\widehat{SS\%PCV}^2_{r,b,t}$ (β_{11})		0.11 (0.0087)***		0.055 (0.0081)***		0.10 (0.018)***
$\Delta ln\widehat{TF\%PCV}^2_{r,b,t}$ (β_{12})		0.039 (0.014)**		0.035 (0.017)**		n.s.
$\Delta GDP_t \times \Delta ln\widehat{SS\%PCV}^2_{r,b,t}$ (β_{13})		0.0043 (0.0021)***		0.0034 (0.0019)*		n.s.
$\Delta GDP_t \times \Delta ln\widehat{TF\%PCV}^2_{r,b,t}$ (β_{14})		n.s.		n.s.		n.s.
$\Delta ln\widehat{Price}_{r,b,t}$ (β_7)	−0.36 (0.035)***	−0.36 (0.034)***	−0.11 (0.017)***	−0.11 (0.017)***	−0.94 (0.058)***	−0.94 (0.057)***
$\Delta HHI_{r,b,t}$ (β_8)	0.000046 (0.000011)***	0.000048 (0.000011)***	0.000036 (0.000012)***	0.000036 (0.000012)***	0.000045 (0.000016)***	0.000047 (0.000016)***
$\Delta SS\%PCVcomp_{r,b,t}$ (β_9)	0.0000071 (0.0000029)**	0.000010 (0.0000029)***	0.000029 (0.0000029)***	0.000030 (0.0000029)***	-0.0000076 (0.0000042)*	n.s.
$\Delta TF\%PCVcomp_{r,b,t}$ (β_{10})	0.00010 (0.000022)***	0.000078 (0.000022)***	0.00013 (0.000022)***	0.00012 (0.000022)***	n.s.	n.s.
Intercept (β_0)	0.59 (0.17)***	0.43 (0.16)***	n.s.	−0.33 (0.154)**	1.13 (0.25)***	1.05 (0.25)***

n.s. = not significant at 10%.
* Significant at $\alpha \leq 10\%$.
** Significant at $\alpha \leq 5\%$.
*** Significant at $\alpha \leq 1\%$.

formats (SS and TF stores) and market share (H_1), followed by the results of the moderation of the economic fluctuation on the effects of distribution on market share (H_2). Then, we report how brand share influences the main moderating effect for the SS compared to the TF channel (H_3). For exposition purposes, we begin the analysis of each hypothesis with the linear effects from Model 1 and then present the non-linear (i.e., convex) effects from Model 2 to test the hypotheses. Table 4 provides the parameter estimates of the relationship between distribution and market share and of the control variables. Table 5 shows the tests for differences between effects.

In addition, we provide graphical representations of the distribution–market-share relationships. Fig. 4 shows the linear effects from Model 1, and Fig. 5 shows the non-linear effects estimated from Model 2.

Distribution–Market-Share convexity in different channel formats

Model 1 shows the distribution-share linear effect is higher in the SS channel (β_3= 0.22, p < 0.01) than in the TF channel (β_4= 0.088, p < 0.01). The difference between these coefficients is positive and significant (β_3 - β_4=0.13, p < 0.01), which is graphically represented in Fig. 4A. We examine the non-linear effect of distribution (i.e., convexity degree) in Model 2 to test H_1. The effect of the first-order %PCV term in the SS channel (β_3= 0.27, p < 0.01) is higher than in the TF channel (β_4= 0.084, p < 0.01). In addition, the degree of convexity of the SS stores (β_{11}=0.11, p < 0.01) is also higher than the degree of convexity of the TF stores (β_{12}=0.039, p < 0.05); both differences are significant (β_3 - β_4 = 0.19, p < 0.01, β_{11} - β_{12} = 0.069, p < 0.01). These results support H_1. The different degrees of convexity for both channel formats considering all brands can be seen in Fig. 5A.

Moderation of economic fluctuation on the distribution–market-share relationship

In Model 1, the linear effect of distribution shows the effect of %PCV on market share in the SS stores (β_5= 0.0074,

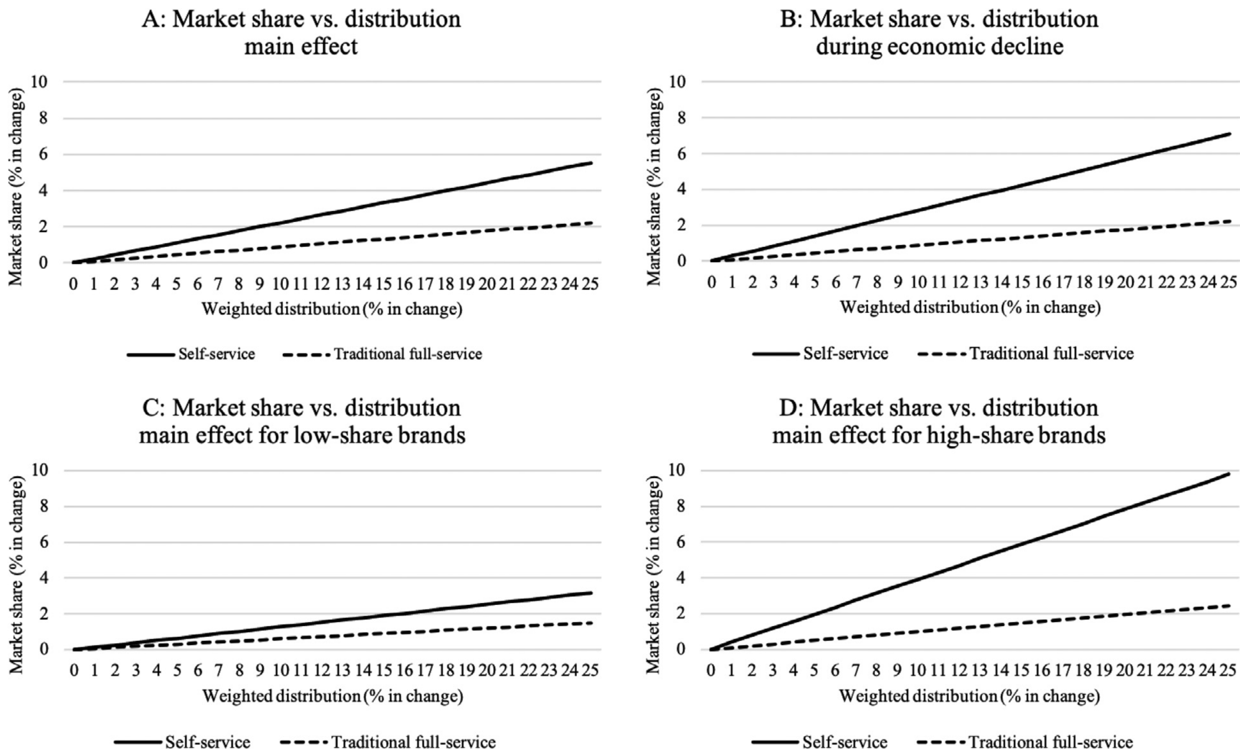

Fig. 4. Effects of %PCV distribution on market share per channel format and market-share position (linear model).
Linear effects estimated by means of the parameters in Model 1.

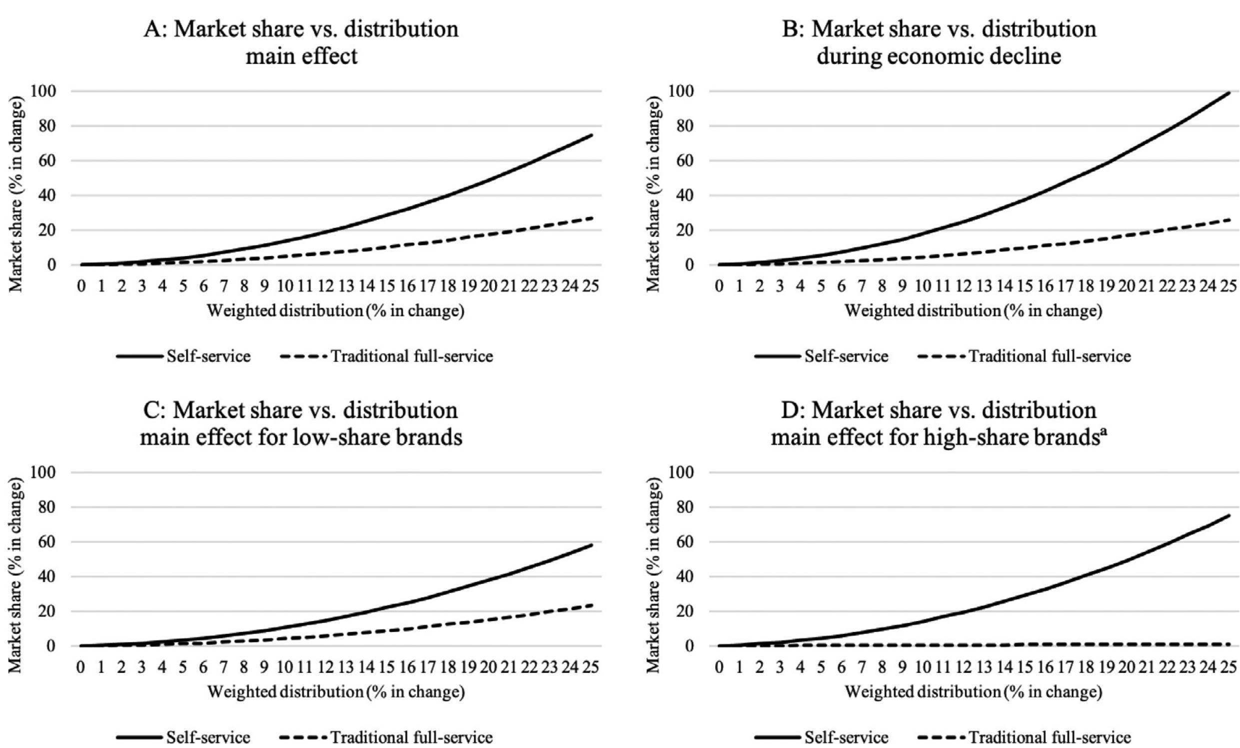

Fig. 5. Effects of %PCV distribution on market share per channel format and market-share position (non-linear model).
Convexity curves estimated by means of the parameters in Model 2.
[a]The effects of distribution on market share in the TF channel for high-share brands is linear because the quadratic term (β_{12}^{high}) is not significant.

Table 5
Differences between the estimated effects.

	All brands	
	Model 1 Coef. (S.D.)	Model 2 Coef. (S.D.)
Differences between the effects of channel type within models		
$\Delta ln\widehat{SS\%PCV}_{r,b,t}$ (β_3) - $\Delta ln\widehat{TF\%PCV}_{r,b,t}$ (β_4)	0.13*** (0.011)	0.19*** (0.016)
$\Delta ln\widehat{SS\%PCV}^2_{r,b,t}$ (β_{11}) - $\Delta ln\widehat{TF\%PCV}^2_{r,b,t}$ (β_{12})		0.069*** (0.015)
Differences between the effects of channel type and market-share position within and across models		
$\Delta ln\widehat{SS\%PCV}_{r,b,t}(\beta_3^{high}) - \Delta ln\widehat{TF\%PCV}_{r,b,t}(\beta_4^{high})$	0.29*** (0.023)	0.28*** (0.013)
$\Delta ln\widehat{SS\%PCV}_{r,b,t}$ $(\beta_3^{low}) -$ $\Delta ln\widehat{TF\%PCV}_{r,b,t}(\beta_4^{low})$	0.067*** (0.013)	0.10*** (0.017)
$\Delta ln\widehat{SS\%PCV}^2_{r,b,t}(\beta_{11}^{high})$ $-$ $\Delta ln\widehat{TF\%PCV}^2_{r,b,t}(\beta_{12}^{high})$		0.080*** (0.025)
$\Delta ln\widehat{SS\%PCV}^2_{r,b,t}(\beta_{11}^{low}) - \Delta ln\widehat{TF\%PCV}^2_{r,b,t}(\beta_{12}^{low})$		n.s.
Linear effects difference-in-differences $(\beta_3^{high} - \beta_4^{high}) - (\beta_3^{low} - \beta_4^{low})$	0.23*** (0.027)	0.18*** (0.022)
Quadratic effects difference-in-differences $(\beta_{11}^{high} - \beta_{12}^{high}) - (\beta_{11}^{low} - \beta_{12}^{low})$		0.060** (0.031)

n.s. = not significant at 10%.
* Significant at $\alpha \leq 10\%$.
** Significant at $\alpha \leq 5\%$.
*** Significant at $\alpha \leq 1\%$.

$p < 0.01$) increases given negative changes in the economy[20]; however, we did not find a significant effect of this relationship in the TF channel (see Fig. 4B).

The results of Model 2 (non-linear) also reveal a significant and positive effect of the first-order %PCV on market share in the SS channel (β_5= 0.0079, $p < 0.01$). When moderated by economic contraction, the degree of convexity in the distribution–market-share relationship also increases significantly (β_{11}= 0.0043, $p < 0.05$) for SS stores, whereas in the TF channel, the first-order %PCV significant and negatively affects market share when moderated by economic decrease ($\beta_6 = -0.0034$, $p < 0.1$), but the change in the degree of convexity (squared term β_{12})is not significant. Thus, we could not find support for H_2, because the changes in the degrees of convexity in the relationship between distribution and market share are different for SS and TF stores as the economy declines, and in the SS channel, the change is the opposite of what we expected (see Fig. 5A and B). In the discussion section, we explore possible implications and rationale for not confirming H_2.

Difference between distribution and market share for the SS and TF channels for high-share and low-share brands

Model 1 shows the linear effect of distribution on market-share is higher in the SS than in the TF channel for both high-share and low-share brands ($\beta_3^{high} - \beta_4^{high} = 0.29$, $p < 0.01$, $\beta_3^{low} - \beta_4^{low} = 0.067$, $p < 0.01$). As shown in Table 5, such difference between channel formats is significantly greater for high-share brands than for low-share brands, because $(\beta_3^{high} - \beta_4^{high}) - (\beta_3^{low} - \beta_4^{low})$ is equal to 0.23 ($p < 0.01$), which is also represented in Fig. 4C and D.

The results of the non-linear model (Model 2) also reveal greater distribution effectiveness of the SS channel in comparison to the TF channel for the high-share brands ($\beta_3^{high} - \beta_4^{high}$= 0.28, $p < 0.01$, $\beta_{11}^{high} - \beta_{12}^{high} = 0.080$, $p < 0.01$). For the low-share brands, the first-order %PCV term of the SS channel is significantly higher than the %PCV term of the TF ($\beta_3^{low} - \beta_4^{low} = 0.010$, $p < 0.01$), whereas the difference in the convexity terms between the SS and TF channels ($\beta_{11}^{low} - \beta_{12}^{low}$) is not significant. The differences of both distribution terms (linear and quadratic) between channel formats are significantly greater for high-share brands than for low-share brands, because $(\beta_3^{high} - \beta_4^{high}) - (\beta_3^{low} - \beta_4^{low})$ equals to 0.18 ($p < 0.01$) and $(\beta_{11}^{high} - \beta_{12}^{high}) - (\beta_{11}^{low} - \beta_{12}^{low})$ equals to 0.060 ($p < 0.05$). The results from Model 2 support H_3 given the higher convexity in the relationship between distribution and market share for the SS channel compared to the TF channel is further increased for high-share brands (see Fig. 5C and D).

Discussion and Implications

According to Kumar et al. (2015, p. 630), "perhaps the most intriguing element of the marketing mix in emerging markets is the effect of distribution on a firm's success." In this article, we expand on previous studies that fall into three

[20] As per previously mentioned, the sign was inverted in the equations because the study focuses on economic contractions

streams of research—distribution effectiveness, distribution in emerging markets, and economic fluctuations—to empirically show how the market-share gains per point of retail distribution could be different depending on the retail channel, economic fluctuations, and market-share position in an emerging market.

Ailawadi and Farris (2020) refer to the convexity curves as a practical way for managers to assess whether brands can have potential market-share gains from their efforts, resources, and strategies to increase retail distribution. Supported by the notion of the convexity curves (Ailawadi and Farris 2020; Wilbur and Farris 2014) and distribution effects in emerging markets (Kumar et al. 2015; Venkatesan et al. 2015), this study extends this prior research, and the findings can be useful for managers to make effective distribution decisions and prioritize their efforts across TF and SS stores in an attempt to influence retailer assortment strategies during economic fluctuations in an emerging market, by considering channel-specific distribution returns (Kumar et al. 2015).

Venkatesan et al. (2015) and Kumar et al. (2015) highlight the importance of distribution gains in both SS and TF channels in an emerging market. Based on the distribution effects observed, although our results support the importance of the TF channel, we contribute to these studies by indicating brands could achieve lower returns on distribution in this channel than in the SS channel.

Our results reveal two major observations. First, the degree of convexity is higher in the SS channel than in the TF channel. This result indicates an opportunity for brands to try to increase distribution in this channel because they can sell more per distribution point, leading to better marginal returns due to the greater degrees of convexity for the distribution–market-share relationship. Conversely, given the lower degree of convexity in the TF channel, managers should monitor their brands for not being over-distributed in this channel format. In this type of situation, brands may benefit from trying to increase demand to gain preference in this channel before focusing on distribution gains that can be costly in this more fragmented format in an emerging-market context (Sharma et al. 2019; Wilbur and Farris 2014). Our results also reveal the effect of distribution on market share varies with the brand market-share position, and the higher convexity in the relationship between distribution and market share for the self-service channel compared with the full-service channel is increased further for high-share brands. Therefore, we suggest brands should carefully consider their additional investments in and distribution efforts toward the TF channel.

Second, our results show a different pattern for the effects of distribution on market share during economic declines. In the full-service channel, brands need more distribution to maintain the same level of market share, whereas in the self-service channel, brands can increase their market share gains per distribution point when the economy weakens. Our interpretation of the higher effects of distribution on market share in SS during economic declines relies on two possibilities. First, consumers may prioritize large-assortment retailers such as SS stores to compare options and find better deals before making their purchases during economic contractions. Second, given that budgetary constraints often occur during economic declines, brands may prioritize distribution through the SS channel during tough economic times, because they incur fewer distribution and transactional costs to serve this channel format (Heide 1994). Because brands may prioritize availability in the SS channel, consumers have more chances to find brands that are widely available at the most relevant SS stores for a specific category.

Therefore, this study can be useful in the go-to-market decisions for brands in an emerging market, depending on the market position (i.e., brand share), channel formats (TF and SS), and the economic fluctuations. Such decisions can help companies in their push and pull decisions, including logistics and sales force. For example, we indicate high-share brands can have lower returns on distribution in the TF channel than in the SS channel and should focus on growing demand with pull marketing activities or even reduce their distribution in this channel. By contrast, these brands have higher returns on distribution in the SS channel and should concentrate on trying to increase distribution in this channel.

Our approach can shed light on distribution decisions in emerging markets because of the complexity involved in these markets, especially considering the channel-governance strategies, balancing push and pull marketing, logistics costs due to the lack of infrastructure, and economic volatility. For example, Brazil started to show signals of recovery in 2019; however, the spread of COVID-19 beginning in March 2020 has hampered the GPD projection for future years. Other emerging markets and even developed economies have faced economic volatility. This recessive path could be an opportunity for brands to gain market share through SS stores. Our study indicates the distribution–market-share relationship is an important element that drives market share differently depending on the different channel type and the economic situation in an emerging market.

Limitations and Opportunities for Future Research

Although we contribute in several ways to the existing literature on the distribution–market-share relationship and channels, our study has some limitations that provide directions for future studies. We control for endogeneity using IVs that allow us to capture the direct effect of distribution on market share to extend prior research in this field (Wilbur and Farris 2014). However, our analysis using the available data is at the aggregate-channel level and regional level; thus, we do not have the information on the store formats at the store level. Such data are not easy to obtain in emerging markets (Burgess and Steenkamp 2006), but future research could use the approach proposed by Jindal et al. (2020) to study inferences at the shopping-trip level (e.g., fill-in trips, major trips, and unplanned trips) in different retail formats in an emerging market, which might account for the relationship between distribution and market share.

Our findings are specific to a recession period in an emerging-market context (i.e., the representativeness of SS and TF stores) and we acknowledge fluctuations[21] in the economy can also happen in developed markets. Thus, future research could use our proposed modeling framework to address the relationship between distribution and market share during economic fluctuations in these markets. We also acknowledge that despite the increase in online channels, they still represent less than 5% of the grocery sales in the analyzed market.[22] Because this share is expected to increase, future research could use some contributions from our modeling framework to analyze the distribution–market-share relationship across offline and online channels. We hope the results this article provides can stimulate more research and further our knowledge within the distribution-effectiveness domain.

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Declarations of Competing Interest

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

Appendix

Table A1
Weighted-distribution instrument.

	Metropolitan area		State interior	
	SS Coef. (S.D.)	TF Coef. (S.D.)	SS Coef. (S.D.)	TF Coef. (S.D.)
Intercept (γ_0)	6.32 (1.37)***	2.13 (0.28)***	12.79 (1.72)***	1.22 (0.18)***
$Distribution\ performance_{ri,b,t}$ (γ_1)	0.92 (0.030)***	0.68 (0.12)***	0.70 (0.033)***	0.29 (0.059)***

*** Significant at $\alpha \leq 1\%$.

Table A2
Price instrument.

	Metropolitan area Coef. (S.D.)	State interior Coef. (S.D.)
Intercept (γ_0)	59.22 (13.71)***	54.47 (8.74)***
$Relative\ Price_{ri,b,t}$ (γ_1)	0.51 (0.11)***	0.59 (0.069)***

*** Significant at $\alpha \leq 1\%$.

[21] Survey of Consumers - University of Michigan, available at < http://www.sca.isr.umich.edu/tables.html>, accessed December 17, 2019.

[22] E-bit, Webshopper Report 2017, 35th Edition, <https://iabbrasil.com.br/pesquisa-ebit-webshoppers-35a-edicao-2017>, accessed December 2019.

References

Aguiar, Mark and Gopinath Gita (2007), "Emerging market business cycles: the cycle is the trend," *Journal of Political Economy*, 115 (1), 69–102.

Ailawadi, Kusum L. (2001), "The retail power-performance conundrum: what have we learned?," *Journal of Retailing*, 77 (3), 299–318.

Ailawadi, Kusum L. and Farris Paul W. (2020). *Getting Multi-Channel Distribution Right*. Hoboken, New Jersey: John Wiley & Sons.

Ataman, M. Berk, van Heerde Harald J. and Mela Carl F. (2010), "The long-term effect of marketing on brand sales," *Journal of Marketing Research*, 47 (5), 866–82.

Bronnenberg, Bart J., Mahajan Vijay and Vanhonacker Wilfried R. (2000), "The Emergence of Market Structure in New Repeat-Purchase Categories: A Dynamic Approach and an Empirical Application," *Journal of Marketing Research*, 37, 16–31.

Burgess, Steven Michael and Steenkamp Jan-Benedict E.M. (2006), "Marketing Renaissance: How Research in Emerging Markets Advances Marketing Science and Practice," *International Journal of Research in Marketing*, 23 (4), 337–56.

Burns, Arthur F. and Mitchell Wesley C. (1946). *Working Plans* (pp. 3–22). *Measuring Business Cycles*. NBER.

Clogg, Clifford C., Petkova Eva and Haritou Adamantios (1995), "Statistical methods for comparing regression coefficients between models," *American Journal of Sociology*, 100 (5), 1261–93.

Dekimpe, Marnik G. and Deleersnyder Barbara (2018), "Business cycle research in marketing: A review and research agenda," *Journal of the Academy of Marketing Science*, 46 (1), 31–58.

Deleersnyder, Barbara, Dekimpe Marnik G., Steenkamp Jan-Benedict E.M. and Leeflang Peter S.H. (2009), "The role of national culture in advertising's sensitivity to business cycles: An investigation across continents," *Journal of Marketing Research*, 46 (5), 623–36.

Diaz, Alejandro, Lacayo Jorge A. and Salcedo Luis (2007). "Selling to 'Mom-And-Pop' Stores in Emerging Markets". *McKinsey Quarterly* (accessed March 20, 2012), [available at https://www.mckinseyquarterly.com/Selling to mom-and-pop stores in emerging markets 1957].

Dinner, Isaac M., Van Heerde Harald J. and Neslin Scott A. (2014), "Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising," *Journal of Marketing Research*, 51 (5), 527–45.

Ehrenberg, Andrew S.C. (1988). *Repeat Buyving: Facts, Theory, and Applications*. New York: Oxford University Press.

Farley, John U. (1964), "Why does 'brand loyalty' vary over products?," *Journal of Marketing Research*, 1 (November), 9–14.

Farris, Paul W. and Ailawadi Kusum L. (1992), "Retail power: monster or mouse?," *Journal of Retailing*, 68 (4), 351–69.

Farris, Paul W., Olver James and de Kluyver Cornelis (1989), "The relationship between distribution and market share," *Marketing Science*, 8 (2), 107–28.

Fok, Dennis, Horváth Csilla, Paap Richard and Franses Philip Hans (2006), "A hierarchical bayes error correction model to explain dynamic effects of price changes," *Journal of Marketing Research*, 43 (August), 443–62.

Gelman, Andrew and Stern Hal (2006), "The difference between "significant" and "not significant" is not itself statistically significant," *The American Statistician*, 60 (4), 328–31.

Heide, Jan B. (1994), "Interorganizational governance in marketing channels," *Journal of Marketing*, 58 (January), 71–85.

Heide, Jan B. and John George (1988), "The role of dependence balancingin safeguarding transaction-specific assets in conventional channels," *Journal of Marketing*, 52 (January), 20–35.

Hunneman, Auke, Verhoef Peter C. and Sloot Laurens M. (2015), "The impact of consumer confidence on store satisfaction and share of wallet formation," *Journal of Retailing*, 91 (3), 516–32.

Jindal, Pranav, Zhu Ting, Chintagunta Pradeep and Dhar Sanjay (2020), "Marketing-mix response across retail formats: the role of shopping trip types," *Journal of Marketing*, 84 (2), 114–32.

Kamakura, Wagner and Du Rex (2012), "How economic contractions and expansions affect expenditure patterns," *Journal of Consumer Research*, 39 (2), 229–47.

Kashmiri, Saim and Mahajan Vijay (2014), "Beating the recession blues: exploring the link between family ownership, strategic marketing behavior and firm performance during recessions," *International Journal of Research in Marketing*, 31 (1), 78–93.

George, Katona (1979), "Toward a macropsychology," *American Psychologist*, 32 (2), 118–26.

Kumar, V., Sunder Sarang and Sharma Amalesh (2015), "Leveraging distribution to maximize firm performance in emerging markets," *Journal of Retailing*, 91 (4), 627–43.

Lamey, Lien, Deleersnyder Barbara, Steenkamp Jan-Benedict E.M. and Dekimpe Marnik G. (2012), "The effect of business cycle fluctuations on private-label share: what has marketing conduct got to do with it?," *Journal of Marketing*, 76 (January), 1–19.

Narasimhan, Laxman, Srinivasan Kannan and Sudhir Karunakaran (2015), "Marketing science in emerging markets," *Marketing Science*, 34 (4), 473–9.

Ou, Yi-Chun, de Vries Lisette, Wiesel Thorsten and Verhoef Peter C. (2014), "The role of consumer confidence in creating customer loyalty," *Journal of Service Research*, 17 (3), 339–54.

Pauwels, Koen, Silva-Risso Jorge, Srinivasan Shuba and Hanssens Dominique M. (2004), "New products, sales promotions, and firm value, with application to the automobile industry," *Journal of Marketing*, 68 (October), 142–56.

Pauwels, Koen, Srinivasan Shuba and Franses Philip Hans (2007), "When do price thresholds matter in retail categories?," *Marketing Science*, 26 (1), 83–100.

Peers, Yuri, van Heerde Harald J. and Dekimpe Marnik G. (2017), "Marketing budget allocation across countries: the role of international business cycles," *Marketing Science*, 36 (5), 792–809.

Reibstein, David J. and Farris Paul W. (1995), "Market share and distribution: a generalization, a speculation, and some implications," *Marketing Science*, 14 (3), G190.

Roberts, John, Kayande Ujwal and Srivastava Rajendra K. (2015), "What's different about emerging markets, and what does it mean for theory and practice?," *Customer Needs and Solutions*, 2 (4), 245–50.

Rossi, Peter E. (2014), "Even the rich can make themselves poor: a critical examination of IV methods in marketing applications," *Marketing Science*, 33 (5), 621–762.

Rutz, Oliver J. and Watson George F. (2019), "Endogeneity and marketing strategy research: an overview," *Journal of the Academy of Marketing Science*, 47 (3), 479–98.

Shah, Denish, Kumar V. and Zhao Yi (2015), "Diagnosing brand performance: accounting for the dynamic impact of product availability with aggregate data," *Journal of Marketing Research*, 52 (2), 147–65.

Sharma, Amalesh, Kumar V. and Cosguner Koray (2019), "Modeling emerging-market firms' competitive retail distribution strategies," *Journal of Marketing Research*, 56 (3), 439–58.

Sheth, Jagdish N. (2011), "Impact of emerging markets on marketing: rethinking existing perspectives and practices," *Journal of Marketing*, 75 (4), 166–82.

Srinivasan, Raji, Rangaswamy Arvind and Lilien Gary L. (2005), "Turning adversity into advantage: does proactive marketing during a recession pay off?," *International Journal of Research in Marketing*, 22 (2), 109–25.

Stock, James H. and Watson Mark W. (1999). "Business Cycle Fluctuations in US Macroeconomic Time Series". In Taylor John B., and Woodford Michael (Eds.), *Handbook of Macroeconomics* (pp. 3–64). Amsterdam: Elsevier Science BV.

van Heerde, Harald J., Helsen Kristiaan and Dekimpe Marnik G. (2007), "The impact of a product-harm crisis on marketing effectiveness," *Marketing Science*, 26 (2), 230–45.

van Heerde, Harald J., Gijsenberg Maarten G., Dekimpe Marnik G. and Steenkamp Jan-Benedict E.M. (2013), "Price and advertising effectiveness over the business cycle," *Journal of Marketing Research*, 50 (2), 177–93.

van Heerde, Harald J., Srinivasan Shuba and Dekimpe Marnik G. (2010), "Estimating cannibalization rates for a pioneering innovation," *Marketing Science*, 29 (6), 1024–39.

Venkatesan, Rajkumar, Farris Paul, Guissoni Leandro A. and Neves Marcos Fava (2015), "Consumer brand marketing through full- and self-service channels in an emerging economy," *Journal of Retailing*, 91 (4), 644–59.

Watson, George F.I.V., Worm Stefan, Palmatier Robert W. and Ganesan Shankar (2015), "The evolution of marketing channels: trends and research directions," *Journal of Retailing*, 91, 546–68.

Wilbur, Kenneth C. and Farris Paul W. (2014), "Distribution and market share," *Journal of Retailing*, 90 (2), 154–67.