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A proposition of analysis of the effects of different channels performance metrics on market share under economic fluctuations in an emerging market

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To my daughter Elisa,
today and always.

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"Retail distribution plays a critical role
in determining market shares: a product must
be offered for sale before it can be purchased."
Kenneth Wilbur & Paul Farris, Journal of Retailing (2014)

RESUMO

Rodrigues, J.M. (2019). *Uma proposta de análise dos efeitos de diferentes métricas de desempenho de canais de distribuição na participação de mercado sob flutuações econômicas em um mercado emergente* (Tese de Doutorado). Faculdade de Administração, Economia e Contabilidade de Ribeirão Preto, Universidade de São Paulo, São Paulo.

Este estudo teve como objetivo analisar como a distribuição no varejo (distribuição ponderada e distribuição numérica) influencia o *market share* em mercados emergentes, dependendo de diferentes formatos de lojas, regiões heterogêneas e flutuações econômicas. Mercados emergentes são complexos, com diversidade de canais e empresas, falta de infraestrutura e recursos e sensibilidade aos ciclos econômicos, o que gera preocupações com a endogeneidade. Foi realizada uma pesquisa quantitativa e descritiva, baseada em dois estudos. Os dados foram coletados em auditorias de varejo no Brasil e incluíram no primeiro estudo 91 fabricantes, 195 marcas e 1.110 SKU's na categoria de refrigerantes, abrangendo, no segundo estudo, 343 marcas em supermercados em sete categorias distintas (cerveja, biscoitos, detergente para a roupa, café em pó, iogurtes, xampu e suco) em três diferentes regiões do Brasil (nordeste, sudeste e sul). Os resultados mostraram que os efeitos da distribuição numérica (ND) versus distribuição ponderada (PCV) na participação de mercado variam de acordo com a região e o formato do canal. Embora o PCV ainda seja uma medida de distribuição relevante, o ND se torna importante em mercados emergentes. As conclusões também sugeriram que o grau de convexidade do *market share* na distribuição muda durante a contração e expansão econômica. O grau de convexidade é menor quando a economia se deteriora. Assim, as marcas disponíveis em lojas que representam uma alta participação nas vendas da categoria tornam-se menos importantes para sustentar ganhos de *market share*. Além disso, os resultados indicaram a importância de métricas não ponderadas, como a distribuição numérica durante tempos econômicos difíceis, enquanto o PCV se torna mais importante à medida que a economia se expande. Portanto, é necessário que os gerentes de marketing compreendam a interação entre o *market share* e a distribuição sob as flutuações econômicas e os diferentes formatos e regiões de varejo.

Palavras-chave: Canais de distribuição. Métricas de marketing. Variáveis instrumentais. Participação de mercado. Painéis dinâmicos.

ABSTRACT

Rodrigues, J.M. (2019). A proposition of analysis of the effects of different channels performance metrics on market share under economic fluctuations in an emerging market (Tese de Doutorado). Faculdade de Administração, Economia e Contabilidade de Ribeirão Preto, Universidade de São Paulo, São Paulo.

This study aimed to analyze how retail distribution (weighted distribution and numeric distribution) influence market share in emerging markets, depending on different retail formats, heterogeneous regions and economic fluctuations. These markets are increasingly complex, with diversity of channels and players, lack of infrastructure and resources, and sensitivity to economic cycles, which generates concerns about endogeneity. For this purpose, a quantitative and descriptive research was conducted based in two studies. The data were collected from retail audits in Brazil and included in the first study 91 manufacturers, 195 brands, and 1,110 stock-keeping units (SKUs) in soft drinks category, covering in the second study, 343 brands through grocery stores (i.e., self-service and full-service) in seven distinct categories (i.e., beer, cookies and biscuits, laundry detergent, powder coffee, yogurts, shampoo, and ready-to-drink juice) across three different regions in Brazil (i.e., northeast, southeast, and south). First, the results also showed that the effects of numeric (ND) versus weighted distribution (PCV) on market share vary with region and channel format. Although PCV is still a relevant distribution measure, ND becomes important in emerging markets. Findings also suggested that the degree of convexity of market share in retail distribution changes during economic contraction and expansion. The degree of convexity is lower when the economy deteriorates. Thus, brands that are available through stores that represent a high share of the total category's sales become less important to sustain market share gains. Furthermore, results indicated the importance of non-weighted measures, such as numeric distribution during tough economic times in an emerging market, whereas, weighted distribution (i.e., PCV) becomes more important as the economy expands. Therefore, it is necessary for marketing managers to understand the interplay between distribution-market share under economic fluctuations, and different retail formats and regions.

Keywords: Distribution channels. Marketing metrics. Instrumental variables. Market share. Dynamic panels.

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LIST OF ABBREVIATIONS AND ACRONYMS

CPG	Consumer Packaged Goods
CSS	Chain Self-Service
GDP	Gross Domestic Product
HHI	Herfindahl-Hirschman Index
ND	Numeric Distribution
PCV	Product Category Volume
SKU	Stock Keeping Unit
TFS	Traditional Full-Service

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1 INTRODUCTION

Besides companies' attention in the so-called emerging markets, there is also interest in studying the phenomena occurring in these markets, which often converge with studies already carried out for developed markets. In the marketing setting, there is an increasing questioning about how marketing variables relate, and the effects generated for the business (Guissoni, Rodrigues, & Crescitelli, 2014).

In order to understand these markets, it is essential to know the dynamics of distribution channels through a series of intermediaries, which vary in size and ownership (individual stores or belonging to some chain network) (Guissoni, 2012). Furthermore, a brand's success in an emerging market is heavily dependent on the extent to which distribution is particularly tailored according to the unique characteristics of the market (Kumar, Sunder, & Sharma, 2015).

Distribution channels are independent organizations that aim to provide a product or service to consumers' use (Palmatier, Stern, El-Ansary, & Anderson, 2014). They allow to build sustainable competitive advantages due to their long-term characteristics, both in planning and implementation, since they require consistent structure based on people and relationships (Neves, Zuubier, & Campomar, 2001).

The performance on multiple channels helps to maximize manufacturers' earnings and to improve their relationship with the customer (Venkatesan, Kumar, & Ravishanker, 2007) and, consequently, it is important to companies that target market share (Bronnenberg, Mahajan, & Vanhonacker, 2000).

In emerging markets, consumer packaged goods (CPG) companies need to manage distribution in a volatile economic environment with an inadequate infrastructure such as physical roads and logistics (Sheth, 2011), e.g., they have to manage their product line offered to consumers through different types of retails (channels) and some more heterogeneous regions compared to developed markets, which increase distribution complexity.

Therefore, this study addresses distribution-share relationship in emerging markets. The distribution variable has received an increasing attention from researchers (Kumar et al., 2015) and there is evidence on the importance of the distribution/share relationship, in addition to its format, as increasing and convex (Reibstein & Farris, 1995; Wilbur & Farris, 2014).

However, the literature has not provided guidance on how to manage the distribution-share relationship in emerging markets, and whether the results observed in developed economies would hold for them.

Under this perspective, this investigation extends the literature on distribution in order to accommodate quick changes in the economy prevalent in emerging markets. Indeed, research conducted in developed markets has not explored the distribution-share relationship during business cycles (Dekimpe & Deleersnyder, 2018). Since brand performance depends on how firms adjust their marketing mix in response to these macro-economic swings (Dekimpe & Deleersnyder, 2018), managers should know whether, and to what extent, distribution effectiveness can vary with economic fluctuations.

Furthermore, this study adds to past research (see Guissoni et al., 2014) by considering the effect of the distribution quality. To account for this quality, it was used the weighted distribution measure (i.e., product category distribution or PCV), which refers to the percentage of category sales made by all stores that stock a given product.

This is particularly relevant in emerging markets due to the dominance of non-traditional channels and large disparities in incomes among the different geographic regions, which makes it difficult to balance the amount of distribution channels or the distribution quality.

Additionally, different from previous studies, this research also used numeric distribution (ND), e.g., the percentage of stores that stock a particular product regardless the category sales made by the stores (Farris, Bendle, Pfeifer, & Reibstein, 2006).

Although ND is not a weighted measure, it is a metric commonly used by consumer package good (CPGs) and market research firms when it comes to less concentrated retail markets (e.g., emerging economies). In these economies, product availability, even in smaller stores, is the key, and therefore, ND is capable to increase the effect of the distribution quality.

Ultimately, this study also contributes to distribution looking for relationship with other marketing metrics and different context like channels, regions, and business cycles. The reason is the number of data and information available. The quantity of data nowadays motivates managers to try to assessment the effectiveness of marketing efforts (Wendel & Kannan, 2016). However, consumer behavior, market competition, and differences in infrastructure result in a challenge to modelling (Rossi, 2014). In fact, the concern about how to identify the real contribution of marketing efforts comes from understanding the endogeneity behind the relationship between marketing variables (Rutz & Watson IV, 2019)

Based on this information, managers can select stores to offer their products instead of searching to reach by selling to as many stores as possible without any criteria such as the category volume within each of these stores (Reibstein & Farris, 1995). In addition, consumer brand manufacturers in emerging markets can have a better understanding of how to tailor their strategies and marketing programs, including distribution strategies to different types of retails focusing on influencing sales and market share.

1.1 Research purpose and objectives

The lack of research on distribution in emerging markets, particularly considering business cycles influences and the effect of the distribution quality, leaded to the following research question:

How does distribution (PCV and ND) influence market share in emerging markets?

Therefore, this study aims to analyze the relationship between different distribution measures (i.e., PCV and numeric distribution) and market share in an emerging market (Brazil). In order to accomplish this goal, the specific objectives are presented:

- To verify how the distribution/share relationship differs according to the type of distribution measure used (i.e., numeric distribution versus product category volume).

- To identify the relationship between different distribution measures and market share according to different retail formats (i.e., self-service and full-service stores) and heterogeneous regions in an emerging market.

- To verify how business cycles can affect emerging markets and can alter companies' distribution activities and performance.

As shown in the specific objectives, this research contrasts two different measures of distribution (PCV and ND) for different retail formats (self-service and full-service). The chain self-service (CSS) belongs to corporate groups and operates with checkout lanes, large assortments, and large retail spaces (Venkatesan, Farris, Guissoni, & Neves, 2015), whereas, traditional full-service (TFS) is also known as mom and pop stores which are family-owned grocers often in neighborhood locations with limited inventory space.

Furthermore, the study is conducted in two regions with different demographic characteristics: Northeast and Southeast of Brazil. The former is the most fragmented retail area in the country while the latter is the most concentrated. In Brazil, the southeast region holds the greatest spending per household, US$ 26,739, while the northeast region holds the lowest, US$ 14,974. However, due to some local policies aimed at enhancing consumer's spending potential, the northeast of Brazil is likely to achieve higher growths, which makes it important to be studied as CPGs have started to target distribution growth in this region with 44 million people living there. Taking the state of São Paulo as an example (i.e., the most developed state in the country), the former region has roughly 23% of the total number of retail stores, which represent 32% of total grocery sales in the country; whereas, the northeast has 28% of the number of retails stores, accounting 15% of the total grocery sales.

The same pattern is observed when breaking down the number of stores in each region per different retail formats. In the northeast, there are 16,100 chain self-services (CSS) stores that accounted for 78% of grocery retail sales in the region, and 109,370 traditional full-service (TFS) stores that accounted for the remaining percentage. Whereas in the southeast, 10,600 retail stores in the CSS format accounted for 85% of the total grocery sales in the region and 37,520 TFS stores made up the remaining grocery sales.

1.2. Research structure

After the introduction, this proposed research is organized into six chapters. Firstly, chapter two includes the theoretical framework necessary to underpin the construction and testing of the hypotheses presented in chapter three.

Chapters four and five present the methodological procedures, encompassing research type, design, data, variables, and modeling. After that, chapter six introduces and discusses the results.

Finally, chapter seven reports the study's main conclusions, implications, and limitations.

2 LITERATURE REVIEW

The literature review addresses the main topics on marketing channels discussion in order to underpin the empirical part of the study.

Specifically, this chapter is organized into four parts. Initially, marketing channels are presented focusing on the strategic decisions involved to companies. Second, a brief overview on evolution and perspectives of marketing channels literature is showed with an emphasis in the recent research revenue underscoring distribution and emerging markets.

Finally, distribution measures are emphasized in an emerging market.

2.1 Marketing channels and strategic decisions

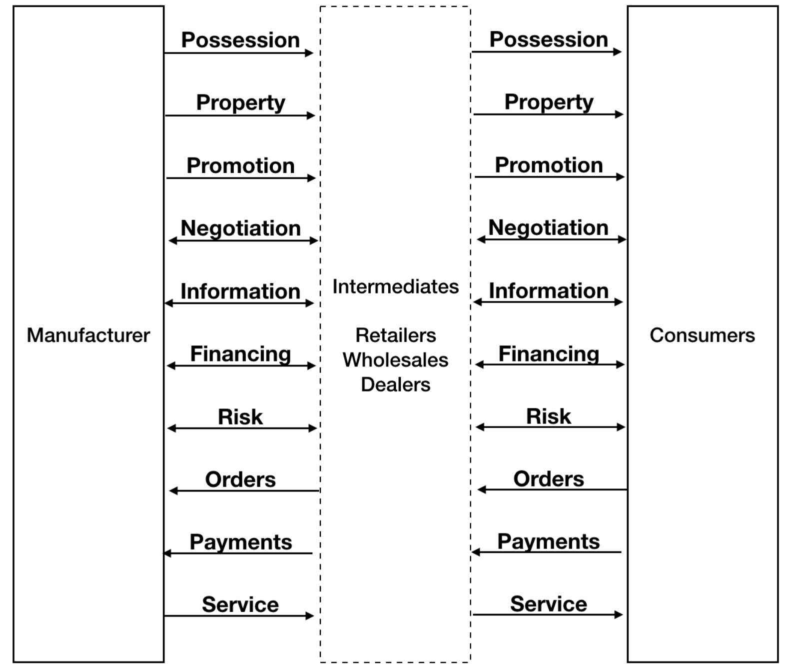
Marketing or distribution channels can be defined as "a set of interdependent organizations involved in a process of generating a product or making a service available for use or consumption" (Palmatier et al., 2014). Neslin et al. (2006, p. 96) conceptualize a channel as "a customer contact point, or a medium through which the firm and the customer interact".

In this process, all members involved in making a product available for use or consumption will be directly involved in marketing flows (Consoli, 2005; Guissoni, 2012). For instance, there are information flows, in which companies share information or even assist their intermediaries in product category management through communication or point-of-sale display enhancements (Guissoni, Consoli, & Rodrigues, 2013). Ownership flows are related to channels where intermediaries can own products (Rosenbloom, 1999). Consoli (2005) presents the marketing flows in distribution channels as follows in Figure 1.

With the diversity of marketing flows and agents, retailers decide whether to add or eliminate channels in their channel mix (Konuş, Neslin, & Verhoef, 2014), while consumers decide whether to adopt new channels or migrate from one channel to another. (Liu, Lobschat, & Verhoef, 2018).

Therefore, under companies' perspective, in order to determine the appropriate channels, go to market is fundamental to marketing mix (Jeuland & Shugan, 1988). Firstly, the company needs to decide which channels it will operate (Lilien, 1979). Second, the company must be alert to competitor's actions, which may drive changes in the channel mix (Liu et al., 2018; Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013; Kumar et al. 2015).

Figure 1 – Marketing flows



Source: Consoli (2005)

While the addition of a new channel creates more value in a turbulent market characterized by high customer demand volatility, by allowing the firm to spread its risk across more channels (Homburg, Vollmayr, & Hahn, 2014), it does not provide support for the effect of demand growth (Geyskens, Gielens, & Dekimpe, 2002), which makes companies' decisions even more complex.

According to Bucklin (1965) and Consoli (2005) distribution channels involve four major points to be considered:

a) channel extension;
b) types of intermediaries;
c) intensity of the channel;
d) number of distinct (multiple) channels serving the same market.

These topics are explored next.

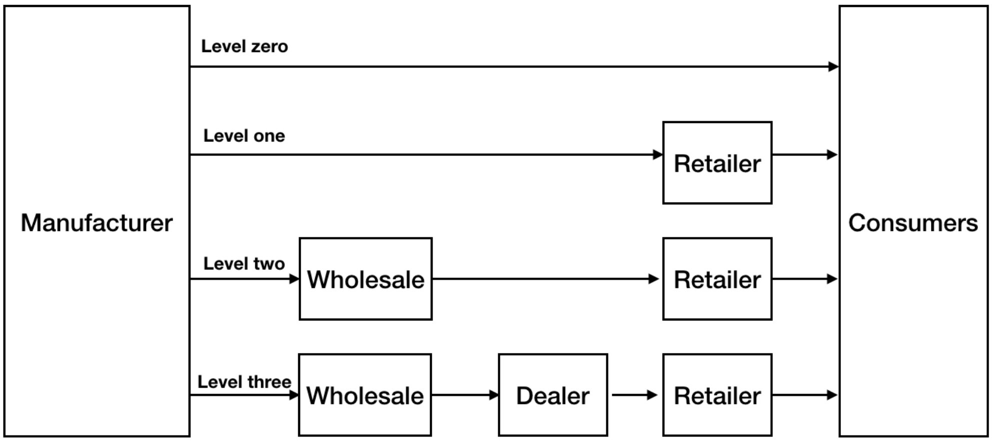
2.1.1. Channel extension

Channel extension involves the number of organizations that will be present from the producer to the end user of the product, being a more direct or short channel, with direct contact of the producing agent with the user, or less directly with several intermediaries

(Pelton, Strutton, & Lumpkin, 1997; Consoli, 2005).

Figure 2 shows the channel and its structure. The strategies adopted to analyze and select a possible extension are: (1) vertical integration, (2) signaling and screening, (3) franchising, and (4) resource expansion–acquisition.

Figure 2 – Channel structure



Source: Pelton et al., (1997)

When the market fails to offer the best options and ends up generating excessive costs, the company can choose to integrate channels rather than using partners to buy or sell. (Anderson & Coughlan, 2002; Rindfleisch & Heide, 1997).

From the point of view of Transaction Cost Economics, verticalization reduces production bottlenecks and increases efficiency even in a market failure (Arya & Mittendorf, 2011). Vertical integration also reduces the agency problem because it gains direct control over the chain, reducing information asymmetry.

One way to avoid the need for verticalization is to use screening processes and signaling actions. Screening is the process in which the company seeks to discover information of potential partners whereas signaling are actions that potential channel partners take to reveal their own characteristics (Chu, 1992, Liu et al., 2018). Thus screening processes and signaling actions can mitigate information asymmetries and facilitate channel selection.

Additionally, instead of assuming all channel responsibilities, manufacturers can use franchise agreements. The company (franchisor) sells the rights of its business model to an independent party (franchisee). Consequently, the franchisee uses its own capital and pays to operate in retail locations that represent the franchiser. In the franchise model there may also be multi-unit agreements, as well as the role of regulation in conflict management (Dant, Weaven, Baker, & Jeon, 2013).

Furthermore, channel selection can provide advantage to its existing resources, as well as developing new capabilities to explore new markets or even the current ones (Barney & Clark, 2007). Acquisitions or partnerships can ensure valuable resources that promote competitive advantage, and can also reduce dependence on other parts, such as franchises.

2.1.2. Types of intermediaries

With regard to the type of intermediaries, McCalley (1996) suggests that there are different types of intermediary organizations, involving wholesalers, agents, and retailers. Consoli (2005), for instance, associates channel flows with the intermediary's ability to add value to end users.

Retailer-specific characteristics, including market position, channel power over dealers, retailer size, sales growth, operating efficiency, and operation experience of different channels, also affect channel value creation. (Liu et al., 2018).

Hence, companies need to determine how they will manage their exchanges with intermediaries (Heide, 1994), considering the roles they play in the marketing flows and their capability to add value to consumers.

2.1.3. Intensity of the channel

Distribution intensity is defined by the number of intermediaries that a manufacturer uses at the level of delivery to the consumer (Stern, El-Ansary, & Coughlan, 1996). This decision differs in different categories. For instance, non-durable consumer products are expected to have much higher levels of distribution than durable products (Frazier & Lassar, 1996).

Overall, the ideal intensity is the one that the product is widely available to customers in order to satisfy their needs without exceeding, since saturation increases marketing costs without offering benefits (McCarthy & Perreault, 1984). In this way, few intermediaries can limit the exposure of the product to the market and the excessive use of intermediaries can harm the image of the brand and its competitive position.

2.1.4. Number of distinct channels

With regard to the decision on the number of channels, the retail literature defines the term multichannel to represent retailers who offer their services by means of more than one store format (Levy & Weitz, 2009).

Then, multichannel marketing refers to the company that uses multiple distribution channels. That is, the manufacturer that seeks through more than one distribution channel to offer its product in different types of intermediaries such as retail stores (Rangaswamy & Bruggen, 2005).

For example, retailers can develop various marketing strategies on whether to add or eliminate a channel, offer a specific marketing mix across channels, or integrate channels (Liu et al., 2018). This thesis uses the same definition of multichannel marketing used in the literature of distribution channels. In Brazil, this multichannel strategy is used by food and beverage manufacturers (Consoli, 2005). According to Consoli (2005), food products and beverages are widely distributed, being found in several points-of-sales and making them available to final consumers.

2.2 Evolution and perspectives of marketing channels – emerging markets

Initially, marketing channels studies were marked by the use of institutional, functional and organizational approaches, and systems that were used to understand marketing channels (Anderson & Coughlan, 2002). Their focus was predominantly economic (Coase, 1937) where efforts were concentrated on seeing distribution channels as flows of goods and services (Watson IV, Worm, Palmatier, & Ganesan, 2015).

Consequently, researches carried out in the early twentieth century considered the interactions among companies such as the optimization or minimization of cost and vertical marketing systems as extensions of the companies themselves.

Non-economic factors were largely ignored (Gattorna, 1978; Neves et al., 2001) until the second half of the century, when these factors started to be valued in the commercialization channels only (Bucklin, 1966, Stern, 1969). In this period, behavior-based researches complemented the discussion (Palmatier, Dant, & Grewal, 2007; Stern & Reve, 1980). Great advances were obtained by the use of transaction cost theory and agency theory (Anderson & Weitz, 1992; Heide & John, 1988), based on sociology, psychology, and organization behavior theories in order to explain possible inconsistencies resulting from economic rationality (Watson IV et al., 2015).

A great deal of work then began to relate and integrate theories regarding to roles, communications and conflicts with studies of power (El-Ansary & Stern, 1972), channel strategy (Frazier & Summers, 1984), channel structures and distribution (Bucklin 1966; Bucklin & Sengupta, 1993), conflict management (Kaufmann & Rangan, 1990), opportunism (John, 1984), and planning process (Neves et al., 2001), which presented breakthroughs due to the benefits of economic integration and behavioral theories in channel study and stimulated a new era of marketing channel relationship (Palmatier, Dant, Grewal, & Evans, 2006).

Consequently, the most recent marketing channel surveys involve e-commerce and internationalization (Grewal, Kumar, & Mallapragada, 2013), and the evolution and integration of multichannel (Ailawadi & Farris, 2017).

In addition, multichannel customer management from aspects of channel selection, multichannel strategy implementation, and channel evaluation are also discussed (Neslin et al., 2006; Neslin & Shankar, 2009), considering the view of how retailers communicate with customers based on customer needs (Kumar, 2010). Finally, a recent literature underscored the need to know the dynamics of distribution channels in emerging markets (Guissoni, 2012).

Sheth (2011) outlines five key characteristics of emerging markets that make them radically different from traditional, developed economies: market heterogeneity, sociopolitical governance, chronic shortage of resources, unbranded competition, and inadequate infrastructure. These markets are highly local and suffer from inadequate infrastructure and lack of resources. Most of the competition comes from unbranded products or services, and consumption is more of a make-or-buy decision and less about what brand to buy (Sheth, 2011).

Hence, in these economies, the retail sector is unorganized and characterized by a large number of small, independently owned stores that stock fewer products (Kumar et al., 2015). There is a wider range of retail formats and important regions for consumer industries to distribute, promote, and sell their products (Kumar et al., 2015; Shah, Kumar, & Zhao, 2015, Venkatesan et al., 2015).

As a result, the distribution decision is more difficult since the unstructured nature of the market provides managers with little information (in the form of data) to make optimal distribution decisions (Kumar et al., 2015).

In this setting, nontraditional channels and innovative access to consumers may be both necessary and profitable (Sheth, 2011). Differently from developed markets, firms must consider store format-specific distribution as opposed to aggregate effects in emerging markets (Kumar et al., 2015).

Therefore, this study contributes to this recent research stream, addressing distribution and market share relationship in an emerging market.

In the following section, the distribution variable is explored in detail.

2.3 Distribution measures in an emerging market

In the consumer goods industry, the variable distribution is associated to the role of manufacturers to offer products to end users through retail organizations, e.g., product line and place. According to Stern et al. (1996), the distribution decision includes the type of intermediary organizations, in which products should be available to be offered to end users.

Despite prior literature focusing on the effects of other marketing mix variables, such as communication activities (e.g., advertising and sales promotion), product and price (Clarke, 1976; Dekimpe & Hanssens, 1999; Pauwels, 2004; Srinivasan, Leszczyc, & Bass, 2000; Weinberg & Weiss, 1982), recent studies started to emphasize the distribution variable (Bronnenberg et al., 2000; Farris, Olver, & Kluyver, 1989; Reibstein & Farris, 1995, Wilbur & Farris, 2014) and notice its relevance especially in emerging markets (Guissoni et al., 2014, Kumar et al., 2015).

Indeed, distribution is capable to analyze the combined effects of the various elements of marketing mix on sales and market share, rather than treating them separately (Ataman, Mela, & Heerde, 2008; Ataman, Heerde & Mela, 2010; Bronnenberg et al., 2000; Pauwels, 2004).

Concerning this aspect, this variable showed, in a developed market, a greater effect on sales compared to other marketing mix variables, such as advertising (see Ataman et al., 2010), and underscored the existence of a close and positive relationship between distribution and market share.

Researches applied to developed markets indicate that the variation in the result of the market share obtained from a specific consumer good is closely related to its level of distribution (Ataman et al., 2008; Bronnenberg et al., 2000; Farris et al., 1989).

Furthermore, this relationship between distribution and share has been described as convex and crescent in developed economies (Bronnenberg et al., 2000; Farris et al., 1989; Reibstein & Farris, 1995; Wilbur & Farris, 2014), e.g., there is a slope from which the growth of market share is more pronounced due to the increase of distribution (Wilbur & Farris, 2014).

In emerging economies, this relationship was highlighted by Kumar et al. (2015), who suggested how companies should allocate efforts in marketing mix activities according to the distribution level required by the type of retail.

In order to measure distribution variable, two options presented in literature are suitable to emerging markets: the weighted distribution measure (i.e., product category distribution or PCV) and the numeric distribution (ND).

While the former refers to the percentage of category sales made by all stores that stock a given product and able to capture the effect of the quality of the distribution in different regions and types of retail (emerging markets), the latter measures the percentage of stores that stock a particular product regardless the category sales made by the stores, which is important to evaluate distribution in less concentrated retail environments (emerging markets).

These two measurements are used as reference in the empirical part of the research. PCV has been widely employed in past researches, whereas ND is an additional contribution of this study.

However, the use of metrics may require some care. Distribution metrics are not the only ones influenced by market share. Consumer preferences, prices and advertising need to be considered by marketing managers and market share effectiveness researchers (Wilbur & Farris, 2014). This issue, as well as many others such as not finding all the variables that control the effects of the distribution-share relationship, brings what the literature calls endogeneity (Rossi, 2014).

Kumar et al. (2015) present endogeneity with the interplay between the push and pull elements of the marketing mix. Pull strategies work towards attracting the customer to the store and thus creating demand. The marketing mix typically used for pull strategies includes price and advertising. On the other hand, push strategies aim to deliver the right product at the right place (store) at the right time. Managers need to be aware about how to manipulate data and their concerns. In fact, concern about endogeneity has been growing in marketing studies (Rutz & Watson IV, 2019). In the next section, the problems faced by researchers and marketing managers in data manipulation are presented with an emphasis on endogeneity issues.

2.4 Issues in distribution measures - endogeneity

The growth of different media, multi-channel capabilities, consumer and industry access to numerous digital devices, and software application diversity has made marketing a data-rich field (Rossi, 2014, Wendel & Kannan, 2016). High-quality data often has a high level of disaggregation, and thus bring a high level of variation in the variables that marketers and academics want to estimate the effects on results, such as sales and profits (Kumar et al., 2015, Wilbur & Farris, 2014, Heerde et al., 2013).

Rutz and Watson IV (2019) state that empirical marketing research often relies on past data to establish "how" and "why" relationships between marketing variables have happened. The goal is always to improve marketing strategies in the future, for example, by reallocating marketing resources (Venkatesan et al., 2015, Kumar et al. 2015) and also find causal effects and produce prescriptive advice for marketing managers to follow.

However, models that use observed data from the past are potentially biased. For instance, when the elasticity of the constructed model does not correctly represent the true effects of a given marketing action. The strategies outlined for the company in this way may not be valid and performance is likely to be compromised (Rossi, 2014; Rutz & Watson IV, 2019).

This concern regarding the validity of the adopted marketing models is named as endogeneity and it is associated to possible biases caused by the marketing mix variables, and other components of the model, considered endogenous. Thus, by imputing endogenous variables, there is a possibility that interpretable parameters and causal relationships can result in unreliable outcomes (e.g., Berry, 1994; Villas-Boas and Winer, 1999; Wooldridge 2015).

Indeed, the subject has been discussed in the main journals (McAlister, 2016). Figure 3 shows this growth in the last two decades. The recognition that marketing variables are defined by companies based on information not always observable by the researcher, led to concern about "endogeneity" and widespread pressure to implement methods of instrument variables in marketing problems (Rossi, 2014).

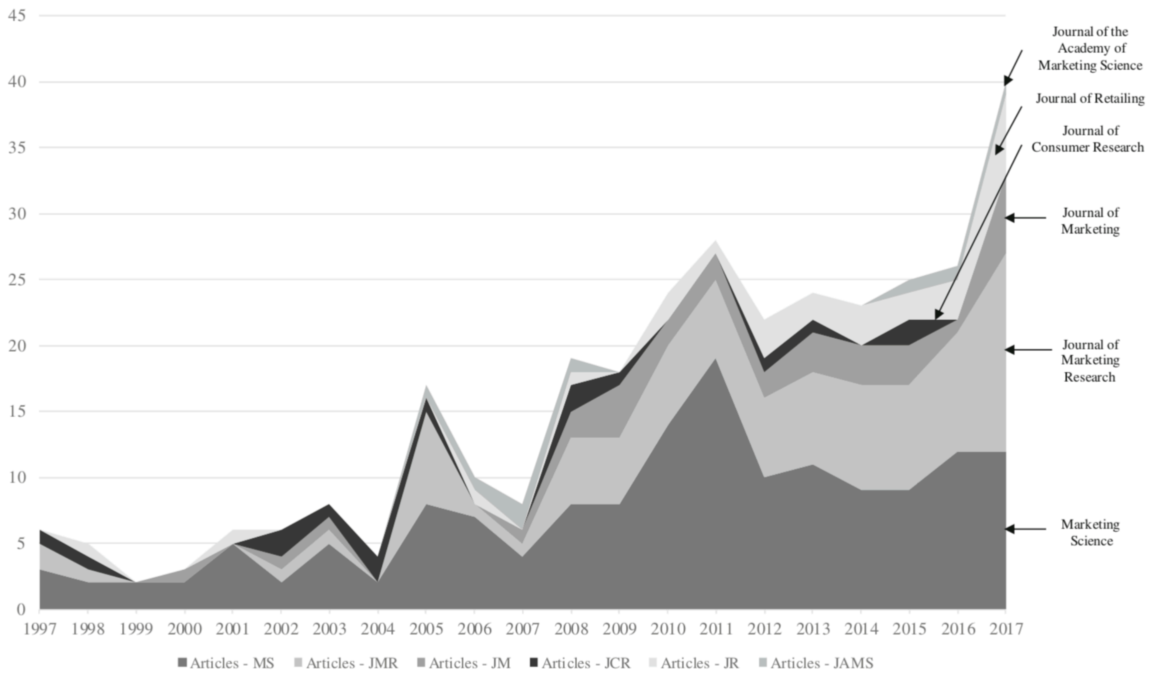
However, there is a difficulty in trying to reach consensus on endogeneity issues for most marketing strategy relevant questions, for both theoretical and practical reasons

(Houston, 2016; McAlister, 2016). Endogeneity is a concern that a perfect solution is not believed to exist (Rutz & Watson IV, 2019).

Even being able to set up a field experiment, controlling external effects can have endogeneity as a concern for establishing causality. The so-called "clean" experiments are rarely achieved in today's world with the agility that information and competition respond (Johnson et al., 2017; Avanzi, Guissoni, Rodrigues, & D'Andrea, 2019).

Among the issues raised by marketing, endogeneity is the most problematic, and potentially different, to resolve (Rutz & Watson IV, 2019). Within empirical research, efforts can be noticed to address the heterogeneity with which a consumer chooses and considers a store (Hunneman et al., 2015) or the effect of product propagation at different times in the country's business cycle (Heerde et al., 2013).

Figure 3 – Marketing articles addressing endogeneity



Source: Rutz and Watson IV (2019)

One of the keys to a good approach to address potential endogeneity problems is the available data and the availability of other supplemental data. Another key is to understand endogeneity in empirical research and discussions on how to address it, and build a good skill base for addressing endogeneity issues. (Ebbes et al., 2016; Papies et al., 2017). The next step to address endogeneity is to understand its potential source to apply in this research: omitted variables, simultaneity, and measurement error.

2.4.1 Bias caused by omitted variables

One of the most common sources of endogeneity is also one of the most difficult to infer a diagnostic due to uncertainty regarding the omission of explanatory (independent) variables. Endogeneity violations may result from omitting a variable that correlates with the explained (dependent) variable, as well as with any of the included explanatory variables (Wooldridge, 2015).

Problems of omitted variables may derive from data unavailability or selection bias, in which observations are non-randomly selected from untreated observations, based on an omitted factor that correlates with dependent variables and independent sources included (Clougherty et al., 2016; Rossi, 2014).

A typical example of variable bias omitted in the marketing context is price endogeneity (Heerde et al., 2013; Ma et al., 2011, Lamey et al., 2012). Companies do not set prices randomly, but consider the consumer response, competition, and seasonality. Generally, the researcher does not observe the pricing mechanism employed by the companies, introducing the omitted variable bias due to the non-randomness of the price (observed) in the data set. These price effects can affect how distribution strategies correlate with brand sales (Kumar et al., 2015) and other marketing mix variables (Venkatesan et al., 2015).

Endogeneity also occurs in digital channels. Selection bias caused by selection algorithms affects the effectiveness of upward advertising campaigns, because if it is not well optimized, the algorithm will look for people similar to the result of conversion behavior (i.e., people who clicked on the ad reported on a social network) and disregard people who have not clicked, considering an audience distinct from the real characteristics of the market. When an omitted variable is not taken into account in the model, it enters the error term variation, and the estimates of the coefficients of the variables included in the analysis suffer from an endogeneity bias (Wooldrigde, 2010; Rutz & Watson IV, 2019).

In practical terms, endogeneity by omitted variables, employing distribution as the explanatory variable (x) and market share as the dependent variable (y), can be described as:

$$y = \beta x + \gamma w + \varepsilon \tag{1}$$

where,

y = desired performance, e.g., market share, total sales

x = distribution efforts,

w = one or more influencing variables, for example, prices, communication at the point of sale or action by competitors,

ε = i.i.d. error term.

If the marketing manager seeks to adapt his marketing strategy using β but does not include γ due to the inability to observe these factors, the estimation will be:

$$y = \beta x + \upsilon \tag{2}$$

With υ being the i.i.d. error term, leading to the following problem.

$$\upsilon = \gamma w + \varepsilon \tag{3}$$

If γ ≠ 0 and x and w are correlated, the term x and error υ will also be correlated. This phenomenon is known as omitted variable bias, making β endogenous. This phenomenon happens in many contexts of marketing research, and it is often impossible to determine all possible explanatory variables, measure them precisely, and include them in the model. Consequently, the researcher is likely to have difficulty accounting for endogeneity in his model with only control variables (Rutz & Watson IV, 2019).

2.4.2 Simultaneity

Simultaneity in variables occurs when one or more explanatory variables are caused simultaneously and reciprocally with the dependent variable specified in a model (Bagozzi 1980; Wooldridge 2015).

In the case of distribution, this would manifest itself as the effect of reaching a higher number of points of sale and the reciprocal effect of sales on obtaining a higher number of points of sale. First, greater distribution increases consumer preference for a particular brand or product (Farris et al., 2006; Wilbur & Farris, 2014). However, if distribution affects consumer preference leading to higher sales, it will generate higher profits. In this case, the company will have higher resources, or will expect larger resources in the future, and may increase its distribution, leading to a feedback effect and possible simultaneity concerns.

Analysis of the data set containing market share (y) and distribution (x) information ignoring simultaneity would result in the model error term correlated with the explanatory variable, producing endogeneity problems and biased coefficient estimates. Similarly, autocorrelation of the dependent variable in previous periods with the explanatory variable in the current period may also result in endogeneity bias (Wooldridge, 2015; Rossi, 2014; Rutz & Watson IV, 2019).

The simultaneity problem is presented as follows, taking again distribution (x) and market share (y) as reference and supposing the model generated by the data is true:

$$y = \beta x_1 + \gamma w + \varepsilon_1 \tag{4}$$

$$w = \delta x_2 + \eta z + \varepsilon_2 \tag{5}$$

Where,

y = desired performance, e.g., market share, total sales;

$x_1 \ e \ x_2$ = distribution efforts at time t = 1 and at time t = 2;

w= one or more influencing variables, for example, prices, communication at the point of sale or action by competitors;

ε_1 e ε_2 = i.i.d. error terms.

If the researcher can only observe y, x and w, the estimated model would be:

$$y = \beta x_1 + \gamma w + \upsilon \tag{6}$$

With υ being the error term and resulting in endogeneity since E (zv) is 0. The main struggle in establishing causal relationships in variables that occur simultaneously is to find a temporal order in which some influence others. For instance, investment in distribution increases sales, but increased sales lead to a larger distribution budget (Venkatesan et al., 2015; Hunneman et al., 2015; Kumar et al. 2015), as do the other marketing mix variables. In a similar context, advertising can not only increase sales and provide a larger budget (Dekimpe & Hanssens, 1995) but also can enhance budget for the other components of the marketing mix (Guissoni, 20112). In these cases, the dependent variable also causes the explanatory variable and, therefore, the error term in the equation is correlated with the explanatory variable, violating OLS (ordinary least squares) assumptions and resulting in biased estimates (Rutz & Watson, 2019; Rossi, 2014; Wooldrigde, 2015).

2.4.3 Measurement error

Another difficulty of empirical marketing research is the possible measurement errors that dependent and independent variables may present. Under this condition, the accuracy of the estimate and the true relationships between constructs may be imperfect or inconsistent.

Examples of measurement errors are sales or advertising numbers, measurements when not taken across all exposure channels may not represent the true mix employed from one company to another (Ataman et al., 2010; Heerde et al., 2013; Naik & Tsai, 2000).

Measurement error in dependent variables usually leads to an increase in error term variation (i.e., residual model error), but allows for an unbiased analysis of the effect of independent variables if they are free of measurement errors (Wooldrigde, 2015). If independent variables are measured with errors, an endogeneity will emerge, will influence the relationship and will need to be addressed. One of the assumptions of OLS models is that the error term should not be correlated with explanatory variables; otherwise, it will result in estimates of biased and inconsistent coefficients (Rossi, 2014; Rutz & Watson IV, 2019). One way to exemplify this condition can be written as:

$$y = \beta x + \varepsilon \tag{7}$$

Where:
y = desired performance, e.g. market share, total sales
x = distribution efforts,
ε = i.i.d. error term

If there is any measurement error in x such that:

$\dot{x} = x + \xi, \xi$ is a measurement error (8)
$y = \beta \dot{x} + \upsilon, \upsilon$ is an error term (9)

Since $\upsilon = \xi\beta + \varepsilon$, both x and υ are functions of ξ, making x endogenous. This bias is known as the attenuation bias and influences the estimate of β relative to zero (Wooldridge, 2015). Thus, the measurement error of distribution efforts creates a biased estimate and may lead the researcher to conclude that distribution does not affect the gain in market share of a brand, when in fact it occurs.

If for any reason, the point of sale of the audit firm collects information from a variable considered by the marketer as dependent (i.e., total sales of a category) with some kind of error (due to sample, measurement process, people involved in data processing) that is not considered systematically related to the explanatory variables of the model, the estimates of interest will not be biased and the measurement error will be captured by the projected error term as predicted.

However, if the measurement error of the dependent variable is correlated with the explanatory variables (e.g., contracting a smaller sample search for low sales products and vice versa), the relationship between them will result in endogenous problems. The researcher's model will be as good as his ability to accurately and consistently measure the phenomenon of interest, otherwise, even the best-specified models will yield dubious results (Rutz & Watson IV, 2019).

2.4.4 Instrumental variables

The endogenous concern in the abundance of potentially explanatory marketing data, for the most part, is not experimentally generated, seeking to control external effects (Avanzi et al., 2019). The data come from passive observational methods, so there is a legitimate concern about how to generate causal inferences using methods such as regression analysis.

Therefore, a traditional solution to the endogeneity bias problem is to use instrumental variable (IV) methods. These methods, by definition, do not use all variation in the data to identify causal effects, but split the variation into what may be considered "clean" or as generated by experimental methods and what is "contaminated" and may result in endogeneity bias.

The first condition of the strength of the instrument, i.e., the ability to potentially correct the endogeneity bias, which is almost always defined as the asymptotic bias of an estimator that uses all variation in the data. An instrument with a high (low) correlation with the endogenous variable is a strong (weak) instrument. IV Methods are asymptotically unbiased only if the instruments are valid. Validity is an unverifiable assumption. Even if valid, IV estimators may have poor sampling properties, including long tails, high RMSE (root-mean square deviation), and bias (Rossi, 2014).

Using this approach, the researcher decomposes the variation in the endogenous variable into two parts: a part correlated with the error term and a second part uncorrelated with the error term used to estimate the model (Rutz & Watson IV, 2019). For the same model presented by equation (10), a use of instrumental variables would be:

$$y = \beta x + \varepsilon \tag{10}$$

$$x = \lambda z^{IV} + \tau \tag{11}$$

Where:

y = desired performance, e.g., market share, total sales,

x = distribution efforts,

z^{IV}= they are instrumental variables, for example, efforts in other channels, other regions, or in distinct segments.

ε e τ = i.i.d. error terms.

The assumption of this model is that the instrumental variable z^{IV} does not enter equation (10). The whole effect of z^{IV} on y is given indirectly by x, but no direct effect can be found. This condition is called an exclusion constraint (Angrist et al., 1996, Wooldridge, 2015). Therefore, the prerequisite for the instrument is that it should not have the same problem as the endogenous variable; otherwise it is considered a poor instrument. Unfortunately, there is no way to "test" the exclusion constraint because the model in which the z^{IV} variables enter the two equations is not identified (Rossi, 2014).

Because of the many challenges that marketing data can provide, the use of method IV needs strong theoretical reasons or empirical evidence that one (or more) explanatory variables are actually correlated with the error term (i.e., are actually endogenous), but with an ability to collect the missing explanatory variable directly (for example, a point of sale expansion decision).

The endogeneity of marketing mix decisions such as distribution or even advertisements can be resolved by using similar but different markets from IVs. The idea is that changing costs in different but related markets would cause similar but exogenous variations in the variable explained among retailers serving different market segments. These costs can drive marketing spend on distribution, advertising, and promotions, and therefore these costs can be used as IVs because they are not correlated with the error term (Dinner et al., 2014; Kumar et al., 2015; Hunneman et al., 2015; Lamey et al., 2012).

When there are several endogenous regressors, there is a need for a corresponding theoretical justification for each of the instruments used. Meeting the criteria of force and exclusion in this situation is not very simple (Papies et al., 2017). In the approach IV, the predicted values of the compromised variable are calculated only with exogenous information (stage 1) and then these exogenous predicted values are used in place of the endogenous variable (stage 2). The values calculated in the first stage are not directly correlated with the error term, thus correcting the endogeneity problem. The literature warns against the use of past (i.e. lagged) iterations of an endogenous variable as a potential instrument; these values have potential as instruments only if there is a way to ensure that shocks not observed in the endogenous variable are limited to the estimation period (Rossi, 2014; Papies et al., 2017). If it is not strong and valid, the solution found by the researcher will simply introduce more errors into the model and fail to solve the original problem.

Taking into account the peculiarities of emerging markets raised by Venkatesan et al. (2015) and Guissoni et al. (2018), this study not only presents a way of correcting the endogeneity using instrumental variables, but also relates the efficiency of distribution with upturn and downturn of economy, e.g., considers the effects of business cycles. These economic changes, recurrent in emerging markets, are explored in the next section.

2.5 Business cycles

Economic recessions are defined as two or three quarters of negative GDP growth (Christiano and Fitzgerald, 2003). They are recurring events in major world economies and are usually the result of several factors. For instance, the recent crisis in Brazil has as its main factor the Operation Car Wash[1] in 2014. Some recessions, however, may be triggered by events in a single sector, such as the mortgage crisis that supposedly started last US recession.

There is agreement that the effects of recession on the economy are widespread. Recessions result in a significant contraction in demand for goods and services, reducing

[1] MPF (2019). A operação Lava-Jato em números no Paraná. (Retrieved from: http://www.mpf.mp.br/grandes-casos/caso-lava-jato/atuacao-na-1a-instancia/parana/resultado, accessed August 20, 2019)

sales, cash flows, and profits (Srinivasan, Lilien, & Sridhar, 2011), which can affect both companies and consumers.

Firms, in response to this contraction, usually answer countercyclically to price (Chevalier & Scharfstein, 1996; Taylor 1999): managers raise their prices. Similarly, they tend to reduce price during expansions.

On the other hand, in a recession, consumers end up with a reduction in the available budget, either by unemployment, by wage cuts or lower returns on investment income[2]. This leads to a reduction in consumption. Another decisive factor to reduce demand in this period is that consumers are beginning to save more and spend money on debt repayments, resulting in a smaller amount available to be spent on consumer goods.

Concerning this aspect, traditional economic analyses focus on budget issues, trying to understand how total consumer spending changes as a function of economic conditions (Deaton, 1992; Hall, 1993; Jappelli & Pistaferri, 2010; Magrabi et al., 1991, Parker & Vissing-Jorgensen, 2009; Kamakura & Du, 2012).

In addition, most of buying behavior is based on habits (Hoyer, 1984). For consumer goods categories, consumers spend little cognitive effort on the choice task and show a high degree of inertia in their purchases during boom times. Conversely, in bad economic times, consumers revise their budgets and live with greater financial constraints and job insecurities (Dekimpe & Dellersyder, 2018; Lamey et al., 2012).

Then, although not an option for all categories of consumer goods, in contractions of the economy, consumers tend to postpone discretionary purchases (Cook, 1999), e.g., they will think twice before making any purchases and they are much more careful when entering a market, always keeping their budgets in mind. In contrast to this conclusion, during boom times, consumers have little incentive to change their usual decisions, so cheaper products are unlikely to be considered direct substitutes (Lamey et al., 2012).

Additionally, in an economic downturn, consumers are more inclined to acquire price information from different locations (Wakefield & Inman, 1993), and they are more price sensitive (Esteimami, Lehmann, & Holden, 2001; Kumar et al., 2015). Thus, compared to periods of expansion, there is a tendency for a greater search for information and its increased weight in decision making creates powerful incentives for consumers to change their buying

[2] EXAME (2016). 2015: o ano em que o brasileiro ficou mais pobre e desempregado. (Retrieved from: https://exame.abril.com.br/economia/2015-o-ano-em-que-o-brasileiro-ficou-mais-pobre-e-desempregado/ accessed August 20, 2019)

behavior of local brands. On expansion, however, dominant brands are more likely to provide compelling reasons enough for consumers to continue with them (Lamey et al., 2012; Hunneman et al., 2015).

However, despite the importance of business cycles (expansions and contractions) to both consumers and companies, there is a large gap in works that study distribution, consumer goods, and business cycles (Dekimpe & Deleersnyder, 2018).

The few existent studies are conducted in aggregate form of data, which is not necessarily descriptive of behavior in the non-durable consumer goods industry. If we consider a more specific level as categories and brands these patterns may be totally different (Dekimpe & Deleersnyder, 2018). Table 1 shows the main studies of non-durable consumer goods and business cycles, which is the focus of this research.

Table 1 – Empirical business cycle research in CPG market

Study	Entity aggregation	Geographic region	Time span	Temporal aggregation
Lamey et al. (2007)	category	Belgium; U.K.; U.S.; West Germany	1971–2004	yearly
Ma et al. (2011)	category; brand	U.S.	2006–2008	monthly
Lamey et al. (2012)	category	U.S.	1985–2005	Yearly
Gordon et al. (2013)	category	U.S.	2001–2006	Quarterly
Heerde et al. (2013)	brand	U.K.	1993–2010	Monthly
Lamey (2014)	category	15 European countries	1991–2008	Yearly
Hunneman et al. (2015)	Stores	Netherlands	2009-2012	Monthly
Dubé et al. (2018)	consumer	U.S.	2004–2012	monthly
This thesis	brand	Brazil	2013-2015	Monthly

Source: Adapted by author from Dekimpe & Deleersnyder (2018)

Furthermore, the business cycle literature can be divided into three streams. The first group consists of studies that relate business cycle fluctuations to the variation in sales between brands, products, and product categories (e.g., Deleersnyder et al., 2004). The second study group examines the relationship between the economic wave and marketing investments. The key question is whether to increase (anti-cyclically) or decrease (pro-cyclically) marketing investments in a recession (e.g., Deleersnyder et al., 2009). Finally, articles from the third group study the effectiveness of marketing mix instruments throughout the business cycle (Gordon, Goldfarb, & Li, 2013; Heerde et al., 2013). This study contributes to previous research by analyzing the effect of business cycles on the performance of CPG distribution across brand-level data.

Hunneman et al. (2015) studied the effect on store satisfaction in the Netherlands during business cycles. This study did not seek to verify the effectiveness of distribution and studies involving channels remain rare in the literature. In fact, Kumar et al. (2015) states the scarcity of distribution articles in emerging markets. The topic business cycles in marketing has great search opportunities. Even variables traditionally used in marketing research such as promotion do not have many studies on how to conduct market contractions (Lamey et al., 2012). These theoretical fronts, with details of the results of each study, are presented in Table 2.

The most common method of measuring fluctuations in business cycles is through changes in a country's gross domestic product (GDP). Another less common form is the use of consumer confidence as an indicator (Curtin, 2007; Katona, 1974; Van Oest & Franses, 2007; Ou et al. 2014). Economic literature has developed various filtering techniques to extract BC information from aggregate economic series. An overview of alternative filtering techniques is provided in Canova (1998), Baxter and King (1999), Christiano and Fitzgerald (1998, 2003) among others. BC filters are designed to separate BC-related fluctuations from other sources of variation in the series of interest, such as short-term fluctuations (irregular or periodic) and/or a long-term trend. These filters are easy to implement and, with appropriate adaptation, can be used on data sets with different levels of temporal aggregation. Interestingly, while filters have been designed and applied in the economic literature to detect BCs in various aggregate economic series, these techniques can also be applied directly to marketing performance or to conduct series of interest to extract the variation that occurs in (and is potentially related to) BC periodicity (Dekimpe & Deleersnyder, 2018).

Table 2 - Main findings in business cycle studies

Study	Effect business cycle on	Main findings
Lamey et al. (2007)	Performance of Private-label share	Private-label success is counter-cyclical, private-label share behaves asymmetrically across BC phases, and switches to private labels in a contraction are partly maintained in subsequent expansions, leading to permanent 'scars' on national-brand performance.
Ma et al. (2011)	Performance of CPG spending: total, across retail formats & across brands	Gasoline prices have a much larger impact on grocery shopping behavior than broad economic factors. A sudden price increase results in a drop-in shopping frequency, while purchase volume shifts away from grocery retailers towards supercenters. A greater shift occurs from regular-priced national brands to promoted ones than to private labels. Among national-brand purchasers, bottom-tier brands lose, mid-tier brands gain, and top-tier brands remain relatively unaffected.
Lamey et al. (2012)	Marketing conduct on advertising; innovations; price premium; promotions	National-brand manufacturers reduce major new product introductions, advertising and promotional pressure, while retailers support their private labels in a contraction, causing a counter-cyclical private-label success that is only partly recovered in subsequent expansions.
Gordon et al. (2013)	Marketing effectiveness of price	Price sensitivity is predominantly counter cyclical; it rises when the economy weakens. In some categories, the opposite holds.
Heerde et al. (2013)	Marketing effectiveness of advertising; price	Although short-term price and advertising elasticities do not change over the BC, long-term elasticities do. In contractions, brand managers should reallocate marketing budgets from advertising to price discounts.
Lamey (2014)	Performance of discounter share	Discounters' popularity increases in contractions and decreases in expansions, but part of the increase remains beyond the contraction.
Hunneman (2015)	Share of Wallet	A positive relationship between satisfaction and share of wallet. This relationship is not affected by business cycle, implying that it is rather stable over time.
Dubé et al. (2018)	Performance of private-label share	Negative income and wealth shocks due to the economic crisis increase households' private-label share in CPG expenditures.

Source: Author adapted from Dekimpe & Deleersnyder (2018)

Overall, studies involving business cycles in emerging markets need greater focus, so this work used the band pass filter proposed by Cristiano & Fitzgerald (2003) to verify the differences in performance in distributions. Given the scarcity of articles on distribution, the work done by this doctoral thesis uses the procedures by Heerde et al. (2013) to implement in emerging markets the concepts established for developed markets (Farris et al., 2006; Wilbur & Farris, 2014).

The subsequent section explains research hypothesis.

3. RESEARCH HYPOTHESIS

The discussion of multichannel distribution refers to one of the oldest marketing subjects (Wilkinson, 2001). Distribution channels are a group of interdependent organizations involved in the process of making a company's products available for use and consumption (Stern, El-Ansary, & Coughlan, 1996).

It is the role of the distribution to make products available in different channels, or types of intermediaries, so that end consumers can purchase and use (Stern et al., 1996). In short, channels are the drivers of consumer's access to products, and the effects of a company's distribution strategy have a considerable impact on its sales and profitability (Wilson, Street, & Bruce, 2008). This proposal focuses on consumer goods, which are products normally distributed by the industries that may or may not pass through wholesalers and distributors to reach retailers, thus being offered to the final consumer (Consoli, 2005).

This study aims to analyze several distribution channels, including the traditional and neighborhood markets, which in emerging economies are much more prevalent than in developed markets (Chatterjee, Kupper, Mariager, Moore, & Reis, 2011). There are efforts being made and own strategies being developed for this channel, manufacturers seek to establish a better relationship with companies, typically family, through category management tools (Guissoni et al., 2013).

The initial group of hypotheses corresponds to the first two specific objectives of this research (first study), while the succeeding group refers to the last specific objective (second study).

3.1 Construction of the first group of hypotheses

As showed in previous literature, emerging markets have a dynamic environment, with wider range of retail formats and important regions for consumer industries to distribute, promote, and sell their products (Kumar et al., 2015; Shah et al., 2015; Venkatesan et al., 2015). The market heterogeneity is present as well as the lack of infrastructure and resources (Sheth, 2011).

As a result, differently from developed markets, firms must consider store format-specific distribution (Kumar et al., 2015) and deal with the latent differences among several regions. This differences in terms of region and channel in an emerging market can have consequences in the distribution – share relationship.

For instance, small stores may play a relevant role on the share of a certain product category (Venkatesan et al., 2015). In addition, this role can be more visible considering numeric distribution rather than product category distribution, because the former accounts for the number of stores.

Therefore, it is expected that the pattern of distribution/share relationship to vary with different regions and store format. More important, it is believed that the importance of a weighted measure that explains the quality of distribution versus a numeric distribution varies depending on the region and the store format analyzed.

This leaded to the first hypothesis:

H_1: The pattern of distribution/market share relationship varies with different regions and channel types.

In line with the previous argument, it is believed that gains in numeric distribution can be especially important compared to gains in PCV in a less concentrated region (i.e., Northeast), since the product category volume is more balanced among different stores than in a more concentrated region where fewer stores account for the majority of the product category volume. Hence, in a more concentrated region, PCV approximates to ND, because the number of stores is small and most of the sales are derived from them, while in a less concentrated region, the number of stores is wider, and the sales derive from several stores.

Thus:

H_{2a}: The gain of numeric distribution is more important than PCV to increase SKU market share in a region with less retail concentration (i.e., Northeast) than in a region with more retail concentration (i.e., Southeast) for both channel self-service and full-service formats.

Further, gains of PCV can be more important in the more concentrated region:

H_{2b}: The degree of convexity between PCV and market share is greater in the more concentrated retail region (e.g., Southeast) than in the less concentrated retail region (e.g., Northeast) for both self-service and full-service channel formats.

Full-service channels such as mom&pop (traditional) are even less concentrated than chain self-service in terms of number of stores and the importance of each one to grocery sales. Thus:

H_{3a}: Numeric distribution is more important to gain share in traditional full-service than self-service stores.

And,

H_{3b}: PCV is more important to gain share in self-service stores than traditional full-service.

Lastly, in the marketing literature, Wilbur and Farris (2014) have found that the degree of convexity is greater in categories with more concentration in the market. This study believes that the same pattern can be observed in both regions in an emerging market regardless the channel. Thus:

H_4: The degree of convexity between PCV and market share is greater in categories with more concentration in sales.

The second group of hypotheses is exhibited next.

3.2 Construction of the second group of hypotheses

Consumers have unmodified preferences for brands that may be changed by in-store attractiveness, determined by such factors as shelf space, the number of sizes and flavors stocked, and other merchandising decisions (Farris et al., 1989).

In a broader setting, their preferences can also be shaped by the economic scenario. Compared to periods of expansion, there is a tendency for a greater search for information and its increased weight in decision making creates powerful incentives for consumers to change their buying behavior of local brands in contraction periods.

However, during an expansion, dominant brands are more likely to provide compelling reasons enough for consumers to continue with them (Lamey et al. 2012, Hunneman et al. 2015).

Consequently, companies also have to adapt their strategies in order to respond to changes in consumer behavior in this period. Since brand performance depends on how firms adjust their marketing mix in response to these macro-economic swings (Dekimpe & Deleersnyder, 2018), managers should know whether, and to what extent, distribution effectiveness can vary with the economic fluctuations, and act according to these economic periods. For instance, in a contraction, a company may alter its distribution strategy to reach more consumers and to create more incentives to them, to fight against a demand reduction in the market as a whole.

In line with this, in economic downturn the relationship between PCV/market share changes. This can be even more visible in emerging markets, where a brand's success relies more in distribution, and it is particularly tailored according to the unique characteristics of the market (Kumar et al., 2015). Nevertheless, even research conducted in developed markets has not explored the distribution-market share relationship during business cycles (Dekimpe & Deleersnyder, 2018).

Thus:

H5a: The pattern of PCV/market share varies over business cycles fluctuations.

Furthermore, Guissoni et al. (2014) show the convexity curve for distribution and share in emerging markets, and considering preferences changes (Kumar et al., 2015, Kamakura & Du, 2012). Therefore, given that business cycles shape and change consumers' preferences, it is reasonable to suppose that:

H5b: The degree of convexity between PCV and market share varies over business cycles fluctuations.

Other studies, focusing on different marketing mix variables can also provide valuable insights on distribution and market share relationship. For instance, Venkatesan et al. (2015)

and Guissoni (2018) highlight the cumulative and permanent effect in emerging markets for marketing-mix efforts.

In addition, Srinivasan et al. (2011) observe across many industries, that firms, from a profit point of view, tend to overspend on advertising in a recession. Complementarily, Heerde et al. (2013) that state that long-term advertising elasticities are lower in a recession, suggesting that advertising should be reduced during that time.

Drawing an analogy from these studies, it is reasonable to infer that companies probably need to invest more in contraction periods in order to maintain their established market share.

Thus:

H6a: The pattern of distribution and market share is greater in economic upturn than in economic downturn.

Similarly, the convexity effect may change due to economics swings because consumers are more price-sensitive (Esteimami, Lehmann, & Holden, 2001; Kumar et al., 2015) and respond negatively to high prices during recessions, reducing demand and directly interfering in companies' market share and distribution. Therefore:

H6b: The degree of convexity between PCV and market share is greater in economic upturn than in economic downturn.

Additionally, emerging markets are less concentrated markets (Sheth, 2015) and, consumers are inclined to acquire price information from different locations in economic downturn (Wakefield & Inman, 1993). This can result in a change to small stores, which may interfere in the total number of points of sales and transfer more importance to ND measure of distribution.

In this way:

H7: ND is more important to gain share in contractions scenarios than in expansion scenarios.

If a preferred brand is not in distributed in a certain store (either temporarily out of stock or not carried by a particular store), consumers who resist compromising may either buy another brand in the same (or reduced) purchase amount, or seek the preferred brand at another store (Farris et al., 1989).

Therefore:

H8a: The pattern of distribution permanent effect is more important to gain share than immediate effect.

Moreover, consumers may adjust their shopping patterns to improve their chances of finding the preferred brand (Farris et al., 1989):

H8b: The degree of convexity of distribution permanent effect is more important to gain share than immediate effect.

Market share is usually increasing and convex in retail distribution, both across brands in a category as well as across SKUs within a leading brand. These findings show that the “double jeopardy” phenomenon faced by small brands is also faced by small-share SKUs within category leaders’ product lines. Distribution/share relationships show greater degrees of convexity in larger product categories and more concentrated categories (Wilbur & Farris, 2014).

Thus:

H9a: The pattern of distribution and share relationship is lower to small-share brands than high-share brands over business cycles.

Beyond that, small-share brands in “double jeopardy" of having small penetration rates and lower repeat rates (equivalently, lower loyalty rates or lower shares of requirements) (Ehrenberg, 1988; Fader & Schmittlein, 1993). If small-share products are not as widely available, repeat purchase rates will be lower (Farley, 1964; Day, 1969; Pessemier, 1982). Thus:

H9b: *The degree of convexity between distribution/share is lower to small-share brands than high-share brands over business cycles.*

Methodological procedures are explained next.

4 METHODOLOGY

This chapter is divided into four parts: (i) research type, (ii) research design and data, (iii) measurements and (iii) data analysis (procedures of dynamic panel regressions).

4.1 Research Type

Due to the fact that this research has a theoretical and practical purpose, e.g., it aims to analyze the relationship between different distribution measures (i.e., PCV and numeric distribution) and market share in an emerging market (Brazil), it can be firstly characterized as an applied research. According to Hair, Anderson, Tatham and Black (2005), an applied research seeks to solve a problem faced by a certain organization in order to assist decision making. The necessity to solve a concrete problem, whether it is an immediate solution or not, is what motivates applied research according to Vergara (2000).

With regard to its nature, this research is, according to Cooper and Schindler (2011) and Hair et al. (2005a), quantitative, because it employs statistical methods to pursue an accurate measurement of the main characteristics of distribution and sales of the new products investigated. The research uses systematic procedures for the description and explanation of the research problem. Generalization of results obtained in a sample for the entire target population is also a characteristic of quantitative works.

Furthermore, this research is also classified as descriptive. According to Hair, Babin, Money, and Samuel (2005), descriptive research is done through the measurement of events and activities. Consequently, the nature of the relationship between the variables of this proposal is descriptive, because both distribution and market share are measured in order to describe a relationship between them. In fact, the search for the association between the variables is one of the objectives of descriptive studies (Cooper & Schindler, 2011).

Lastly, according to its methodological procedures, the present research can also be characterized as a survey that, according to Gil (2002), presents as main characteristic the collection of data from secondary databases previously collected (as displayed on section 4.3). Next section shows the research design.

4.2 Research design and data collection

The research hypotheses were tested through two complementary studies. The first, conducted in the beverage category (soft drinks), aimed to investigate how the relationship between market share and distribution can vary over different circumstances in an emerging market (i.e., how the companies conduct their distribution strategies and select the best stores to sell their products, considering different retail formats and heterogeneous regions).

Data were compiled by a major retail-audit firm, which is considered to be the census of available products in Brazil. This firm allowed the data access of a large beverage company in the country with its soft drinks, which included 91 manufacturers, 195 brands, and 1,110 stock-keeping units (SKUs) for soft drinks, broken down by each analyzed channel format, beverage type, and region at the SKU level. The databases analyzed were monthly and available from January 2010 to January 2014, and provided information concerning distribution, sales, market share, and product's starting sales.

As additional information, the database offers data on products marketed by the three largest beverage manufacturers in the country, allowing the verification on different channels. Initially, channels of 5 or more checkouts were provided, markets smaller than 1 to 4 checkouts, the traditional market consisting of small business owners or family members that own grocery stores and bakeries.

In fact, the selection of soft drinks category, including carbonated and non-carbonated beverages, is actually due to the good mix of retail formats and regional contrasts[3]. The fastest-growing non-carbonated drinks are distributed through chain self-service and traditional full-service (i.e., mom and pop). Arguably, other features make soft drinks a suitable choice. Although carbonates still remain the most valuable soft drinks, the consumption of this beverage type has shown signs of decline as the sales of other beverages options such as non-carbonated soft drinks increased. For instance, ready-to-drink juices, energy drinks, and ready-to-drink tea have grown as well as consumers are moving away from cola carbonates to non-carbonated beverages in the search for healthier consumption.

This change adds extra complexity to the distribution system in this category, since brands should manage the availability of different soft drinks beverages in channels with structural differences in emerging markets. Sales through chain self-service are important, but

[3] USDA Foreign Agricultural Service (2016), Brazil: Retail Foods.

traditional full-service stores make up almost half of soft drinks sales in these markets[4] and brands need to balance market share and distribution relationship to optimize their efforts in a more fragmented retail environment provided by emerging markets.

On the other hand, the second study, aimed to verify when the intrinsic characteristics of this market (in this case, business cycle fluctuations) could change the effectiveness of a brand. To achieve this goal, data from stores combined information about seven CPG distinct categories (i.e., beer, cookies and biscuits, laundry detergent, powder coffee, yogurts, shampoo, and ready-to-drink juice) across three different regions in Brazil (i.e., northeast, southeast, and south) from November 2013 to November 2015. The data included 155 manufacturers, with 380 brands, and 812 sub brands and it was provided from the same retail-audit firm.

4.3. Measurements

This section introduces research variables, illustrating their measurements. In both studies, to measure distribution (i.e., the independent variable), product category distribution (PCV) and numeric distribution (ND) were employed. Furthermore, market share (i.e., the dependent variable) was also measured in both settings, considering sales volume and revenues.

However, these studies present some particularities. The first used channel intensity (Herfindahl-Hirschman Index) and SKU's size (Value Density) as independent variables in order to account for endogeneity and control retailers' actions in different formats. On the other hand, the second employed different brands and distinct regions as additional independent variables to avoid endogeneity concerns associated with business cycles. The business cycles used gross domestic product (GDP) as basis to obtain the economic waves and retail-audit company areas to compare different regions.

These measurements are explained in the subsequent topics.

4.3.1 Product category distribution

The product category volume (PCV) is a refinement of the most used distribution measure, particularly in developed markets. The ACV approach weights a product's distribution by the

[4] Euromonitor International Report (2013), "Carbonates: Can New Markets Keep Growth Fizzing?"

total dollar volume sold through a particular store. Thus, ACV gives more distribution credit for an item that is carried in a large-dollar-volume store than in a small-dollar-volume store (Ataman et al., 2010). It is often simply known as weighted distribution among retail-audit companies. The purpose of the measure of PCV according to Farris, Bendle, Pfeifer and Reibstein (2006) is to check the availability of a product over the channel importance for product category sales.

$$\%Product\ Category\ Volume = \frac{Total\ Sales\ of\ Stores\ Carring\ Brand}{Total\ Sales\ of\ All\ Stores} \tag{12}$$

4.3.2.Numeric distribution

Another important metric is the number of physical stores involved in its supply chain that can have implications for delivery systems, cost of servicing, and market share. At this point, the numeric distribution measure shows the percentage of stores that carry a given product (Farris et al., 2006). It is important to observe that SKU can have a high numeric distribution, but that does not mean it is present in the most important category stores as PCV would assess or even in the most important stores considering all categories' sales as ACV would show.

$$\%Numeric\ Distribution = \frac{Number\ of\ Stores\ Carring\ Brand}{Total\ Number\ of\ Stores} \tag{13}$$

Ailawadi and Farris (2017) argued that marketers typically rely on weighted measures reported by retail-audit companies and that they are better than numeric measure because they may require thousands of smaller stores (e.g., mom and pop) to equal the potential of even a small fraction of big retail stores (e.g., Walmart). However, they argue that numeric distribution is an important measure to account for the important role of smaller stores in emerging markets, which is the case of this research.

4.3.3 Market share

Market share is an important metric that has been intensively studied by researchers and marketers (Farris et al. 2006, Guissoni, 2012). When analyzed in conjunction with sales revenue, marketing managers gain a source of information to decide what their priorities will be, future trends, and declining markets (Guissosi & Neves, 2011). A company's market share gains can be related to total market growth, as well as capturing market share from competitors. The latter is generally much more expensive than the former. The loss of market share is a way of signaling serious long-term problems (Wilbur & Farris, 2014). Long-term problems often require strategic planning adjustments (Neves et al., 2001).

To measure market share, this study employed:

$$Volume\ Market\ Share = \frac{Sales\ Volume}{Total\ Market\ Sales\ Volume} \tag{14}$$

The formula can be changed to invoice SKU by multiplying the volume sold by the price of each SKU. Revenue market share differs from unit market share because it represents the prices at which goods are sold.

$$Revenue\ Market\ Share = \frac{Sales\ Revenue}{Total\ Market\ Sales\ Revenue} \tag{15}$$

In this research, the revenue share was used in the first study, when price for each SKU's was available. In the second study, the volume share was used for all categories.

4.3.4 Herfindahl-Hirschman Index

The Herfindah-Hirschman Index is a measure to determine the concentration of the product in relation to the category and indicates the amount of competition among the category. Therefore, it reflects channel intensity.

This metric derived by adding the squares of the individual market shares of all the players in a market. This index ranges from 0 to 1 and high numbers indicate the domination for a product/brand in a category (Farris et al. 2006).

$$HHI = \sum_{i=1}^{N} SKU\ market\ participation_i^2 \tag{16}$$

Wilbur and Farris (2014) show that more concentrated categories exhibit more convex relationships between market share and retail distribution. Power is distributed more unevenly across brands in more concentrated categories; so leading SKUs' manufacturers wield greater influence with consumers and retailers. They are able to achieve relatively greater levels of retail distribution for their product lines.

4.3.5 Value density

The value density is the relationship between SKU price and the sales volume. This metric indicates when SKU has more volume participation than revenue participation (Wilbur & Farris, 2014).

$$Value\ Density = \frac{SKU\ price}{Volume} \tag{17}$$

Therefore, this measure is capable to show SKU's size.

4.3.6 Gross Domestic Product

Gross Domestic Product (GDP) is the sum of all final goods and services produced by a country, state, or city, usually within a year. All countries calculate their GDP in their respective currencies[5].

Countries such as Brazil have large differences in GDP generation by state, so in order to reduce the bias produced by the variation of national states, São Paulo region was used for the analysis. The GDP of the State of São Paulo is the highest among all states of the country and, in 2016, it was R$ 2,038,005.00, which is a percentage of 32.52% of the total national GDP. Specifically, GDP values of the State of São Paulo were used as a basis of calculation of the Value Added (VAs) of 17 branches and economic activity: agriculture; transformation industry; construction; production and distribution of electricity, gas, water and sewage, and urban cleaning; trade and repair and maintenance services; transport, storage and mail; accommodation and food services; real estate activities and rents; public administration,

[5] IBGE (2019). Produto Interno Bruto – PIB. (Retrieved from: https://www.ibge.gov.br/explica/pib.php, accessed 10 August, 2019).

health and education; information services; health and education market; financial intermediation, insurance and supplementary social security; services provided to families and associations; business services; and domestic services.

The sum of the value added (VA) of these activities form the total VA that added the taxes less subsidies make the Gross Domestic Product. To measure, in terms of volume, VA, Tax and GDP indicators, approximately 250 significant variables are used for sectoral monitoring.

The aggregation of the sector indices, as well as the final result, is made from the Laspeyres formula, volume index, with weights from the previous year, which results in a series of moving base indices. This method has an advantage over pure fixed base, as it keeps up to date the weights in which the series are aggregated, as recommended by the United Nations.[6].

Then, the monthly Laspeyres index is expressed by:

$$L_{0_{q,y}} = \frac{\sum_i p_{i,0} \times q_{i,q,y}}{\sum_i p_{i,0} \times q_{i,0}} \tag{18}$$

Where:

$L_{0_{q,y}}$: Laspeyres volume index that measures the change in volume between the mean of the year (0) and the month q of year y, with the mean of the year (0) as the base period;

$p_{i,0}$: price of product i, in the base year (0);

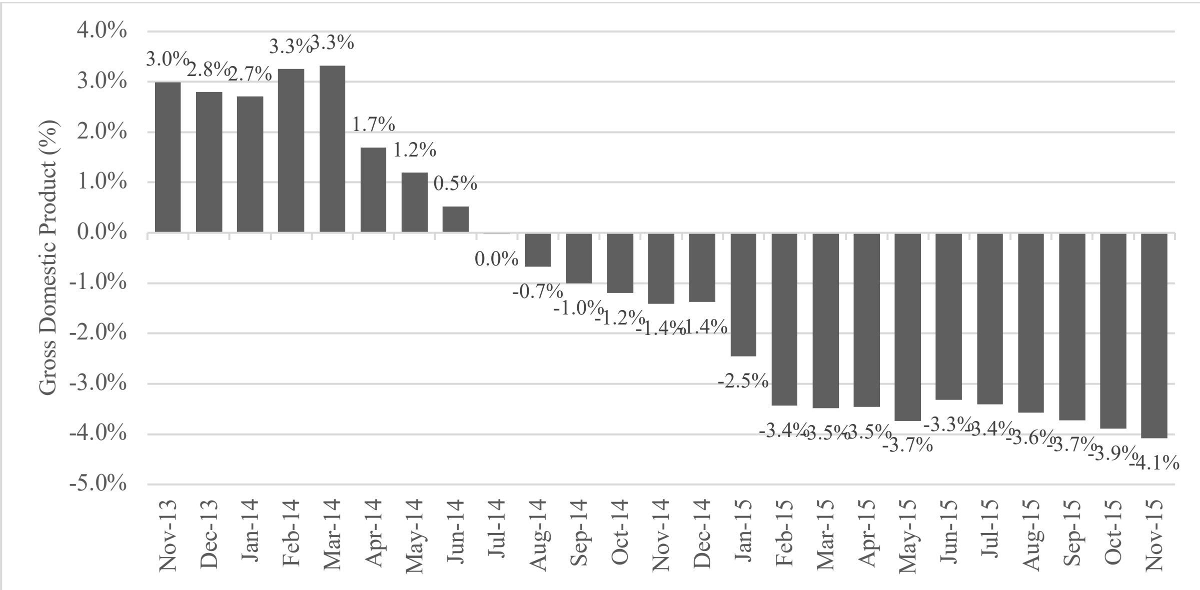
$q_{i,q,y}$: quantity of product i, in month q of year y;

$q_{i,0}$: quantity of product i, in the base year (0).

Figure 4 shows the values for the monthly variation of the gross domestic product of the State of São Paulo accumulated in the year compared to the same period of the previous year for the research analysis period. The purpose is to provide a more strategic and actual view, unlike previous work that uses quarterly or annual basis, and thus offer greater decision-making opportunity.

[6] SEADE (2019), Produto interno bruto – Mensal. (Retrieved from: http://catalogo.governoaberto.sp.gov.br/dataset/757-produto-interno-bruto-pib-mensal, accessed 10 August, 2019).

Figure 4 – Monthly variation in gross domestic product of São Paulo State



Source: SEADE (2019)

4.3.7 The retail-audit firm coverage areas

The retail-audit firm coverage areas is a global information as the research firm is present in over 100 countries with leading positions in the retail information markets. Data were provided from collection of channel sales scan information, along with causal information collected at various points of sales. These are the configurations that allow to identify sales of a product and also to define marketing and sales strategies. Company data includes a wide range of channels: supermarkets, hypermarkets, wholesalers, pharmacies, convenience stores, grocery stores, warehouses, wineries, and others small business.

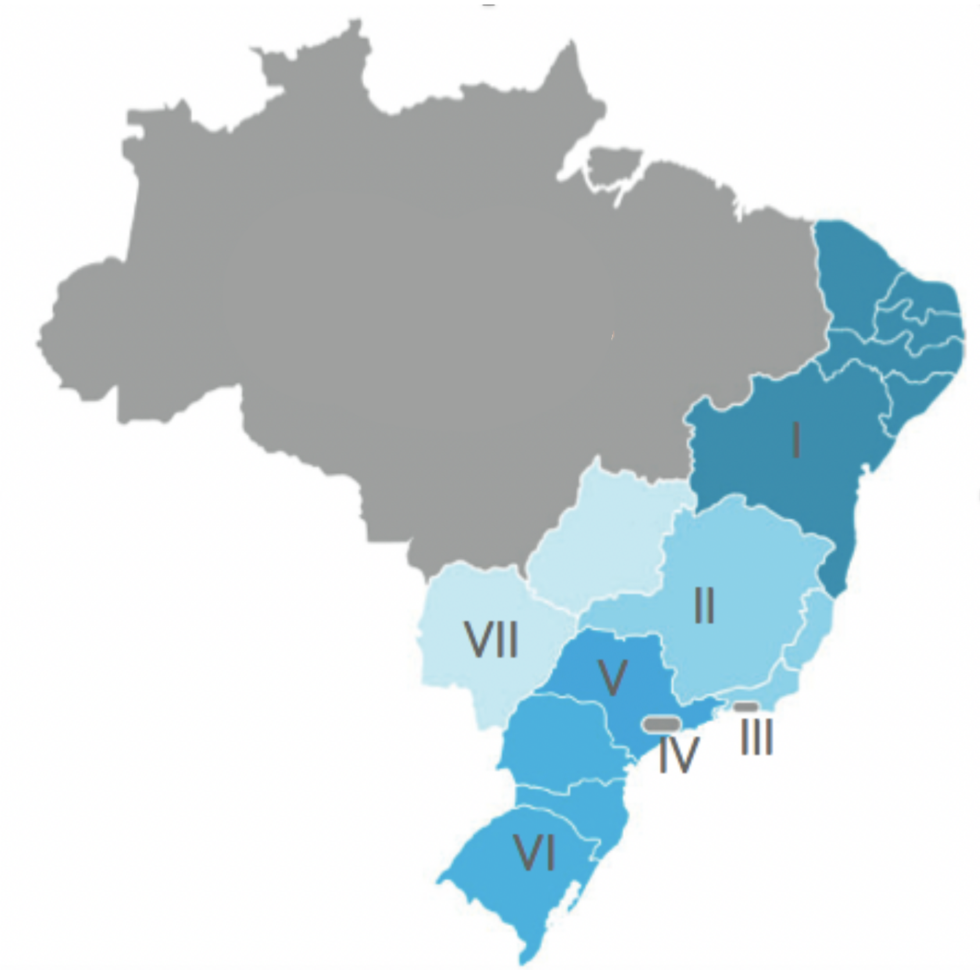
Considering the retail-audit firm areas coverage in Brazil, the company split Brazil in seven areas, as follows:

- area I: Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Bahia, Sergipe, Piauí, and Maranhão;
- area II: Minas Gerais, Espírito Santo and countryside of Rio de Janeiro;
- area III: Metropolitan region of Rio de Janeiro;
- area IV: São Paulo metropolitan capital area;
- area V: São Paulo state, except metropolitan capital area;
- area VI: Paraná, Santa Catarina, and Rio Grande do Sul;

- area VII: Distrito Federal, Goiás, Mato Grosso do Sul, and Mato Grosso.

In the second study, the six first regions were used. The reason behind this decision is the more intensive participation of retail-audit firm in these areas than area VII and the rest of the country. The number of audit category is greater and more detailed in the first five regions, including the categories.

Figure 5 – Coverage areas



Source: The audit company

The next section introduces data analysis procedures.

4.4 Data analysis: procedures of dynamics panel regressions

In both studies, the analysis will be performed based on econometric techniques. According to Hanssens, Parsons and Schultz (2001) and Guissoni and Neves (2011), the application of econometric techniques in marketing allows to capture (a) the immediate effect of marketing activities in sales; (b) the carryover effect, that is, the one that marketing activities "carry" for future sales periods; (c) the feedback effect, because it considers all variables of the model as endogenous and also includes a function of past or lagged values of these variables; (d) the effect on sales attributable to each marketing variable or activity, that is, it captures only the incremental sales to be generated by an activity known as purification of results (Guissoni & Neves, 2011).

Overall, the studies have analyzed data across the channels and regions in which the number of cross-sectional units is relatively small, and the number of time periods is relatively large.

In retail, it is common having a great number of units and time periods and therefore, panel data analyses are more oriented towards cross-section analyses. Heterogeneity across units is an integral part of the analysis (Rossi, 2014; Pauwels, 2018).

A basic framework for panel data can be generalized by the following regression:

$$y_{it} = \alpha_{it} + \beta x_{it} + \varepsilon_{it} \tag{19}$$

Where y_{it} is a dependent variable (in this proposal the market share is the dependent variable) for i-SKU in a t-period, α_{it} is a constant term that captures the individual effect, β is the coefficient for PCV and ND, x_{it} is each SKU independent observation and ε_{it} is the error associated with each estimation. The classical regression model specifies that

$$E[\varepsilon_{it}] = 0, \tag{20}$$

$$Var[\varepsilon_{it}] = \sigma^2, \tag{21}$$

$$Cov[\varepsilon_{it}, \varepsilon_{js}] = 0 \qquad if\ t \neq s\ or\ i \neq j \tag{22}$$

To estimate models using panel data, Generalized Least Squares (GLS) was used.

4.4.1 Generalized least squares

The preference for different models changed over the time. In the past, it was more common to marketing researchers use the univariate and multivariate time series.

Traditionally, until the 1970s, econometric models for temporal analysis focused on the classification of variables as endogenous and exogenous (Bruggemann, 2004; Eisfeld et al., 2007). From 1980 to nowadays, with the possibility to obtain more data and information, the more usual models became multiple time series models (Pauwels, 2018). Another important issue that has driven this change is because the limitation of univariate time series analysis models for marketing is that it does not deal with cause and effect situations (Hanssens, Parsons, & Schultz, 2001).

On this aspect, dynamic panel regression also suited to capture the time dependence of both dependent and independent variables and how they relate to each other over time.

Generally, marketing data includes repeated measures (in regular interval, i.e., months, years or quarters) over the time (Farris et al., 2006; Guissoni, 2012). Thus, it is common to see in marketing panel data the following situation:

$$Var[\varepsilon_{it}] = \sigma^2\Omega, \tag{23}$$

Where Ω can be a matrix identity (only values in the diagonal) and the regression is an Ordinary Least Square Regression (OLS). However, in some cases the matrix Ω has only values in the diagonal and these values distinct one than other and zeros in the off-diagonal elements. In this case, the dependent variable y_{it} is not correlated but has unequal variance, while is the matrix with the values of off-diagonal are different of zero the observations are correlated (Greene, 2003; Wooldrigde, 2015).

In both cases where Ω is different than identity matrix the OLS estimator is not optimal. Then, the Generalized Least Square is recommend use with the estimator for β:

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1} \times X\Omega^{-1}y \tag{24}$$

Where X is the matrix of independent variables (i.e., the measure of distribution and others marketing metrics), X' is the transpose matrix of matrix X and Ω^{-1} is the inverse matrix of matrix Ω and y is the dependent variable (i.e., the market share). The equation (23) is similar to the classic OLS estimator, only with the Ω matrix to control the correlation between observations.

$$\hat{\beta} = (X'X)^{-1} \times Xy \tag{25}$$

4.4.2 Heteroskedasticity and autocorrelation

In panel data, most deviation comes from error variances specific to the cross-sectional unit. This makes that Ω from equation (23) is different from matrix identity ($\Omega = I$). According to Greene (2003) the variance of disturbance i, u_i, is not constant across observations but not correlated with u_j, such:

$$E(u_i u_j) = \sigma^2 \begin{bmatrix} \frac{\sigma_1^2}{\sigma^2} & 0 & \cdots & 0 \\ 0 & \frac{\sigma_2^2}{\sigma^2} & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & & \frac{\sigma_n^2}{\sigma^2} \end{bmatrix} = \sigma^2 \Omega \tag{26}$$

Under homoskedasticity, $\Omega = I$. However, under heteroskedasticity, statistical inference would be biased, and t-statistics and F-statistics are inappropriate. A heteroskedasticity-robust t statistic can be obtained by dividing an OSL estimator by its robust standard error (for zero null hypotheses). The usual F-statistic, however, is invalid. Instead, it is necessary to use the heteroskedasticity-robust Wald statistic (Greene, 2003; Wooldridge, 2015).

In marketing data, the number of observations per cross-sectional unit, are not constant across units in which time for each SKU or brands. New products can be launched and, this way, not accounted in previous period t or discontinued by manufacturer in some moment.

The robust-variance estimator is used in the context of heteroskedasticity. There are also methods to provide inference (i.e., standard errors and confidence interval) which are robust to model misspecification for conditional heteroskedastic, autocorrelation, and non-normal errors using (Rossi, 2014). Over panels with larger N than T (i.e., panels with many brands or SKU in a short period), the robustness against heteroskedasticity and autocorrelation can generate clustering errors by N (Wooldridge, 2003; Wooldridge, 2015). In this research, the number of N (i.e., brands or SKU) is greater than T. Bearing this fact in mind, in presence of heteroskedastic or autocorrelated, it is necessary to adjust the estimator using clustering errors by N.

4.4.3 Vectors autoregressive regression

Autoregressive models for multivariate time series analysis, such as VAR, allow more complete models to be expressed, considering the interrelationship between variables (Guissoni, 2012). This is particularly interesting when one wants to separate a variable by its time series properties.

Both managers and marketing researchers mind whether the performance of distribution (or other marketing mix activity) changes in immediate (short-term) or permanent (long-term) period (Pauwels, 2004; Heerde et al., 2013; Venkatesan et al., 2015). Likewise, some marketing actions are often considered 'tactical' tools, such as price promotions to boost sales – but may hurt brand performance in the long-term (Mela et al., 1997; Pauwels et al., 2002; Guissoni et al., 2018).

The distinction between short-term and long-term marketing effectiveness permeates discussions on dealing with recessions, on retailer category, store performance (Srinivasan et al., 2004), and manufacturer brand equity (Keller, 1998). Additionally, the VAR models are simpler to estimate and interpret than autoregressive moving-average (ARMA) estimators, and because of that, they are commonly used for response models in marketing (Dekimpe & Hanssens, 1999; Srinivasan, Leszczyc, & Bass, 2000; Hanssens et al., 2001; Pauwels, 2004). In emerging markets, the VAR was used to determine the response of variables of marketing for marketing mix efforts (Guissoni et al., 2018; Venkatesan et al., 2015; Kumar et al., 2015). A simple way to describe fluctuations in market share is with a first-order autoregressive, i.e., an AR (1) process is assumed that market share at t-1 affects market share at t:

This can be represented in the next equation:

$$y_t = \mu + \varphi y_{t-1} + \varepsilon_t \tag{27}$$

With, y_t the brand sales performance or brand share in the month t, μ a constaint, and ε_t a disturbance term. This model states that brand share in period t is determined by share in the previous period t-1. Pauwels (2018) presents the three situations depending on the value of φ:

- If $|\varphi| < 1$, the effect of past market share (and thus any 'shock' that has affected past market share) diminishes as we move into the future. Such time series are called *stationary*, because it has a time-independent mean and variance. This situation is typical for market performance of established brands in mature markets (e.g. Bass & Pilon, 1980; Nijs et al., 2001).

- If |φ| = 1, the effect of sales in y_{t-1} has a permanent effect on market share. Market share will not revert to a historical level but will *evolve*. This situation has been demonstrated for smaller brands and in emerging markets (Pauwels & Dans, 2001; Slotegraaf & Pauwels, 2008).
- If |φ| > 1, the effect of past sales (and thus of past shocks) becomes increasingly important. Such explosive time series behavior appears to be unrealistic in marketing (Dekimpe & Hanssens, 1999).

4.4.4 Unit root test

In marketing, if sales of a particular brand or product change suddenly, the question that arises is whether this change is temporary or permanent, such as whether a portion of sales shock will persist over time and affect long-term behavior (Hanssens et al., 2011). That is, when the behavior of the time series does not revert to deterministic components, the series have a unit root (Pauwels, 2018).

Thus, if time series have unit roots they need to be treated before the econometric model can be validated, as stationary processes have a finite variance and their future values are relatively easy to predict (Pauwels, 2018). The most common root unit starts test by redefining the AR (1) from (27) as follow:

$$z_t = \mu + \gamma y_{t-1} + \varepsilon_t \quad (28)$$

$$z_t = y_t + y_{t-1} \quad (29)$$

$$\gamma = \varphi - 1 \quad (30)$$

The unit root null hypothesis is when $\gamma = 0$. This test is known as the *Dickey–Fuller test* (Dickey & Fuller, 1981).

However, the t-statistic that is obtained through special tables cannot be evaluated with the regular tables of the t-distribution. The generalization of the Dickey–Fuller test to an AR(p) process yields the Augmented Dickey–Fuller test (Pauwels, 2018). This test is based on a reformulation of the AR(p) process as:

$$z_t = \mu + \gamma y_{t-1} + \delta_1 z_{t-1} + \delta_2 z_{t-2} + \cdots + \delta_p z_{t-p} + \varepsilon_t \qquad (31)$$

Similar to Dickey-Fuller test, the Augmented Dickey-Fuller (ADF) tests the null hypothesis $\gamma = 0$. A large number of lagged first differences should be included in the *ADF* regression to ensure that the error is approximately white noise (Pauwels, 2018; Grenne, 2003). Enders (2003) offered an iterative procedure to implement these different test specificities, which was employed in marketing papers (e.g. Slotegraaf & Pauwels, 2008; Srinivasan et al., 2004).

4.4.5 The band pass filter

The band pass filter was used to capture the business cycle (BC) in Brazilian economy. With the cyclical fluctuations it is possible to check the business cycles on distribution effectiveness. For this, the Chrristiano-Fitzgerald (CF) random-walker filter (Christiano & Fitzgerald, 2003) was adopted.

BC filters were explored in the literature of marketing in different context involving GDP and marketing series of data such as sales (Deleersnyder et al., 2004), private-label share (Lamey et al., 2007, 2012), discounter share (Lamey, 2014), and marketing conduct series such as advertising, innovations, promotion, and regular prices (Deleersnyder et al., 2009; Lamey et al., 2012; Heerde et al., 2013), share of wallet and satisfaction (Hunneman et al., 2015), and procyclical behavior of advertising expenditure (Deleersnyder et al., 2009; Srinivasan, Lilien, & Sridhar, 2011).

Precisely, three different BC filters are commonly used in marketing studies: Hodrick-Prescott (HP) low-pass filter (Hodrick & Prescott, 1997), Baxter and King band-pass (BP) filter (Baxter & King, 1999), and Christiano and Fitzgerald (CF) random walk band-pass filter (Christiano & Fitzgerald, 2003).

The difference between them is associated to the type of information that is retained after filtered. The low-pass filter allows all fluctuation that occurred over a period of more than 8 periods, corresponding to long-term fluctuations. That exceeds the period of an economic cycle. The band pass-filter, in turn, passes the entire fluctuation of a given period (usually defined as an economic cycle of 1.5 to 8 years). Thus, the result of filtering is already the BC component (Dekimpe & Deleersnyder, 2018). Both the Baxter and King (1999) and the Christiano and Fitzgerald (2003) filters are built on this band pass principle.

Furthermore,

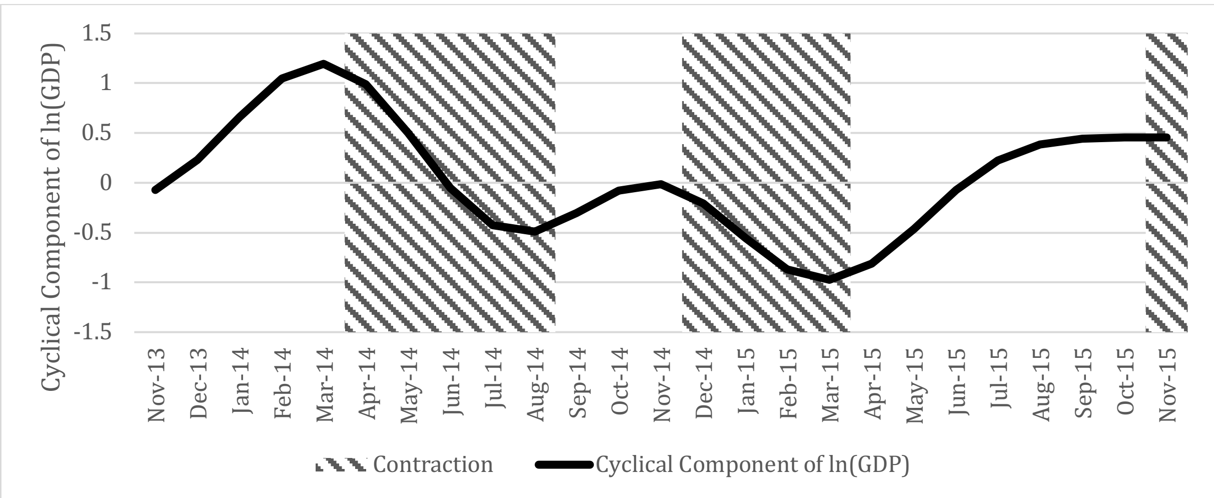
According to Dekimpe and Deleersnyder (2018) the key for correct choice of filter is the temporal aggregation of the data. HP and BP filters produce similar results. The problem with the HP filter is that it retains seasonal noises and other short-term noises to values at a lower level of aggregation (i.e. months, quarters). In these cases, the BP filters are preferred.

In this work, CF random walk filter was chosen over the more general BP filter to avoid losing observations at the beginning and end of the series (Heerde et al., 2013).

Specifically, CF filter was applied to log-transformed monthly GDP data from São Paulo State. Figure 6 shows the cyclical component (cyclical deviation) from the long-term trend in the log-transformed GDP series. The downswing reflects the Brazilian crisis in 2014 and 2015.

This study classified, as the previous studies, the periods with an increase in the cyclical component as expansions and periods with a decrease as contractions (Lameuy et al., 2007, 2012; Steenkamp & Fang, 2011; Heerde et al., 2013). In figure 6, dashed zones represent contractions and white zones represent expansions.

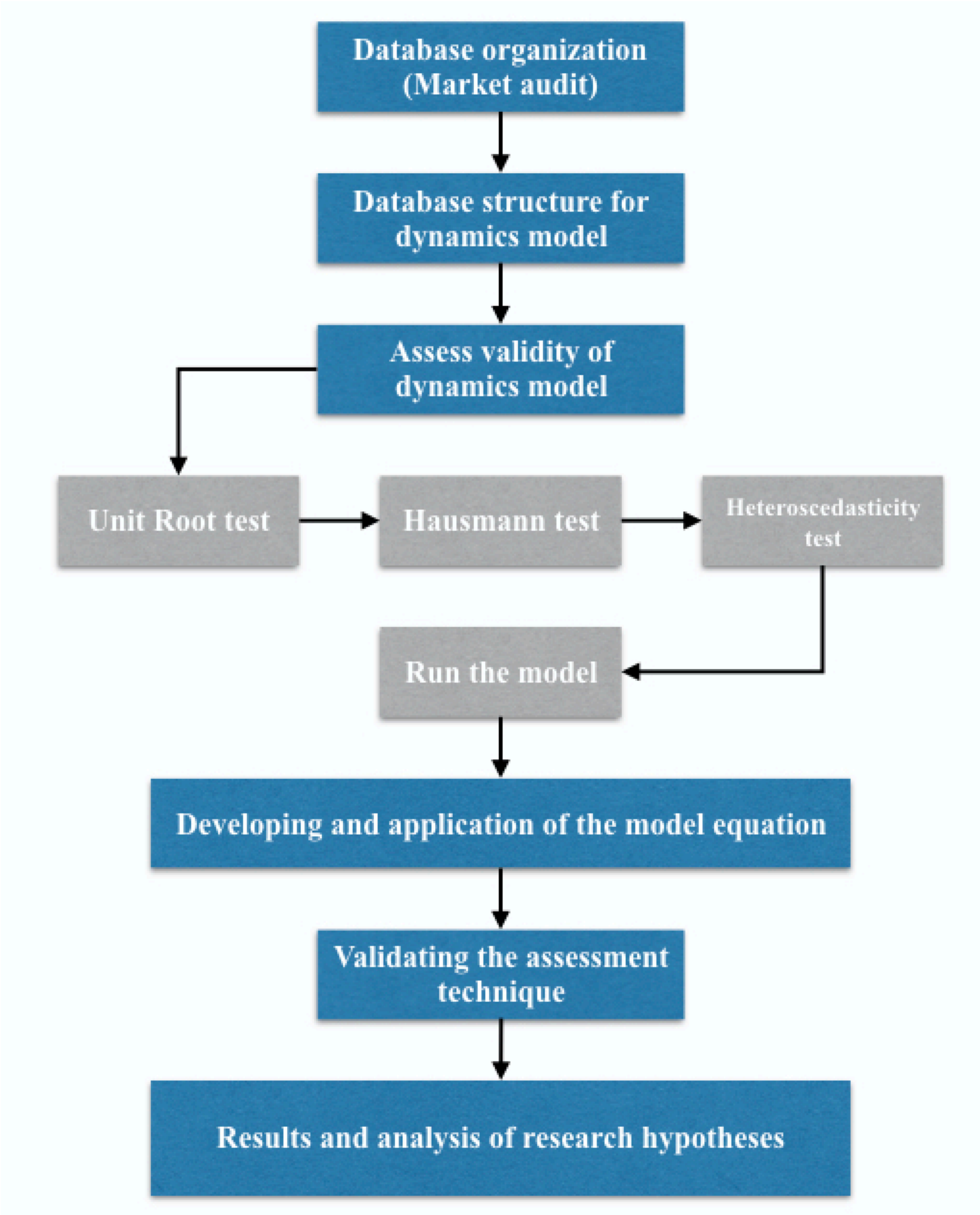
Figure **6** – Cyclical deviations from the change trend in the log-transformed GDP for São Paulo Stata (2013-2015)



Source: Author

The figure 7 displays the procedures used in this doctoral thesis.

Figure 7 – Procedures for developing the research



Source: Author

In the next section, modelling and validation are underscored.

5 MODELLING AND VALIDATION

According to the methodology applied in this thesis and following already consolidated methods for modeling marketing mix variables, especially distribution (Dekimpe & Hanssens, 1995; Kumar et al., 2015; Wilbur & Farris, 2014) in conjunction with business cycles (Heerde et al., 2013; Lamey, 2014; Dubé et al., 2017), it is necessary to understand the demand model in order to allow discussions about distribution effects.

Thus, the model allows the understanding of the effects of the relationship between the different distribution strategies for the beverage channel and also enables to understand the differences between business cycle fluctuations at the brand level. Specifically, about value prediction, among the quantitative methods for this purpose are found explanatory methods and time series methods (Makridakis & Wheelwright, 1985).

According to Hanssens, Parsons and Schultz (2001, p. 251), "variables of interest to marketing managers and researchers, such as sales, market share, price, and marketing investments, vary over time." Thus, simply because there is a fluctuation of these variables, the study of the dynamics of marketing variables in a time series is related to the study of these variations:

- by themselves: for example, how current sales relate to past sales and how they impact distribution over time. How current market share gain influences competitors' action over time; or
- by other variables: for example, how current market coverage influences current and future market share levels (Hanssens, Parsons, & Schultz, 2001) or how business cycle fluctuation shows differences between sales in the present and the future. (Heerde et al., 2013).

According to Pasquotto (2010, p. 11), "the explanatory methods seek a relationship between the variable we want to predict and other variables that explain the variation of the former." That is, there is a set of exogenous (independent) variables that help to explain and predict a given endogenous (dependent) variable. However, the interdependence between independent and dependent variables is one of the limitations of these methods. On the other hand, time series econometrics, considered in this study, contributes precisely to overcome this limitation (Guissoni, 2012).

In order to verify the relationship between ND and PCV, four subcategories of beverages were analyzed in different channels and regions. As a final result of this doctoral thesis, it is expected to analyze more categories and join other non-beverage categories to generalize the results for the CPG market.

5.1 First model

The results of first group of hypotheses encompassed three stages. First, descriptive data was presented in order to show characteristics of soft drinks in different regions (Brazil's southeast and northeast) and channels (chain self-service and traditional full service).

This research addressed the average sales per SKU, number of manufacturers, number of brands, number of SKUs, market share, product category volume (PCV), and numeric distribution (ND) from January 2010 to December 2013. Second, it was exposed a model free of explanation to visualize the pattern of the relationship between market share and PCV from the raw data. Finally, in order to accomplish the objective of these previous results, a panel data analysis with a generalized least squares (GLS) random effects linear regression model was used and the first-difference variables monthly were applied to control the serial correlation.

5.1.1 Descriptive statistics

Table 3 described information about four different types of soft drinks: carbonated soft drinks, energy drinks, ready to drink (RTD) juice, and RTD tea, totalizing 3.8 billion of units sold to consumers (cases of 24 units of 8 ounces) from 1,110 SKUs. In order to illustrate the data from the store audits, Table 1 showed the results for each region and channel.

Similarly, the average item (SKU) reported that market share was higher in the traditional full-service than self-service stores for both analyzed regions. However, Table 3 also suggested some contrasts across regions. Overall, market share per SKU was higher in the northeast, where there were fewer SKUs for soft drinks than in the southeast.

Table 4 illustrated that the average PCV and ND per SKU was higher in the southeast than the northeast for both channels. As expected, the maximum PCV was higher than maximum ND since there is a high distribution cost to serve all retail stores in the market and some logistics barriers due to the considerable number of retail stores in Brazil.

Table 3 – SKU descriptive data

	Num. Manufacturer	Num. Brands	Num. SKUs	SKU market shares (basis points)		
				Avg.	Med.	Max.
Northeast						
CSS	62	118	654	0.96	0.11	47.33
TFS	36	73	500	1.15	0.13	52.78
Southeast						
CSS	66	128	970	0.67	0.08	47.4
TFS	54	112	743	0.95	0.09	41.75

Source: Author

Table 4 – PCV and ND descriptive

	SKU %PCV (basis points)			SKU %ND (basis points)		
	Avg.	Med.	Max.	Avg.	Med.	Max.
Northeast						
CSS	22.17	9	99	11.59	4	94
TFS	12.85	5	97	7.11	3	87
Southeast						
CSS	26.63	15	100	15.77	5	99
TFS	17.83	7	99	9.88	3	95

Source: Author

5.1.2 Models

For each different channel and region, a common model was estimated in order to describe the relationship between distribution and market share. It was used panel data regression with random effects to control the interaction between PCV and numeric distribution. Equation (32) specifies a common parameters model and follows the assumptions used by Wilbur and Farris (2014). The relationship is a PCV and ND second-order polynomial and data pool across categories to make the most general statement possible:

$$\begin{aligned}\Delta s_{kt} = \beta_0 + \beta_1(\Delta\%PCV_{kt}) + \beta_2(\Delta\%PCV_{kt})^2 + \beta_3(\Delta\%ND_{kt}) + \beta_4(\Delta\%ND_{kt})^2 \\ + \beta_5(\Delta\%PCV_{kt})(\Delta\%ND_{kt}) + \varepsilon_{kt}\end{aligned} \tag{32}$$

where Δs_{kt} is the changes in market share of SKU k in period t and period t-1, the β terms are parameters to be estimated, and ε_{kt} is an error term representing the effects of all non-distribution factors on market. The β_5 estimated the relationship between PCV/ND.

Wilbur and Farris (2014) suggest a different model to analyze the quantitative findings of the model with the use of variables in differences due the fact that %PCV tends to be very small and cannot identify category-specific quadratic effects. In this study, it was used variables in differences to control the temporal dependency.

Further, it estimates parameters to contrast variations in the shape of the relationship of distribution measures (PCV, ND) across regions and channels across beverage types in the data. Equation (33) shows the Region Channel Category-Specific Model where every SKU k belongs to exactly one category c in a Channel j and a Region r, denoted rj_k.

$$\begin{aligned}\Delta s_{kt} = \beta_0 + \beta_{1_{rj_k}}(\Delta\%PCV_{kt}) + \beta_{2_{rj_k}}(\Delta\%PCV_{kt})^2 + \beta_{3_{rj_k}}(\Delta\%ND_{kt}) \\ + \beta_{4_{rj_k}}(\Delta\%ND_{kt})^2 + \beta_{5_{rj_k}}(\Delta\%PCV_{kt})(\Delta\%ND_{kt}) + \varepsilon_{kt}\end{aligned} \tag{33}$$

Similar to Wilbur and Farris (2014), the category-specific parameters were replaced with category characteristics to help to explain when the distribution/share relationship is more or less convex in the data. The Category Characteristics Model in Equation (34) has category *c* with a set of *l=1,…,L* category characteristics x_{ckl}, including an intercept, share dispersion (as measured by Herfindahl-Hirschman), line length (number of SKU's in the period), value density (SKU price/volume ratio) and SKU to consumer per dollar share in the period, and beverage types (Energy Drinks, Carbonated Soft Drinks, RTD Juice, and RTD Tea).

$$\begin{aligned}\Delta s_{kt} = \sum_{l=1}^{L} x_{rj_k l}\,[\beta_{0l} + \beta_{1l}(\Delta\%PCV_{kt}) + \beta_{2l}(\Delta\%PCV_{kt})^2 + \beta_{3l}(\Delta\%ND_{kt}) \\ + \beta_{4l}(\Delta\%ND_{kt})^2 + \beta_{5l}(\Delta\%PCV_{kt})(\Delta\%ND_{kt})] + \varepsilon_{kt}\end{aligned} \tag{34}$$

5.1.3 Parameter Estimates

The equation regression diagnostics were reported in table 5. This approach implies that the relationship portrayed in both graphs and models was not solely due to the effect of distribution on market share. Instead, the quasi-equilibrium of share and distribution result from consumer preference in part due to manufacturer pull, manufacturer distribution efforts and resources, and retailer stocking decisions.

Table 5 – Regression diagnostics for the first model

	N. Obs.	D.F.	R-Sq.	RMSE	Chi-Sq
Common Parameters Model	53788	5	0.0480	0.3024	2714.32
Channel and Region-Specific Model	53788	20	0.0625	0.3001	3585.34
Channel and Region Characteristics Model	53788	167	0.1369	0.2884	8503.66

Source: Author

5.2 Second model

The results for the second group of hypotheses included six stages. As the previous sections, the descriptive analysis was presented for all seven categories in the region of São Paulo. The data displayed the consolidate data from CS channel, and addressed the number of manufacturers, brands and sub-brands for each category, market share, PCV and ND from November 2013 to November 2015.

Second, the construction of IV regressions and models' regressions are exposed due the necessity of IV regression to control the endogeneity depending on whether or not the error terms are conditional heteroskedastic or autocorrelated (Rossi, 2014). This concern resulted in a necessity to produce a better estimator to analyze the pattern of distribution and share relationship over business cycles. The section shows the modeling uses GLS fixed effect with clustering error by brands to control heteroskedasticity and autocorrelation and first-difference monthly to prevent from autocorrelation and unit roots from brands.

The next two sessions introduce the necessary tests to validate the instrumental variables. Subsequently, the validation of the second stage of the model using instrumental variables and market share are presented.

5.2.1 Descriptive analysis

Table 6 summarized the categories sub-brand information. The study had more manufacturers in RTD Juice (47 companies), and more brands in Shampoo category (105 brands). The cookies and biscuit category had the high percentage of sub-brand over brands (i.e., regular cookies and biscuit brand has, an average, 5.44 sub-brands per brand). On the other hand, cookies and biscuit category was the least concentrate market, with the lower average share per sub-brand (0.32). The most concentrate market is yogurt category, with an average share of 2.09 per sub-brand.

Table 6 – Sub-brand descriptive data

	Num. Manufacturer	Num. Brands	Num. Sub-brands	SKU market shares (basis points)		
				Avg.	Med.	Max.
Category						
Beer	9	27	116	1.05	0.03	29.00
Cookies and Biscuit	29	72	392	0.32	0.06	5.63
Laundry detergent	14	29	144	0.85	0.08	40.42
Powder Coffee	29	43	81	1.47	0.11	39.46
RTD Juice	47	60	110	1.21	0.14	35.15
Shampoo	27	105	362	0.37	0.17	4.39
Yogurt	8	35	62	2.09	0.56	18.15

Source: Author

Table 7 showed the differences between numerical and weighted distribution for the seven categories. The yogurt category has the highest weighted distribution, with an average of 49.13%. This means that, on average, a yogurt brand can be found in stores that together account for half of the category's total sales. In contrast, it was clear that the same category had an average of 7.23% of numerical distribution, which implied that although yogurt is stocked in stores that represent a large turnover for the category, these stores represented a very small percentage of the total stores. Even the maximum value of the yogurt category was relatively lower than the others (26% numerical distribution).

All categories had high maximum PCV values, which meant that several brands were looking to increase their share in stores that represent high revenue for their category. The only category that also made use of a more intensive distribution in relation to total sales points was the beer category. There were brands that reached 88% of total stores and it was also the category with the highest average among all the ones used in this research (10.02). Regarding the dispersion of brands in relation to their distribution, the median provided the information that half of the brands reach low distribution values, except shampoo and yogurt.

Table 7 - Sub-brand PCV and ND descriptive

	SKU %PCV (basis points)			SKU %ND (basis points)		
	Avg.	Med.	Max.	Avg.	Med.	Max.
Category						
Beer	26.33	18	99	10.02	2	88
Cookies and Biscuit	25.08	14	99	5.68	3	65
Laundry detergent	28.97	21	100	4.42	2	52
Powder Coffee	20.71	12	96	3.46	1	58
RTD Juice	20.03	14	97	5.33	2	61
Shampoo	41.46	43	97	5.54	5	22
Yogurt	49.13	52	98	7.23	4	26

Source: Author

5.2.2 Models

For the southeast region CS channel was estimated a business cycle model to describe the relationship between distribution and market share over business cycles. The problem of endogeneity bias was controlled by IV for distribution measures (PCV and ND). Then equation (31) specifies a PCV IV regression and used the other regions to control the endogeneity.

The reason behind this choice was the competition in the emerging markets, which is different from developed economies (Sheth, 2011). The distinct situation in each region for infrastructure, brands competition and availability resources make strategies vary from one to other (Kumar et al., 2015). Additionally, in emerging markets, the marketing effectiveness changes in different channels (Venkatesan et al., 2015) and regions (Guissoni et al., 2018). For this case, the model used the five regions to estimate the value of distribution of a brand in the southeast region, as follow:

$$\begin{aligned}\%PCV_t^{cb^{a5}} = \beta_0 + \beta_1 \times \%PCV_t^{cb^{a1}} + \beta_2 \times \%PCV_t^{cb^{a2}} + \beta_3 \times \%PCV_t^{cb^{a3}} \\ + \beta_4 \times \%PCV_t^{cb^{a4}} + \beta_6 \times \%PCV_t^{cb^{a6}} + TimeFixedEffects + u_t^{cb}\end{aligned} \quad (35)$$

Where $\%PCV_{mt}^{a5}$ is the weight distribution by sub-brand b from a category c in a month t for area 5 (southeast region). The time fixed effect controlled the regional differences from seasonality and other monthly effects. The equation (35) employed each region data as an independent variable. It was especially important to control some big events in the period, such as Fifa World Soccer Cup 2014 in June and July.

Similar to equation (35), this study estimated the results for ND to the southeast area, in the following equation:

$$\%ND_t^{cb^{a5}} = \beta_0 + \beta_1 \times \%ND_t^{cb^{a1}} + \beta_2 \times \%ND_t^{cb^{a2}} + \beta_3 \times \%ND_t^{cb^{a3}} + \beta_4 \times \%ND_t^{cb^{a4}} + \beta_5 \times \%ND_t^{cb^{a6}} + TimeFixedEffects + u_t^{cb} \tag{36}$$

Where $\%ND_t^{cb^{a5}}$ is the numeric distribution by sub-brand b from a category c in a month t for area 5 (southeast region). Each region is an independent variable and the same time-fixed effects was used.

To estimate both contraction and expansion periods, it was used a method similar to Heerde et al. (2013), in which they employed the GDP from England to determine the business cycle fluctuation over periods by CF band-pass filter (Christiano & Fitzgerald, 2003). It was applied the CF filter to log-transformed GDP series. In the previous studies, the use of quarterly GDP data led researchers to do interpolation to compound the entire data (Heerde et al., 2013; Pauwels et al., 2004; Srinavasan et al., 2009).

This study used data in monthly aggregation and did not need to use interpolations, bringing more variability to the model, which was necessary to adapt equations (37) and (38) from Heerde et al. (2013) model. Second, the CF filter, excluded the trend pattern from business cycles. This is important in an increase contraction scenario where downstream waves can bring bias to expansion periods. The expansion and contraction variables were defined as follow:

$$Expansion_t = \begin{cases} CF\_lnGDP_t^{SE} - CF\_lnGDP_{t-1}^{SE} & if\ \Delta lnGDP_t^{SE} > 0 \\ 0 & if\ \Delta lnGDP_t^{SE} \leq 0 \end{cases} \tag{37}$$

$$Contraction_t = \begin{cases} CF\_lnGDP_t^{SE} - CF\_lnGDP_{t-1}^{SE} & if\ \Delta lnGDP_t^{SE} \leq 0 \\ 0 & if\ \Delta lnGDP_t^{SE} > 0 \end{cases} \tag{38}$$

The first model was a variation of common-parameters equation (32) from Wilbur and Farris (2014). The model (39), shows the business cycles model and it was possible to verify the interaction between distribution and marketing share over business cycles.

$$\begin{aligned}\Delta s_t^{cb} = \beta_0^{cb} &+ \beta_1^{cb} \times contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \\ &+ \beta_2^{cb} \times contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2 \\ &+ \beta_3^{cb} \times expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \\ &+ \beta_4^{cb} \times expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2 + \beta_5^{cb} \times trend + \varepsilon_t^{cb}\end{aligned} \tag{39}$$

To capture the immediate (short-term) and permanent (long-term) effects of distribution, the study adopted the parsimonious error correction specification (Fok et al., 2006; Pauwels, Srinivan, & Franses, 2007; Heerde, Helsen, & Dekimpe, 2007; Heerde, Srinivasan, & Dekimpe, 2010, Heerde et al., 2013), i.e., a model that uses a two lagged first difference variable to control the long-term effect. The equation (36) shows the business cycle time model:

$$\begin{aligned}\Delta s_t^{cb} = \beta_0^{cb} &+ \beta_1^{cb} \times contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \\ &+ \beta_2^{cb} \times contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2 \\ &+ \beta_3^{cb} \times expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \\ &+ \beta_4^{cb} \times expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2 \\ &+ \varphi \left[\Delta s_{mt-2} - \beta_5^{cb} \times contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)\right. \\ &- \beta_6^{cb} \times contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)^2 \\ &- \beta_7^{cb} \times expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right) \\ &\left.- \beta_8^{cb} \times expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)^2 - \beta_9 \times trend\right] + \varepsilon_t^{cb}\end{aligned} \quad 40)$$

As stated before (see sections 4.4.3), the present work employed the Dickey-Fuller Augmented Test, or ADF (Dickey & Fuller, 1981), given the objective of estimating the autoregressive model and verifying whether the data series is stationary. The table 8 presented the results for ADF in the share volume. For all cases, it was not necessary any concerns about unit root. The results supported the rejection of null hypothesis of unit-root, and therefore, the series had a stationary process.

Table 8 - ADF Test for Market Share

Variable	Lags	Constraint	Trend	ADF	
Share	0	No	No	-6.07	***
	0	Yes	No	-6.08	***
	0	Yes	Yes	-6.08	***

*p<0.10; **p<0.05; ***p<0.01
Source: Author

As Kumar et al. (2015) and Heerde et al. (2013), this research considered the cross effect of competitors moderating the effect of the distribution ratio and market share. As variable, it was used for each category the total distribution of that competitors (i.e. all manufacturers except the manufacturer of the brand), which is a strong indicator of the distribution of a product line, as opposed to an individual SKU or brand (Farris et al., 2006), thus:

$$\%PCV_{comp_t}^{cb} = \sum_{i=0}^{n}\sum_{j=1}^{m} \%PCV_{ijt}^{c} - \sum_{i=0}^{m} \%PCV_{it}^{cb} \tag{41}$$

Where $\sum_{i=0}^{n}\sum_{j=1}^{m} \%PCV_{ijt}^{c}$ is the sum of weight distribution of all brand for brand *i* in the company *j* in the time *t*, and $\sum_{i=0}^{m} \%PCV_{it}^{cb}$ is the sum of total weight distribution of all brands *i* for a manufacturer of *cb* brands.

Other important control was the cross effect of TF markets, because in the contraction consumers can change their purchase behavior, decreasing their search cost and looking for a product in different places. This pattern could be controlled by total PCV from traditional market. This metric indicates the importance of this channel for a specific brand, thus:

$$\%PCV_{trad_t}^{cb} = \sum_{i=0}^{n}\sum_{j=1}^{m} \%PCV_{trad_{ijt}}^{c} \tag{42}$$

Where, $\sum_{i=0}^{n}\sum_{j=1}^{m} \%PCV_{trad_{ijt}}^{c}$ is the sum of PCV from full-service (traditional) channel for brand i in the company j in the time t. In this way, the equation (43) expands the common parameter model with the cross-effect of the market, thus:

$$
\begin{aligned}
\Delta s_t^{cb} = \beta_0^{cb} &+ \beta_1^{cb} \times contraction_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \qquad (43) \\
&+ \beta_2^{cb} \times contraction_t \times \Delta(\%\widehat{PCV}_t^{cb})^2 \\
&+ \beta_3^{cb} \times expansion_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \\
&+ \beta_4^{cb} \times expansion_t \times \Delta(\%\widehat{PCV}_t^{cb})^2 \\
&+ \beta_5^{cb} \times contraction_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right) \\
&+ \beta_6^{cb} \times expansion_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right) \\
&+ \beta_7^{cb} \times contraction_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \times \Delta\left(\%\widehat{ND}_t^{cb}\right) \\
&+ \beta_8^{cb} \times expansion_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \times \Delta\left(\%\widehat{ND}_t^{cb}\right) \\
&+ \beta_9^{cb} \times contraction_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right) \\
&+ \beta_{10}^{cb} \times expansion_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right) \\
&+ \varphi^{cb} \Big[\Delta s_{mt-2} - \beta_{11}^{cb} \times contraction_t \times \Delta\left(\%\widehat{PCV}_{t-2}^{cb}\right) \\
&- \beta_{12}^{cb} \times contraction_t \times \Delta\left(\%\widehat{PCV}_{t-2}^{cb}\right)^2 \\
&- \beta_{13}^{cb} \times expansion_t \times \Delta\left(\%\widehat{PCV}_{t-2}^{cb}\right) \\
&- \beta_{14}^{cb} \times expansion_t \times \Delta\left(\%\widehat{PCV}_{t-2}^{cb}\right)^2 \\
&- \beta_{15}^{cb} \times contraction_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right) \\
&- \beta_{16}^{cb} \times expansion_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right) \\
&- \beta_{17}^{cb} \times contraction_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right) \\
&- \beta_{18}^{cb} \times expansion_t \times \Delta\left(\%\widehat{PCV}_t^{cb}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right) - \beta_{19} \times trend\Big] \\
&+ \varepsilon_t^{cb}
\end{aligned}
$$

5.2.3 Validation of instrumental variable for weighted distribution

Table 9 presented the result of the Hausman test for PCV instrument in other regions. The result showed strong evidence rejection of the null hypothesis (p = .000). Thus, there are time-invariant characteristics that may affect the prediction result. Consequently, it was decided to use fixed effects for the regression of the PCV instrument.

Table 9 - Hausman test for PCV instrument

	Coefficients			
	Fixed	Random	Difference	S.E.
$\%PCV_{mt}^{a1}$	0.1222	0.1107	0.0115	0.0015
$\%PCV_{mt}^{a2}$	0.1851	0.1912	-0.0061	0.0013
$\%PCV_{mt}^{a3}$	0.0580	0.0546	0.0034	0.0010
$\%PCV_{mt}^{a4}$	0.3534	0.3638	-0.0104	0.0014
$\%PCV_{mt}^{a6}$	0.2132	0.2084	0.0048	0.0018
Chi2(5) =	123.41			
Prob2>Chi2=	0.0000			

Source: Author

Just as region variables have unique characteristics, the period has specific events, such as World Cup 2014 and cultural events only in the southeast region. Thus, in addition to considering the fixed effect of the characteristics, it is also necessary to observe the time-fixed effects. Table 10 reported the results for the time-fixed effects test showing the need to control the effect for the regressor (p = .000). The fixed effect control was then performed for the instrument.

Table 10 - Testing for PCV time-fixed effects

F (24, 16724)	=	3.91
Prob > F	=	0.000

Source: Author

The heteroskedasticity test was performed for the model. Table 11 showed that there is a need for variability control within the model (p = .000), so the model needed to use a robust model for the instrument variables.

Table 11 - Wald test for PCV groupwise heteroskedasticity

chi2 (850)	=	6.60E+32
Prob>chi2	=	0.000

Source: Author

5.2.4 Validation of the instrumental variables model for numerical distribution

For numeric distribution the same procedure was conducted. Initially, the same fixed and random effects test was applied to determine the need to control effects. Table 23 displayed similar results to those found for the PCV, so the fixed effects model was also adopted for ND.

Table 12 - Hausman test for ND instrument

	Coefficients			
	Fixed	Random	Difference	S.E.
$\%ND_{mt}^{a1}$	0.1339	0.1261	0.0078	0.0023
$\%ND_{mt}^{a2}$	0.2118	0.2257	-0.0139	0.0021
$\%ND_{mt}^{a3}$	0.0594	0.0642	-0.0048	0.0014
$\%ND_{mt}^{a4}$	0.1915	0.2010	-0.0094	0.0017
$\%ND_{mt}^{a6}$	0.3015	0.3011	0.0004	0.0023
Chi2(5) =	92.52			
Prob2>Chi2=	0.0000			

Source: Author

Considering the fixed model, the time-fixed effects were estimated for the ND variable. Table 13 showed similar results for the PCV. Indeed, ND also has effects related to the different months of the year between brands (p = .000), and there is a need to control this effect on the dependent variable.

Table 13 - Testing for ND time-fixed effects

F (24, 16724)	=	3.91
Prob > F	=	0.000

Source: Author

The Wald test also confirmed the presence of heteroskedasticity for the sample (p = .000) for its ND. As in the case of the PCV instrument, the ND instrument will also be robust to heteroskedasticity.

Table 14 - Wald test for ND groupwise heteroskedasticity

chi2 (850)	=	6.60E+32
Prob>chi2	=	0.000

Source: Author

5.2.5 Validation of the second stage of the model

After parameter estimation, the same procedures were conducted for the second stage. Hausman's test initially presented the same situation as IV regressions. The test indicated the fixed effects model (p = .000) better than random effects.

Table 15 - Hausman test for business cycle equation

	Coefficients			
	Fixed	Random	Difference	S.E.
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	-0.0017	-0.0020	0.0003	0.0001
$contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	-0.0009	-0.0010	0.0001	0.0001
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0034	0.0039	-0.0005	0.0001
$expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	0.0018	0.0019	-0.0001	0.0001
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0000	0.0000	0.0000	0.0000
$trend$	-0.0017	-0.0020	0.0003	0.0001
Chi2(5) =	20.65			
Prob2>Chi2=	0.0009			

Source: Author

Due the control for time-fixed effects in the first stage of regression, this was not a concern in the second stage. Table 16 showed the results for the second stage (p=.000).

Table 16 - Testing for business cycles model time-fixed effects

F(23, 15758)	=	0.91
Prob > F	=	0.5915

Source: Author

The results for Wald Test for the second stage indicated that the model suffered with heteroskedasticity and needed to be controlled with the robustness estimator.

Table 17 - Wald test for business cycles model groupwise heteroskedasticity

chi2 (840)	=	8.80E+12
Prob>chi2	=	0.000

Source: Author

5.2.6 Parameter estimates

The equations regression diagnostics were reported in Table **18**. It is important to note that this approach tries to approximate the results to the effect of distribution on market share. Nevertheless, similar to the first modeling, the quasi-equilibrium of share and distribution has interaction of consumer, manufacturer and retailers, and the importance of each one in the metric is not possible to capture.

Table 18 - Regression diagnostics

	N. Obs.	D.F.	R-Sq.	RMSE	F-statistic	Prob. > F
PCV IV model	17603	29	0.845	0.2055	112.77	0.000
ND IV model	12337	29	0.800	0.2025	48.30	0.000
Business cycle model	16625	5	0.011	0.0014	20.83	0.000
Business cycle time model	14854	10	0.011	0.0015	8.65	0.000
Extended business cycle model	10608	18	0.014	0.002	25.73	0.000

Source: Author

6 RESULTS AND EMPIRICAL APPLICATIONS

In this session, the empirical results for the two models are presented. The first model reported the direct relationships between the different distribution measures, making it possible to understand how these strategies converge and diverge in an emerging country scenario within the same category. For the applications of the business cycles, the results display that the differences in the gains of distribution efforts are affected by the business cycles.

The models are introduced as follows: first a free-model version of the first model is presented indicating the differences discussed in this work. Later, the results obtained in the design of both models are exposed. A management discussion on the impacts of business cycles for different brands is also presented.

6.1 Analysis of the first hypothesis group

6.1.1 Free model evidences

Prior literature on the relationship of distribution measures and market-share plots the distribution and market share by SKU to visualize the pattern of the studied relationship (Guissoni et al., 2014; Reibstein & Farris, 1995; Wilbur & Farris, 2014). It plots the distribution levels and market shares of SKUs for different channel and region.

Overall, Figures 8 to 11 reported the crescent and convex relationship between PCV and market share, but they also demonstrated different patterns across channels and regions. This is an insight that can collaborate to further support of H1.

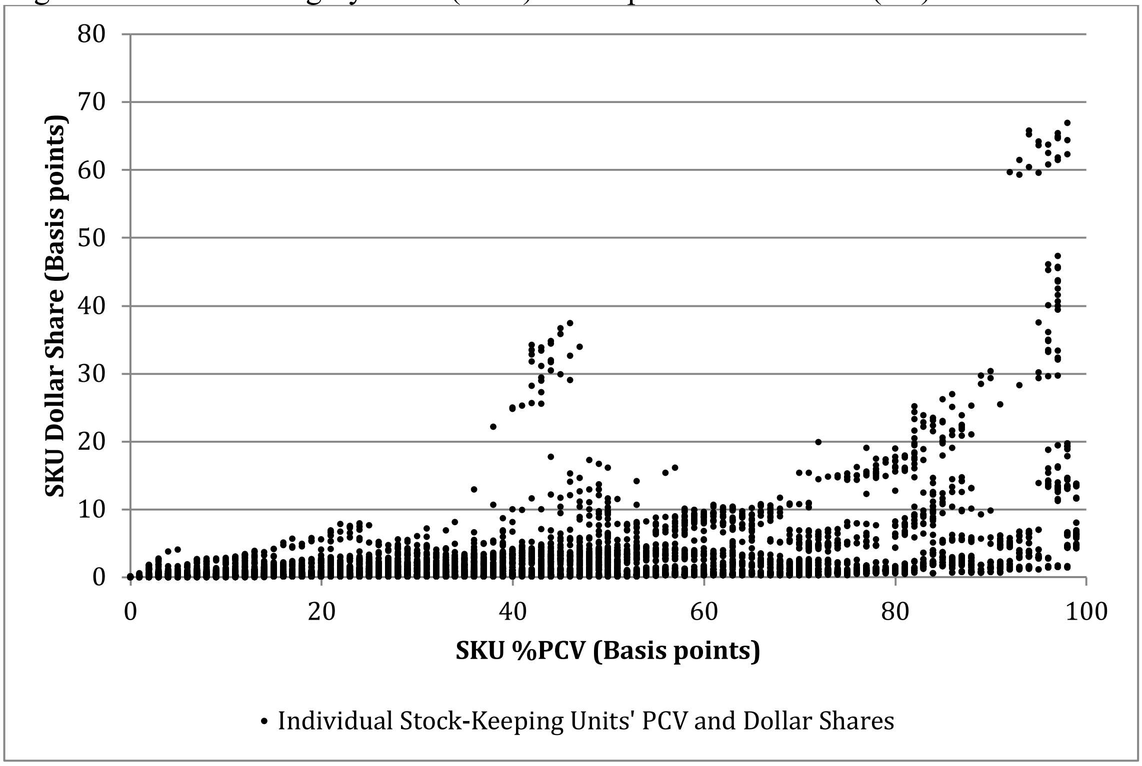
The plots also suggested that higher share products had to achieve higher levels of PCV in the southeast than the northeast. This is consistent with H2, because the southeast is a more concentrated region, and therefore PCV is more important once only a small number of stores account for the product category volume. In contrast, the northeast, as a less concentrated region, relies less in PCV due to its elevated number of stores that contribute to market share.

They also indicated that products in TF achieved a higher share with lower PCV than in CS, which is a positive indicator to H3.

Although the relationship between numeric distribution and market share also varied by channel and region, Figures 12 to 15 showed that the numeric distribution had a different pattern compared to PCV. In some cases, products with lower numeric distribution reported higher market share. Thus, it can observed that some high-share products were bumping up against maximum numeric distribution and therefore were gaining share from increased preference and/or in-store push efforts.

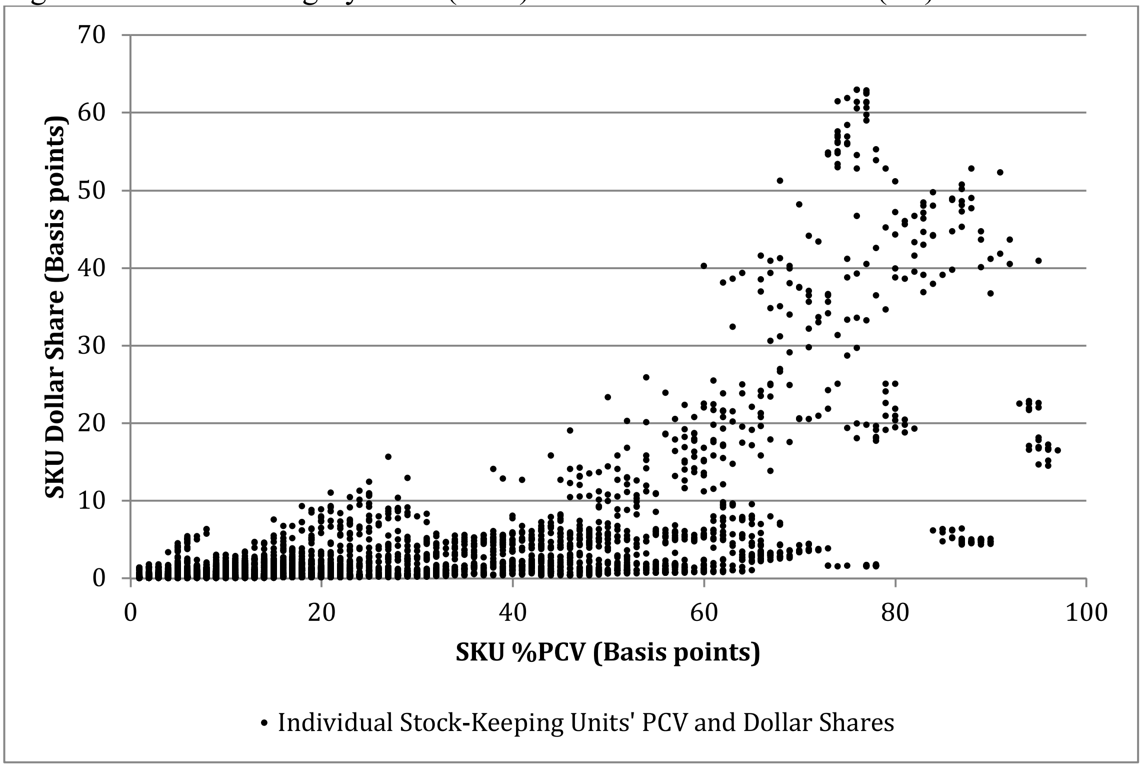
These differences were not statistically significant and the figures are only an indicative of how a weighted versus a non-weighted distribution measure, in the aggregate, had a different distribution-share relationship and motivates the research questions, since this study aimed to understand these measures of distributions and their relationship with market share.

Figure 8 – Product category value (PCV) for corporate self-service (CS) in the northeast



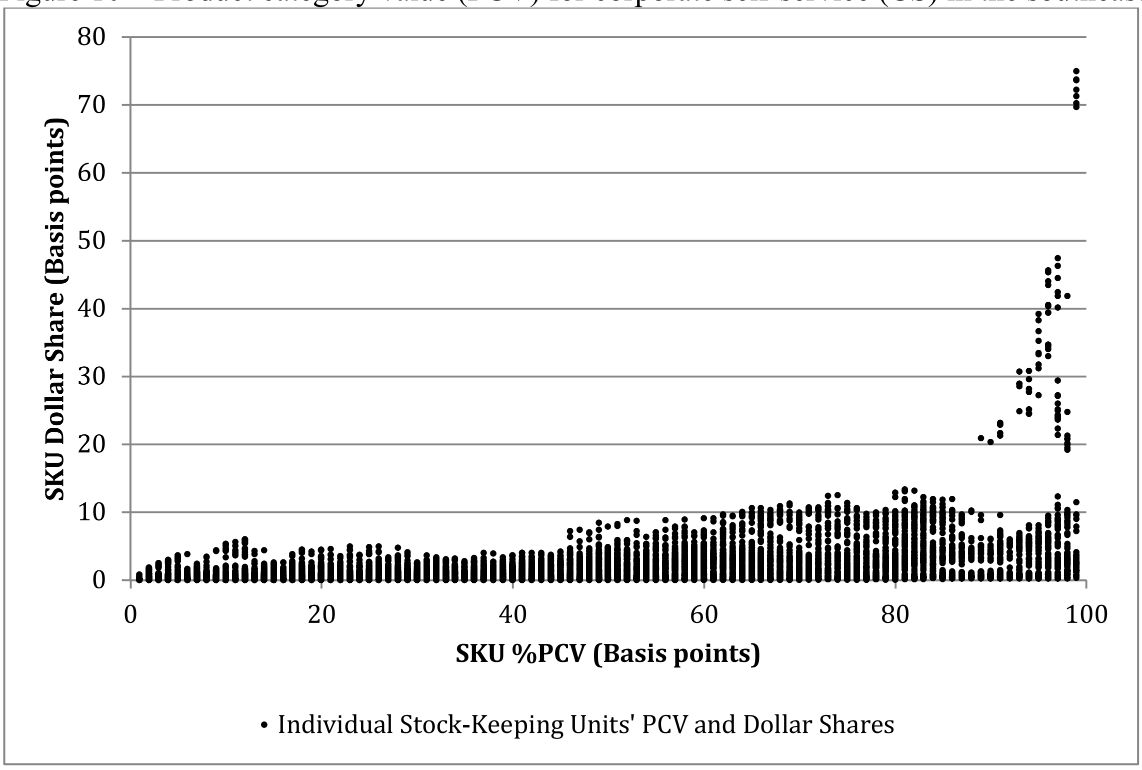
Source: The author

Figure 9 – Product category value (PCV) for traditional full-service (TF) in the northeast



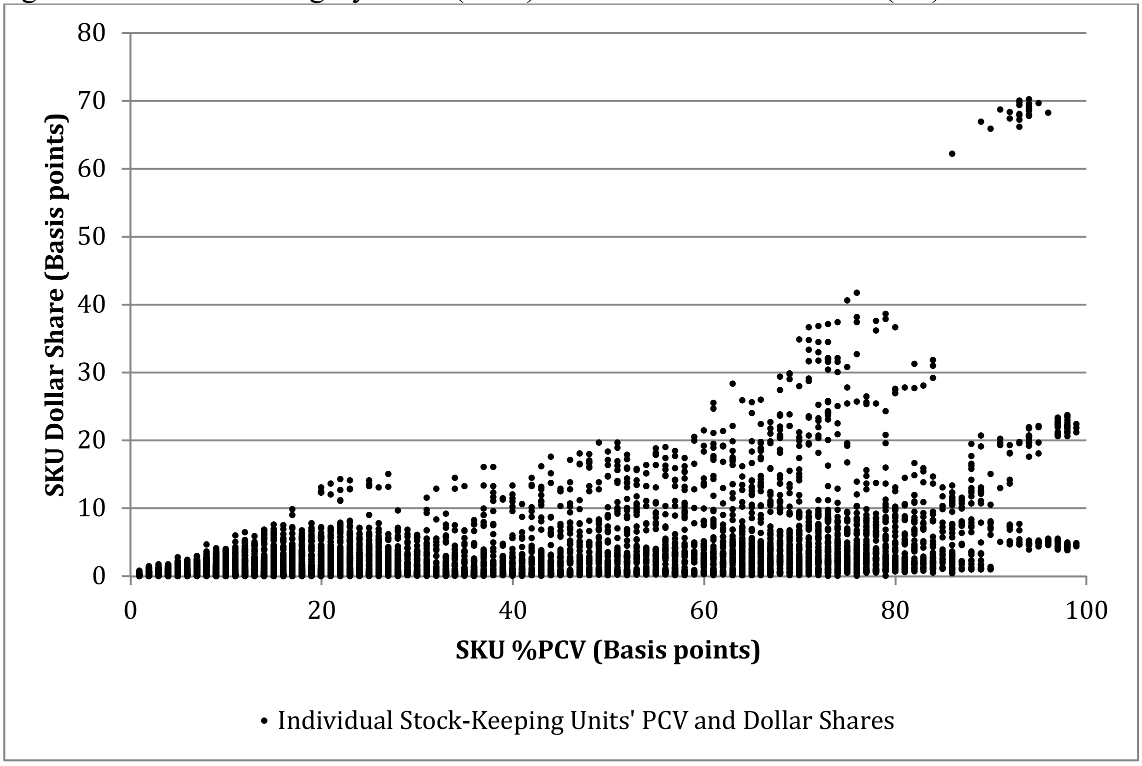
Source: The author

Figure 10 – Product category value (PCV) for corporate self-service (CS) in the southeast



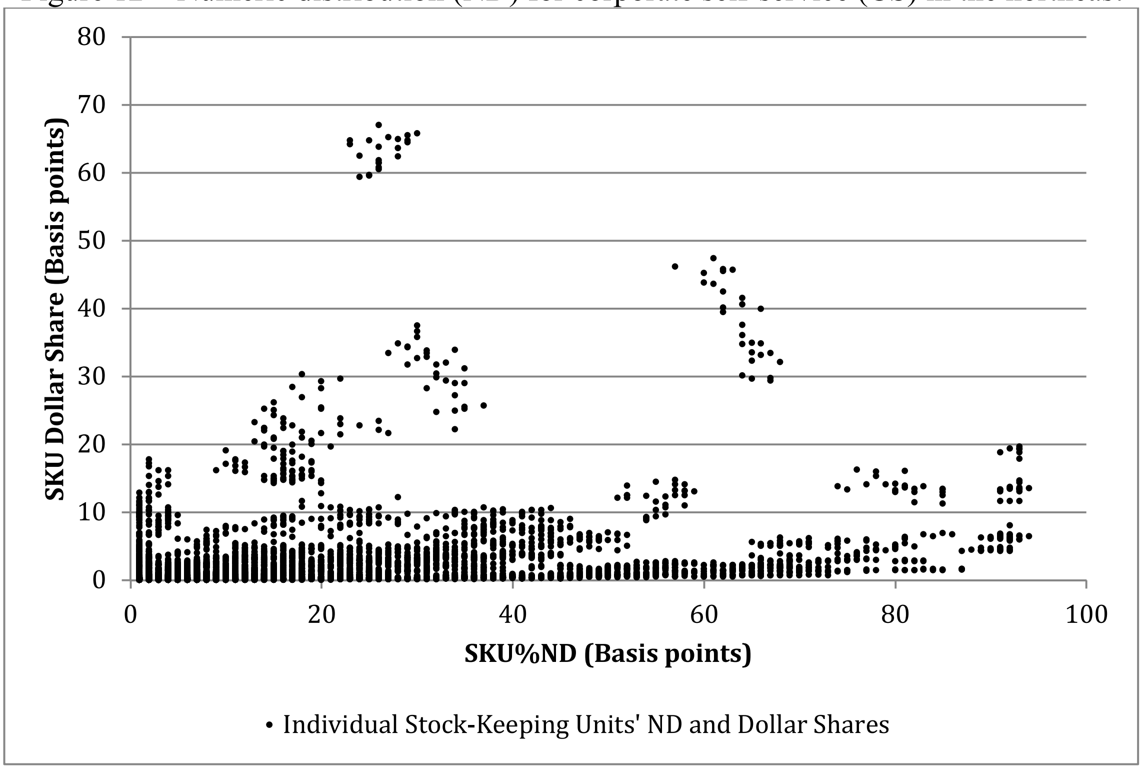
Source: The author

Figure 11 – Product category value (PCV) for traditional full-service (TF) in the southeast



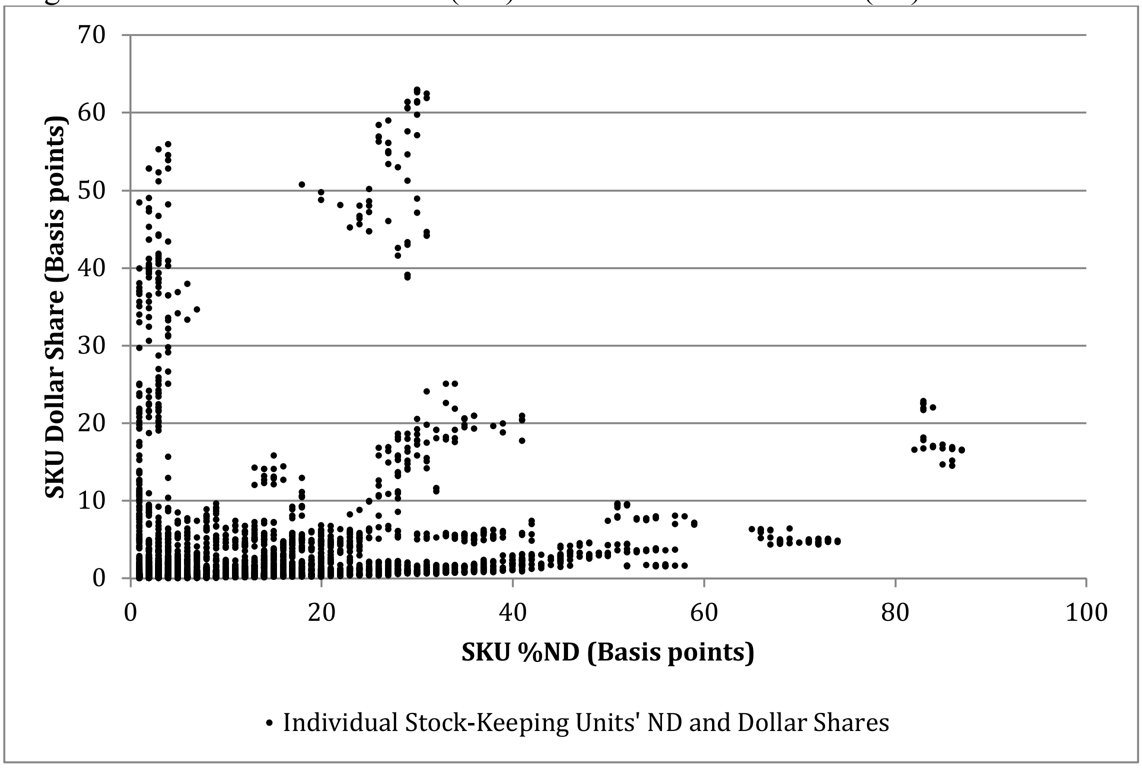
Source: The author

Figure 12 – Numeric distribution (ND) for corporate self-service (CS) in the northeast



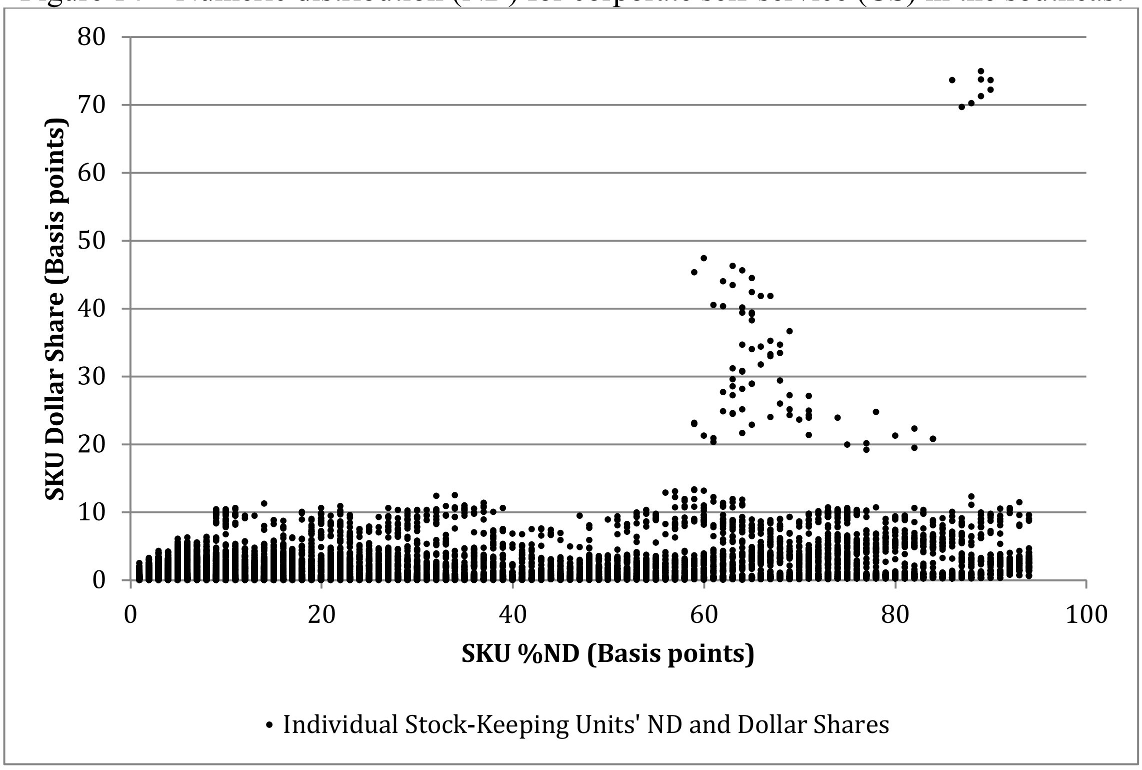
Source: The author

Figure 13 – Numeric distribution (ND) for traditional full-service (TF) in the northeast



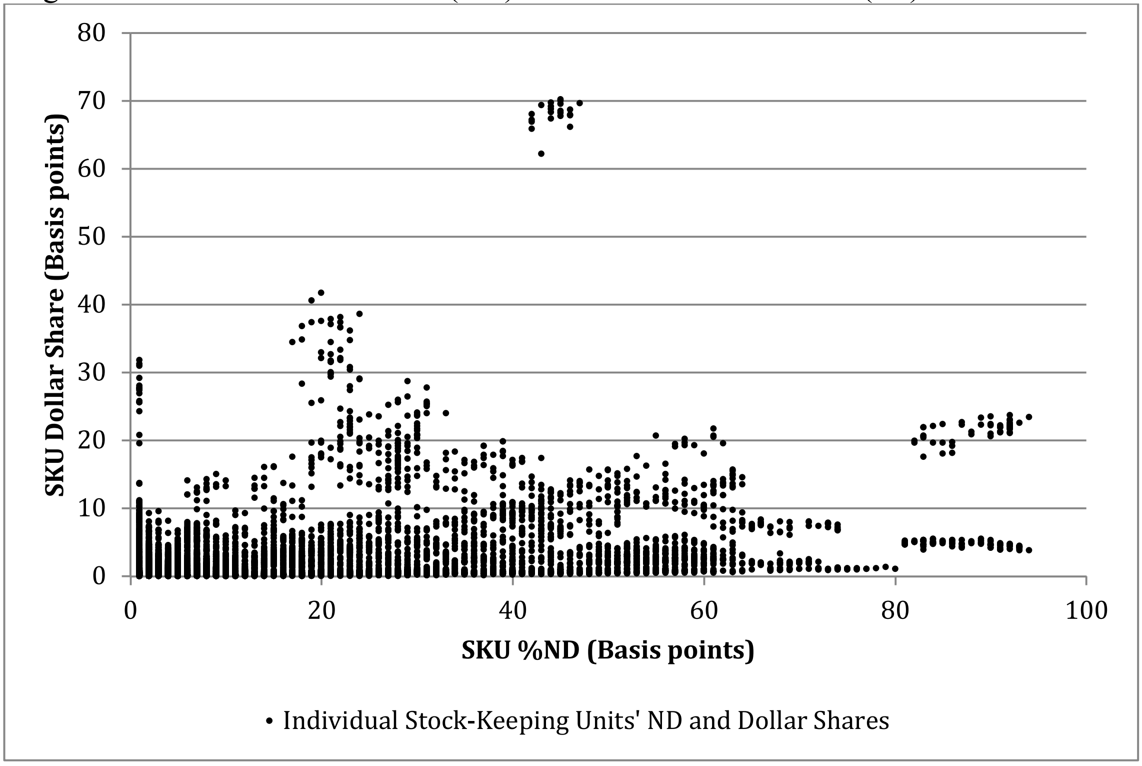
Source: The author

Figure 14 – Numeric distribution (ND) for corporate self-service (CS) in the southeast



Source: The author

Figure 15 – Numeric distribution (ND) for traditional full-service (TF) in the southeast



Source: The author

6.1.2 Parameter estimates

Table 19 displayed the relationship between PCV, ND, and market share using the common parameters model showing in equation (32). The effect of PCV was significant, positive and convex across the different channels and regions analyzed. The slope of ND was significant, negative and concave across the dataset. It was possible to verify that the relationship between PCV and ND was negative. These results confirm the hypothesis H_1 that the pattern of distribution/market share relationship varies with different regions and channel types.

Table 19 – Common parameter estimates

	Main Effect		
	Param. Est.		(T-Stat.)
%PCV	0.01171	***	10.79
(%PCV)^2	0.00021	***	15.81
%ND	-0.00098		-0.62
(%DN)^2	-0.00012	***	-6.1
(%PCV) x (%DN)	-0.00017	***	-3.42
Constraint	-0.00143		-1.09

*p<0.10; **p<0.05; ***p<0.01

Source: Author

Table 20 underscored the region and channel parameter estimates as established in equation (33). In the full-service channel, %PCV and the slope $(\%PCV)^2$ have a higher effect on share than in chain self-service stores for both regions.

The estimates also showed that this effect was higher in the northeast (for both channels) than in the southeast. Therefore, it seems to be more difficult to gain preference in the southeast, where there are more competing products as described in Table 1. This result refute the hypothesis H_{2b} that the degree of convexity between PCV and market share is greater in the more concentrated retail region (e.g., Southeast) than in the less concentrated retail region (e.g., Northeast) for both self-service and full-service channel formats.

In terms of numeric distribution, the pattern was different. Overall, the slope $(\%ND)^2$ was concave, showing that an increase in numeric distribution does not necessarily lead to an increase in market share after a certain level. In the northeast, gains in numeric distribution (%ND) were preferable in the CS format because they were not significant in TF. Whereas, in the southeast numeric distribution is more important in TF (.006, $p<.05$) than CS (-.004, $p<.05$). This result refute the hypothesis that the gain of numeric distribution is more important than PCV to increase SKU market share in a region with less retail concentration (i.e., Northeast) than in a region with more retail concentration (i.e., Southeast) for both channel self-service and full-service formats.

The significant coefficients for both %ND and $(\%ND)^2$ allowed to observe that in the northeast CS the relationship between numeric distribution with market share was concave and decreasing above 43% of ND ($\Delta s_{kt} = 0 = \beta_3(\Delta\%ND_{kt}) + \beta_4(\Delta\%ND_{kt})^2 = -{}^{\beta_3}/_{\beta_4} = {}^{.01540}/_{-.00036} \approx 43\%$).

In the southeast TF, although the same pattern was found, this relationship was also concave and decreasing but above 24% of ND. Therefore, the results indicated that the gain of numeric distribution was important to drive market share but until a certain extend. In the other two situations (i.e., southeast CS and northeast TF), there were no benefits from gaining ND to influence share.

Indeed, in northeast TF the increase in ND had a negative effect on market share (-.0006, $p<.05$); thus, the quality of distribution (i.e., products distributed through the most important retail stores for a given category) was more important than the reach (i.e., selling to any TF store in the northeast regardless the importance of the category). This results refute the hypothesis H_{3a} that numeric distribution is more important to gain share in traditional full-service than self-service stores. Further, although there was not a significant coefficient of the slope $(\%ND)^2$ in southeast CS, the %ND was significant and had a negative effect on market share. Therefore, in southeast CS, the quality of distribution was more important than reaching. This results confirm hypothesis H_{3b} that PCV is more important to gain share in self-service stores than traditional full-service.

Table 20 – Region and channel parameter estimates

		Northeast				Southeast			
		CSS		TFS		CSS		TFS	
Δ%PCV	Param. Est.	0.01161	***	0.03322	***	0.00947	***	0.01013	***
	(T-Stat.)	3.98		9.79		6.09		4.93	
Δ(%PCV)^2	Param. Est.	0.00030	***	0.00067	***	0.00013	***	0.00028	***
	(T-Stat.)	8.23		14.81		6.86		11.17	
Δ%ND	Param. Est.	0.01540	***	-0.00279		-0.00472	**	0.00698	**
	(T-Stat.)	3.84		-0.39		-2.2		2.24	
Δ(%DN)^2	Param. Est.	-0.00036	***	-0.00061	***	0.00000		-0.00028	***
	(T-Stat.)	-6.21		-4.1		0.13		-6.17	
Δ(%PCV) x Δ(%DN)	Param. Est.	-0.00048		-0.0006		-0.00013	***	-0.00006	
	(T-Stat.)	-1.29		-0.38		-2.6		-0.28	
Constraint	Param. Est.	-0.00195							
	(T-Stat.)	-1.48							

*p<0.10; **p<0.05; ***p<0.01
Source: Author

A characteristic category model was then estimated to extend this analysis and help to understand how product characteristics govern the patterns in the relationship between ND and PCV with market share. Table 21 shows the parameter estimates from equation (34).

Table 21 – Category characteristics model parameter estimates

		Main Effect		Δ %PCV		Δ (%PCV)^2	
		Param. Est.	(T-Stat.)	Param. Est.	(T-Stat.)	Param. Est.	(T-Stat.)
Intercept							
Northeast	CSS	0.00546	0.66	**0.01779**	2.41	**0.00044**	4.2
	TFS	-0.01084	-0.75	**0.09628**	13.2	**0.00116**	8.74
Southeast	CSS	-0.01557	-1.57	**0.03935**	7.17	**0.00024**	3.06
	TFS	-0.01152	-0.98	**0.06559**	11.75	**0.00095**	11.84
Interaction with….							
SKU number							
Northeast	CSS	-0.00023	-0.75	**-0.00109**	-3.13	**0.00002**	4.42
	TFS	0.00036	1.51	0.00008	0.23	0.00000	0.41
Southeast	CSS	-0.00027	-0.97	-0.00006	-0.28	0.00000	-0.24
	TFS	-0.00006	-0.19	-0.00037	-1.21	**0.00001**	2.92
HHI							
Northeast	CSS	**3.78897**	4.68	**-3.37905**	-5.29	**0.05593**	6.77
	TFS	**7.46490**	14.14	0.22819	0.71	0.00085	0.28
Southeast	CSS	**0.59732**	1.66	0.05770	0.21	0.00071	0.21
	TFS	**0.78026**	2.15	**-0.60913**	-2.51	**0.01038**	4.63
Value Density							
Northeast	CSS	-0.06559	-1.63	0.02590	0.83	-0.00013	-0.21
	TFS	**0.11361**	1.82	**0.25664**	5.68	**-0.00961**	-8.78
Southeast	CSS	-0.00091	-0.08	-0.00241	-0.28	**0.00050**	3.11
	TFS	**0.04292**	2.87	**0.02702**	2.32	**-0.00075**	-2.78
Category: Carbonated Soft Drink							
Northeast	CSS	-0.00271	-0.3	**-0.01855**	-2.19	**-0.00031**	-2.67
	TFS	0.01039	0.83	**-0.09252**	-9.92	**-0.00090**	-5.76
Southeast	CSS	**0.01151**	1.93	**-0.04125**	-6.93	**-0.00014**	-1.68
	TFS	0.00500	0.57	**-0.06388**	-10.3	**-0.00090**	-10.11
Category: RTD Juice							
Northeast	CSS	-0.00585	-0.53	**-0.01582**	-1.71	-0.00016	-1.19
	TFS	0.01050	0.7	**-0.07475**	-7.88	**-0.00076**	-4.26
Southeast	CSS	0.00805	0.94	**-0.03407**	-4.27	-0.00016	-1.48
	TFS	-0.00047	-0.04	**-0.06945**	-9.59	**-0.00042**	-3.72
Category: RTD Tea							
Northeast	CSS	0.00768	0.44	-0.00647	-0.53	**0.00051**	3.31
	TFS	**-0.20638**	-5.56	**0.10777**	3.92	**-0.00170**	-7.05
Southeast	CSS	**0.01588**	2.07	**-0.02914**	-4.75	-0.00006	-0.65
	TFS	-0.00644	-0.51	**-0.02552**	-2.46	**-0.00091**	-8.48

Table 22 – Category characteristics model parameter estimates (finish)

		Δ %DN		Δ (%DN)^2		Δ (%PCV) x Δ(%DN)	
		Param. Est.	(T-Stat.)	Param. Est.	(T-Stat.)	Param. Est.	(T-Stat.)
Intercept							
Northeast	CSS	**0.06646**	5.01	**-0.00091**	-3.65	**0.00382**	1.72
	TFS	**0.07602**	2.37	-0.00182	-1.58	**0.02273**	3.52
Southeast	CSS	0.00547	0.62	**0.00036**	2.47	0.00011	0.11
	TFS	**0.09614**	5.28	**-0.00450**	-7.81	**-0.00406**	-1.93
Interaction with….							
SKU number							
Northeast	CSS	**0.00130**	2.82	**-0.00002**	-3.32	0.00001	0.15
	TFS	**-0.00125**	-2.45	**0.00007**	5.59	**-0.00021**	-2.15
Southeast	CSS	0.00022	0.77	0.00000	-0.96	0.00000	-0.43
	TFS	0.00015	0.37	-0.00001	-1.28	-0.00004	-1.28
HHI							
Northeast	CSS	**5.11380**	4.07	**-0.06289**	-2.96	-0.23538	-1.31
	TFS	**-6.01521**	-4.62	**0.33620**	8.02	**-0.61873**	-2.34
Southeast	CSS	-0.57879	-1.49	**0.00864**	1.84	**-0.05303**	-3.08
	TFS	**-2.27518**	-3.83	29.00000	0.27	**0.14624**	2.87
Value Density							
Northeast	CSS	0.01115	0.19	-0.00018	-0.15	**-0.02451**	-6.38
	TFS	-0.23453	-1.57	**0.01034**	1.73	**0.11559**	3.53
Southeast	CSS	-0.00547	-0.38	**-0.00075**	-1.99	-0.00051	-1.28
	TFS	-0.02110	-1.01	0.00014	0.17	-0.00016	-0.09
Category: Carbonated Soft Drink							
Northeast	CSS	**-0.05029**	-3.54	**0.00075**	2.94	**-0.00519**	-2.26
	TFS	**-0.07472**	-2.27	**0.00221**	1.91	**-0.02717**	-4.05
Southeast	CSS	-0.00466	-0.51	**-0.00030**	-2.03	-0.00035	-0.34
	TFS	**-0.09396**	-5.08	**0.00449**	7.78	**0.00459**	2.17
Category: RTD Juice							
Northeast	CSS	**-0.04845**	-3.29	**0.00070**	2.55	-0.00319	-1.16
	TFS	-0.00895	-0.24	**0.00449**	3.54	**-0.03381**	-4.64
Southeast	CSS	0.01430	1.29	**-0.00071**	-4.01	0.00033	0.22
	TFS	**-0.04275**	-1.88	**0.00406**	6.02	**0.00481**	1.69
Category: RTD Tea							
Northeast	CSS	**0.27853**	5.77	**-0.00711**	-4.23	**0.02424**	3.78
	TFS	**-2.62853**	-11.34	**0.66420**	11.34	0.01436	1.01
Southeast	CSS	**0.08844**	6.37	**-0.00134**	-2.98	-0.00157	-1.36
TFS	TFS	**0.32200**	8.18	0.00092	0.27	-0.00225	-0.49

Notes: All boldfaced coefficients have $p<.10$
Energy Drink is the base case.

Source: The author

Table 23 supported further understanding of the interactions with product characteristics and showed the shape of average marginal effects of each variable.

Table 23 – Shape of average marginal effect

	0 < % PCV < 100				0 < % DN < 100			
	Northeast		Southeast		Northeast		Southeast	
	CSS	TFS	CSS	TFS	CSS	TFS	CSS	TFS
Intercept	Convex	Convex	Convex	Convex	Convex	Linear	Convex	Convex
SKU Number	Convex	Linear	Linear	Convex	Convex	Convex	Linear	Linear
HHI	Convex	Linear	Linear	Convex	Convex	Convex	Convex	Linear
Value Density	Linear	Convex	Convex	Convex	Linear	Convex	Convex	Linear
Category: Carbonated Soft Drink	Convex	Convex	Convex	Convex	Convex	Convex	Convex	Convex
Category: RTD Juice	Linear	Convex	Linear	Convex	Convex	Convex	Convex	Convex
Category: RTD Tea	Convex	Convex	Linear	Convex	Convex	Convex	Convex	Linear

Source: Author

The category characteristics model underpinned the following findings. First, although the relationship between PCV and share was increasing convex, the magnitude of this relationship varies mainly across different types of product categories (i.e., beverage type). This was consistent because of the non-significance found in most of the cases for the other variables in the regression (i.e., HHI, value density and product variety).

In order to illustrate the variation across different types of products, as shown in Table 4, RTD tea had more convexity compared to the other beverage types within northeast TF for PCV. Further, PCV also had a positive and significant coefficient for energy drinks (.096, $p<.10$).

Nevertheless, the negative and significant coefficient of PCV for RTD Juice and carbonated soft drinks might be evidence that product categories that were more fragmented (i.e., higher numeric distribution and PCV) with lower preference (share per PCV) benefit less from an increase in PCV.

It is important to highlight that according to the raw research data, carbonated soft drinks and RTD juice had in common the high ND, PCV and lower share per PCV compared to RTD tea and energy drinks.

Furthermore, the measure of numeric distribution had more variation depending on specific product characteristics in terms of its relationship with market share than the measure of PCV, which was mainly related to the beverage type. This variation implied that the relationship between numeric distribution and market share could be convex or concave depending on both the beverage type and its channel and region.

In energy drinks, the relationship between ND and market share in northeast CS was concave and decreasing above 37%. In contrast, still considering energy drinks, this relationship in southeast CS was convex and increasing above zero.

Further, the number of SKUs was analyzed. The estimates exhibited that the effects of this variable on the relationship between numeric distribution and market share was not as impacting in the southeast as it was observed in the northeast.

To verify the share dispersion within channels and regions it was used the measure of Herfindahl-Hirschman (HHI) Index calculated using SKU-level market share. In the marketing literature, Wilbur and Farris (2014) have found that the degree of convexity is greater with more concentration in the market share (i.e., higher HHI). In this study, it was observed that for a higher HHI, the numeric distribution had a higher effect on market share than the effect of PCV on market share. In the case of higher value density (i.e., product value), the effect of PCV on market share was overall higher than ND, except for northeast TF. Thus, this result indicated the importance of the quality of distribution (PCV) for products with higher value.

6.2 Analysis of the second hypothesis group

6.2.1 Parameter analysis

Table 24 presented the results for the regression of distribution in other regions of the country. The findings demonstrated a large fixed impact of the months of the year in relation to the various brands. All regions had a significant coefficient, being region 4, metropolitan region of São Paulo, the largest similarity parameter (.351, $p = .000$) followed by region 6 (.210, $p = .000$). The smallest but still significant relationship was with area 3 (.058, $p = .000$) of the Rio de Janeiro metropolitan area.

Table 24 - Results for PCV IV regression

Variable	Param. Est.	T-stat	p-value	
Constraint	0.310	32.33	0.000	***
$\%PCV_{mt}^{a1}$	0.1236	8.45	0.000	***
$\%PCV_{mt}^{a2}$	0.1842	11.87	0.000	***
$\%PCV_{mt}^{a3}$	0.0581	4.84	0.000	***
$\%PCV_{mt}^{a4}$	0.3508	21.19	0.000	***
$\%PCV_{mt}^{a6}$	0.2097	10.89	0.000	***
Time fixed effects				
Nov-13	-0.017	-2.10	0.036	**
Dec-13	0.0023	0.24	0.811	
Jan-14	-0.001	-0.10	0.924	
Feb-14	-0.027	-2.68	0.008	***
Mar-14	-0.019	-1.77	0.077	*
Apr-14	-0.032	-2.81	0.005	***
May-14	-0.04	-3.44	0.001	***
Jun-14	-0.025	-2.17	0.030	**
Jul-14	-0.028	-2.24	0.026	**
Aug-14	-0.036	-2.92	0.004	***
Sep-14	-0.026	-2.09	0.037	**
Oct-14	-0.051	-4.29	0.000	***
Nov-14	-0.037	-3.12	0.002	***
Dec-14	-0.029	-2.31	0.021	**
Jan-15	-0.043	-3.43	0.001	***
Feb-15	-0.039	-3.04	0.002	***
Mar-15	-0.035	-2.80	0.005	***
Apr-15	-0.036	-2.89	0.004	***
May-15	-0.041	-3.11	0.002	***
Jun-15	-0.036	-2.77	0.006	***
Jul-15	-0.039	-2.94	0.003	***
Aug-15	-0.055	-4.07	0.000	***
Sep-15	-0.055	-4.14	0.000	***
Oct-15	-0.063	-4.75	0.000	***

*p<0.10; **p<0.05; ***p<0.01

Source: Author

Table 25 exhibited the results of the regression estimation for ND. All regions were statistically significant. The region with the highest coefficient was region 6 (.298, p = .000), the southern region of the country, together with region 2, and the central region of the country (.211, p = .000).

Table 25 – Results for ND IV regression

Variable	Param. Est.	T-stat	p-value	
Constraint	0.198	19.54	0.000	***
ND_{mt}^{a1}	0.135	7.24	0.000	***
ND_{mt}^{a2}	0.211	12.6	0.000	***
ND_{mt}^{a3}	0.062	5.61	0.000	***
ND_{mt}^{a4}	0.190	10.82	0.000	***
ND_{mt}^{a6}	0.298	15.04	0.000	***
Time fixed effects				
Nov-13	-0.006	-0.67	0.504	
Dec-13	0.004	0.36	0.721	
Jan-14	-0.015	-1.3	0.196	
Feb-14	-0.032	-2.85	0.005	***
Mar-14	-0.038	-3.14	0.002	***
Apr-14	-0.028	-2.29	0.022	**
May-14	-0.038	-3.08	0.002	***
Jun-14	-0.023	-1.81	0.071	*
Jul-14	-0.022	-1.57	0.117	
Aug-14	-0.042	-2.97	0.003	***
Sep-14	-0.039	-2.84	0.005	***
Oct-14	-0.047	-3.36	0.001	***
Nov-14	-0.047	-3.23	0.001	***
Dec-14	-0.032	-2.27	0.024	**
Jan-15	-0.040	-2.83	0.005	***
Feb-15	-0.037	-2.55	0.011	***
Mar-15	-0.041	-2.83	0.005	***
Apr-15	-0.034	-2.29	0.022	**
May-15	-0.030	-1.96	0.050	*
Jun-15	-0.039	-2.67	0.008	***
Jul-15	-0.050	-3.44	0.001	***
Aug-15	-0.058	-3.85	0.000	***
Sep-15	-0.044	-2.91	0.004	***
Oct-15	-0.054	-3.67	0.000	***

*p<0.10; **p<0.05; ***p<0.01

Source: Author

When Table 24 and Table 25 are compared, there is a difference between regions that were more related to the southeast region, showing the differences between both strategies. Brands had their weighted distribution strategy more similar to regions with greater urban concentration, whereas numerical strategy was better explained by areas with greater geographical distances. In both cases, region 3, city of Rio de Janeiro, had the lowest relationship with the other channels. Both equations were used as the basis for stage 2 regression.

Table 26 presented the results for business cycle model over economic downturn the effect of distribution change. The contraction had always a negative impact in cyclical component, and because of that, the contraction interaction needed to be interpreted in an opposite signal.

In addition, distribution effectiveness decreased from expansion (.0034, p=.000) to contractions periods (.0017, p=.000). This result confirmed the hypothesis H_{5a} that the relationship between market share and distribution varies over business cycles. The slope of relationship of share and distribution also changed, from expansion (.0018, p=.000) to contraction (.0009, p=.000). These results supported the hypothesis H_{5b} that the degree of convexity between PCV and market share varies over business cycles fluctuations. Therefore, findings indicated that expansion and contraction have different pattern to share-distribution relationship. In other words, the preference for a product changes in contraction periods in relationship to economic upturn.

Table 26 - Business cycle interaction with distribution elasticity

Variable	Param. Est.	T-stat	p-value	
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	-0.0017	-7.63	0.000	***
$contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	-0.0009	-4.89	0.000	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0034	6.92	0.000	***
$expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	0.0018	6.37	0.000	***
Trend	0.0000	-2.17	0.030	**
Constraint	0.0002	2.21	0.027	**

*p<0.10; **p<0.05; ***p<0.01
Source: Author

In the business cycles time effect model, table 27 reported that distribution relationship with share had differences in immediate effect from expansion (.0035, p=.000) to contraction (.0018, p=.000) periods.

The permanent effect had significative coefficients for upturn waves (.0013, p=.002) and downturn waves (.0005, p=.024) of the economy. That result confirmed the hypothesis H_{6a} that the pattern of distribution and market share is greater in economic upturn than economic downturn. Even immediate effect and permanent effect is greater for expansions. Furthermore, the permanent slope of convexity between distribution and share changed in expansion (.0008, p=.001) and contraction (.0004, p =.007) scenarios. These results supported the hypothesis H_{6b} that the degree of convexity between PCV and market share is greater in economic upturn than economic downturn.

Table 27 - Business cycles time effects model

Variable	Param. Est.	T-stat	p-value	
Δs_{mt-2}	-0.0774	-2.19	0.029	**
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	-0.0018	-5.88	0.000	***
$contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	-0.0009	-4.56	0.000	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0035	5.73	0.000	***
$expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	0.0020	5.72	0.000	***
$contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	-0.0005	-2.26	0.024	**
$contraction_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	-0.0004	-2.71	0.007	***
$expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	0.0013	3.15	0.002	***
$expansion_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	0.0008	3.25	0.001	***
Trend	0.0000	-1.44	0.151	
Constraint	0.0001	1.39	0.164	

*p<0.10; **p<0.05; ***p<0.01
Source: Author

Subsequently, in order to analyze the market environment, it was necessary to extend the business cycles model with the cross-effects with competitors and different distribution strategies. Then, the model followed the steps of Heerde et al. (2013), who verified the impact of advertising and price in sales using the market as control variables.

Table 28 showed the results for the extended business cycles model. The immediate effects were significant and higher in expansion (.0039, p = .000) with a slope (.0022, p = .000) and decrease in contraction (.0025, p = .000) with a lower slope (.0012, p = .000).

The consumer preference decreased in downturn waves. This situation implied that the manufacturer needed to distribute more to maintain their market share levels. In fact, with less effect and a lower slope (speed of share gain) the small manufacturer had less opportunities to compete by share with companies established in the market that have higher distribution levels.

The competitor cross elasticity was only significant for the permanent effect in contraction (.0317, p = .037). In contraction periods, consumers change their purchasing behavior and look for stores with more different brands available (Farris et al., 1989;

Kamakura & Du, 2012). The companies, in downturn, can gain a permanent preference carrying their products on stores with a large number of different brands.

Table 28 - Extended business cycle model

Variable	Param. Est.	t-stat	p-value	
Δs_{mt-2}	-0.0789	-2.13	0.033	**
Distribution immediate effect				
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	-0.0025	-5.06	0.000	***
$contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	-0.0012	-4.25	0.000	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0039	5.23	0.000	***
$expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	0.0022	4.93	0.000	***
Distribution permanent effect				
$contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	-0.0007	-2.70	0.007	***
$contraction_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	-0.0005	-2.59	0.010	**
$expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	0.0015	2.73	0.007	***
$expansion_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	0.0009	2.93	0.004	***
Competitors cross elasticity				
$contraction_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right)$	0.0073	0.42	0.676	
$contraction_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	-0.0317	-2.09	0.037	**
$expansion_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right)$	-0.0306	-1.23	0.220	
$expansion_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	0.0035	0.10	0.918	
Distribution strategies cross elasticity				
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\widehat{\%ND_t^{cb}}\right)$	-0.0043	-3.69	0.000	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\widehat{\%ND_t^{cb}}\right)$	-0.0026	-3.07	0.002	***
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right)$	0.0000	0.56	0.575	
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right)$	-0.0000	-2.52	0.012	**
Trend	0.0000	-0.74	0.460	
Constraint	0.0001	0.66	0.508	

*p<0.10; **p<0.05; ***p<0.01

Source: Author

A significative result was the relationship between PCV and ND. In expansion periods companies are discouraged to gain market share carrying their product in the most number of stores as possible (-0.0026, p=,002). Conversely, in the contraction periods, the recommendation is the opposite: the companies need to stock their product in the most number of stores (.0043, p = .000). Therefore, gain in ND revealed an interesting strategy for emerging market over business cycles fluctuations. These results confirmed hypothesis H_7 that ND is more important to gain share in contractions scenarios than expansions scenarios.

At last, the relationship between PCV and TF channel was significant only for expansion periods, e.g., the coefficient is very small in relation to the other (-.00001, p = .012) but showed that companies need to explore the traditional market in contraction periods to gain market share. In contraction periods, consumers reduce their search cost and are motivated by more restrict budget, searching for products in TF market (Sheth, 2011; Dekimpe & Dellersnyder, 2018).

6.2.2 Other results from applied model

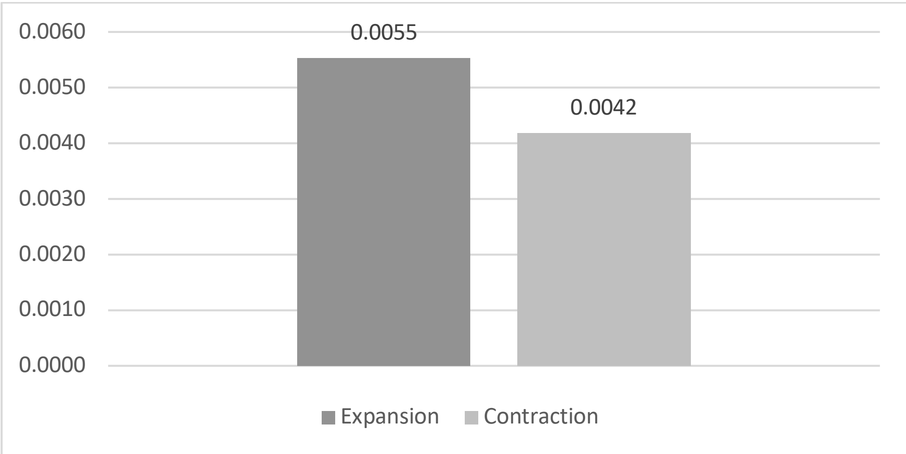
In this section, some results obtained by the extended business cycle model were discussed. First, the studies analyzed the impact of up- and downturn in the economy and how the effectiveness change over business cycles. Second, it was introduced the Deltha method, used by Heerde et al. (2013), to derivate the standard deviation and also to obtain the permanent effect of business cycles (e.g., $-\varphi^{cb} \times \beta_{13}^{cb}$) and estimate the impacts of fluctuations on distribution. Finally, the relationship between business cycles and small-share and high-share brands was addressed.

Relationship between distribution and share at intensive fluctuations

In order to check the changes in distribution at intensive fluctuations, the study used empirical evidences from the period to show the differences between contraction and expansion periods. In Figure 6, the peak of cyclical component occurs in February 2014 (1.195), and the nadir occurs in March 2015 (-.974). The most intensive increasing occurred between March 2015 and October 2015 (a difference of 1,430), while the largest decline occurred between April 2014 and August 2014 (a difference of -1,685). The study employed these changes to estimate the differences between elasticity and convexity of distribution and market share.

Figure 16 illustrated the difference for immediate effect of distribution in market share. The difference between expansion and contraction dropped 24.25% (1 - .0042/.0055 = 0.2425). In an intensified downturn the effectiveness of distribution dropped in ¼. This was significant for brands that wanted to maintain their levels of market share. Brands available in few stores with low representativity in the category volume sales had difficulty to maintain their share.

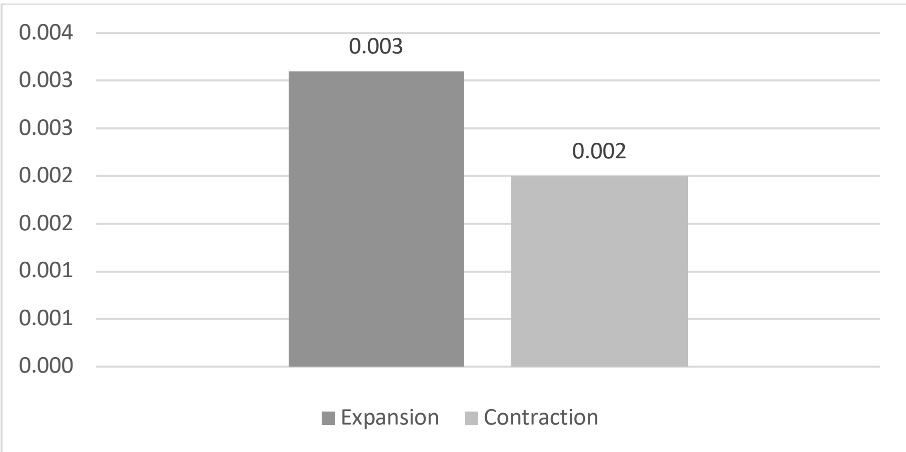
Figure 16 – Immediate effect of distribution elasticity at intensive fluctuations



Source: Author

Figure 17 showed the difference for distribution convexity in intensive expansion (.003) and intensive contraction (.002). Brands usually loss 33% of velocity in contraction. Brands had more difficult to obtain share by gains in distribution.

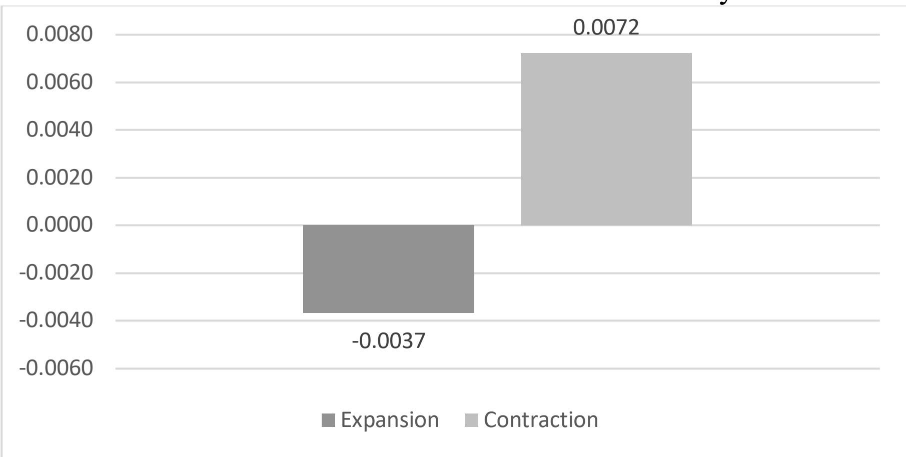
Figure **17** - Immediate effect of distribution convexity at intensive fluctuations



Source: Author

Figure 18 displayed the result to use more numeric distribution to gain share, i.e., stock products in stores with less PCV. The findings indicated a different pattern for the companies: while in upturns they need to avoid gain more ND than PCV (-.0037), in downturns they gain with ND (.00072), an increase of 297%. This suggested to managers of brands in emerging markets that an intensive coverage in contraction can be a good strategy.

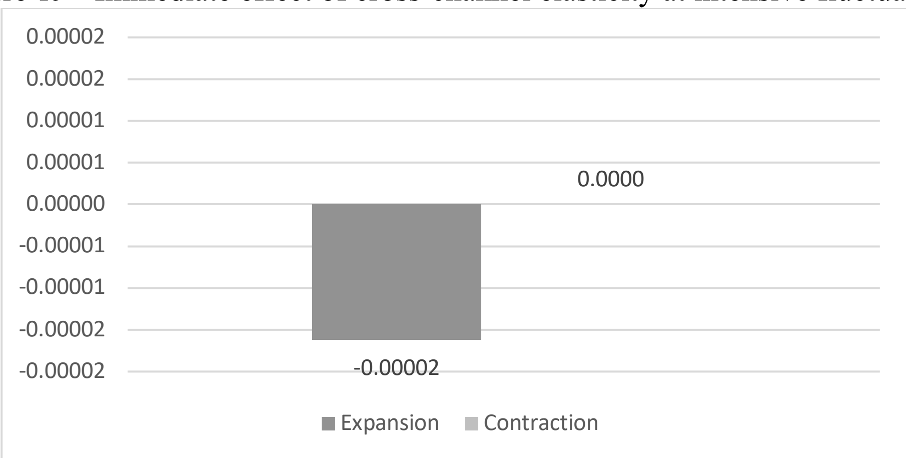
Figure 18 - Immediate effect of cross-numeric distribution elasticity at intensive fluctuations



Source: Author

Additionally, Figure 19 reported the cross-channel effect. The effect of distribution in expansion was negative (-.00002). In contraction, on the other hand, it was not found evidences that effectiveness of distribution changed.

Figure 19 - Immediate effect of cross-channel elasticity at intensive fluctuations



Source: Author

In order to capture the permanent effect, this study followed Heerde et at. (2013) that use Deltha Method to estimate the parameters. Table 29 presented the results.

In contraction, the distribution elasticity decreased (.0095, p = 0.046) regarding expansions (.01888, p = .075). The permanent effect of distribution convexity decreased over business cycles. Companies need to gain more share in contractions periods (.0062, p=.0065) than expansion periods (.0116, p= .066) in order to keep their market share level. The results for competition were inconclusive, with no significant results.

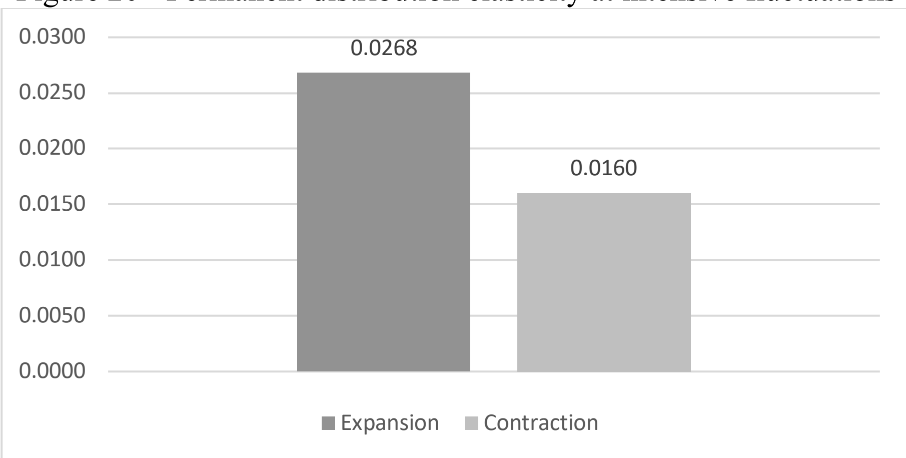
Table 29 – Permanent effect of extended business cycle model

Variable	Param. Est.	T-stat	p-value	
$contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	-0.0095	-2.00	0.046	*
$contraction_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	-0.0062	-1.85	0.065	*
$expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	0.0188	1.79	0.075	*
$expansion_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	0.0116	1.84	0.066	*
$contraction_t \times \Delta\left(\%PCV_{comp\,t-2}^{cb}\right)$	-0.4018	-1.59	0.111	
$expansion_t \times \Delta\left(\%PCV_{comp\,t-2}^{cb}\right)$	0.0448	0.10	0.919	

Source: Author

Figure 20 showed the permanent effect of distribution elasticity decreased 40,40% in this period.

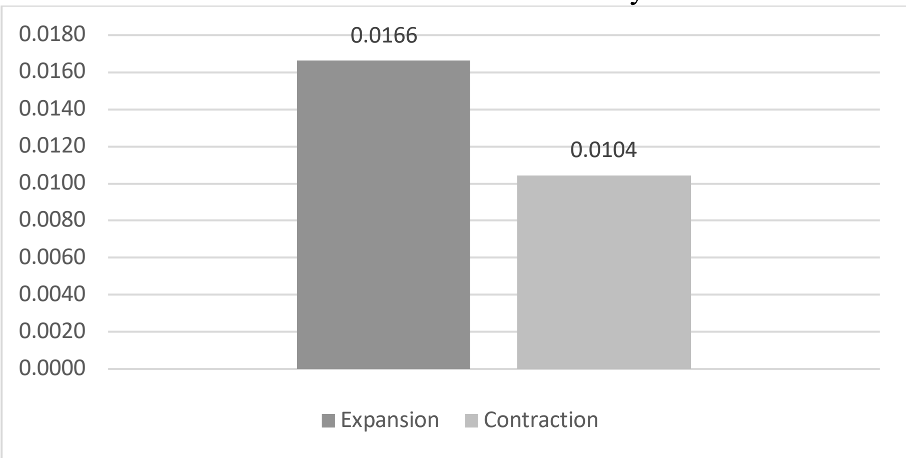
Figure 20 - Permanent distribution elasticity at intensive fluctuations



Source: Author

Figure 21 exposed the permanent effect of distribution convexity for expansion (.0166) and contraction (.0104) in downturns of economy. The small brands with less distribution had more problems to gain share.

Figure 21 - Permanent effect of distribution convexity at intensive fluctuations



Source: Author

The findings exhibited a higher elasticity in permanent effect (.0095, p = .046) than immediate effects (-.0025, p =.000) in contraction periods. In expansion periods, this difference is more accentuated and make permanent effect (.0188, p = .000) higher than immediate effect (.0039, p = .000). The results supported the hypothesis $H8_a$ that the pattern of distribution permanent effect is more important to gain share than immediate effect. These findings expand the discussion presented by Venkatesan et al. (2015) where they identify the immediate and permanent effect in an emerging market. Managers need to keep the product in the point of sales if they want to gain share.

Additionally, this study contributed to Wilbur and Farris (2014) research, in which the distribution convexity can be described as a convex and crescent curve. However, they do not explore the differences between immediate and permanent effect. In contraction periods, the permanent effect (.0062, p = .065) was higher than immediate effect (.0012, p =.000), for expansion periods, it was the same permanent (.188, p = .075) and immediate effect (.0039, p = .000) relationship.

These results confirmed the hypothesis H_{8b} that the degree of convexity of distribution permanent effect is more important to gain share than immediate effect. This implies that brands gain velocity and more preference over time and keep their products in the stores for long time. This is particularly important due to the fact that Wilbur and Farris (2014) state that small brands with low distribution have difficulty to gain share. The double jeopardy can penalize more the small brand, as it has no share, it is difficult to keep the point of sale being neglected by other brands.

This situation makes it important to study the differences between high-share brands and small-share brands.

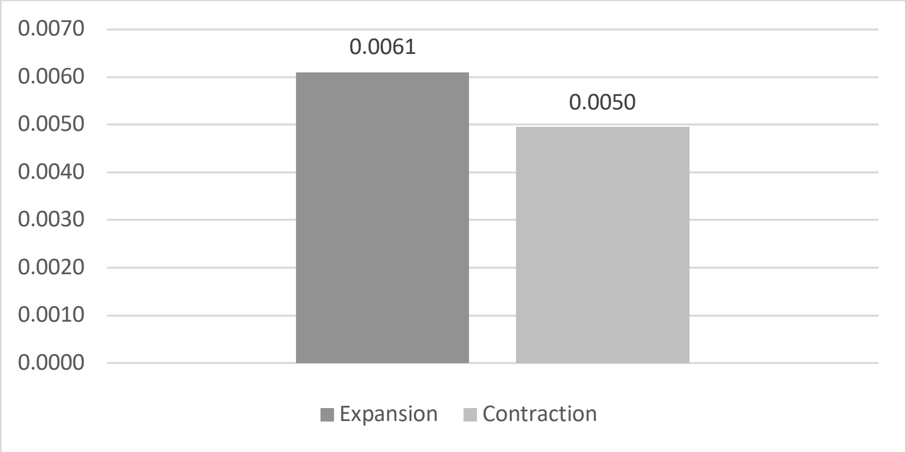
“Double Jeopardy” effects

In order to test the “double jeopardy” effects (Wilbur & Farris, 2014) in which small brands have more difficulty to gain share than brands with higher share, this study followed the same steps of Heerde et al. (2013). First, the data were divided in two groups: one with brands that market share was higher than category market share median, called high-share brand; and other group with brands that market share was lower than category market share median, called small-share brands. Second, the same procedures for equation (43) were made and the results demonstrated the relationship for low and high-share brands and distribution.

Therefore, Figure 22 and Figure 23 showed the difference between high-share and small-share brands. The elasticity of high-share brands decreased 18.83% while small-share brands reduced 11.49%. However, although the decrease in high-share brands had been greater, they remain to have a higher elasticity rather small-share brand. These results confirm hypothesis H_{9a} that the pattern of distribution and share relationship is lower to small-share brands than high-share brands over business cycles.

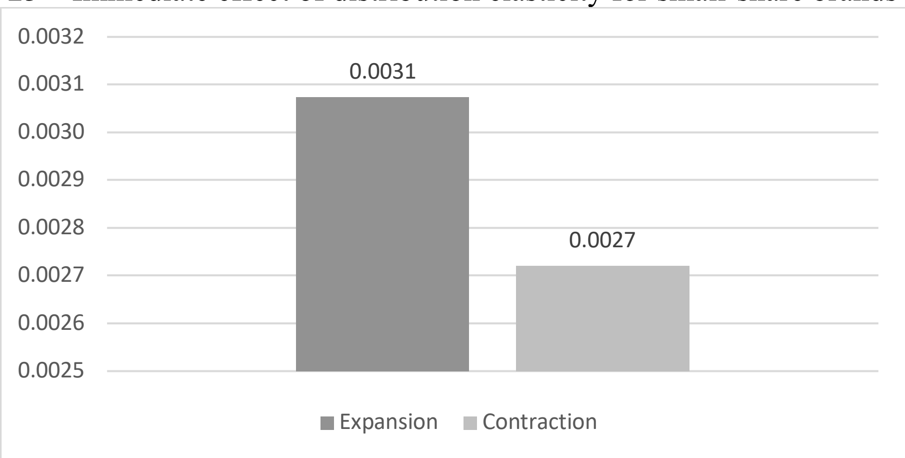
These findings complement the ones found by Wilbur and Farris (2014). The small brands suffer with “double jeopardy” and this situation aggravates the downturn of economy. The figure 24 and figure 25 presented the convexity of distribution. The high-share brands convexity decreased 36,69% from expansion (.0039) to contraction (.0023) and small-share reduced 20.34% from expansion (.0014) to contraction (.0011). High-share brands lost more convexity than small-share brands. Still, high-share had an advantage over small-share. These findings confirm hypothesis $H_{9b:}$ the degree of convexity between distribution/share is lower to small-share brands than high-share brands over business cycles.

Figure 22 – Immediate effect of distribution elasticity for high-share brands



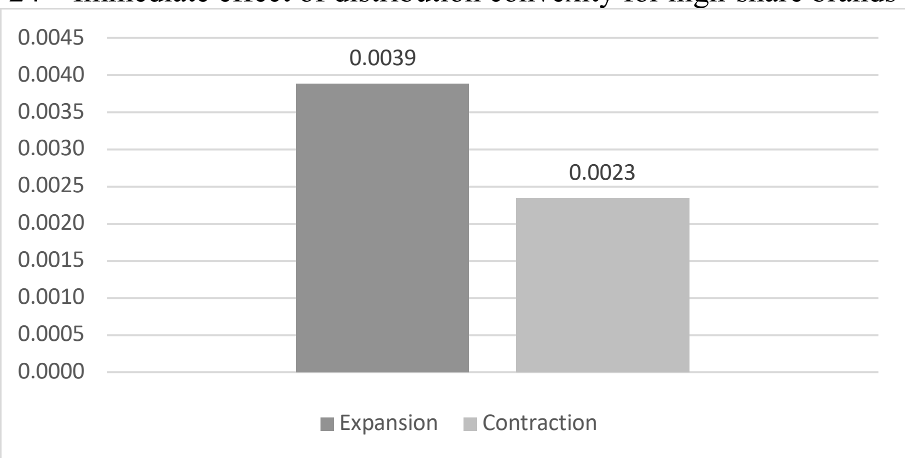
Source: Author

Figure 23 – Immediate effect of distribution elasticity for small-share brands



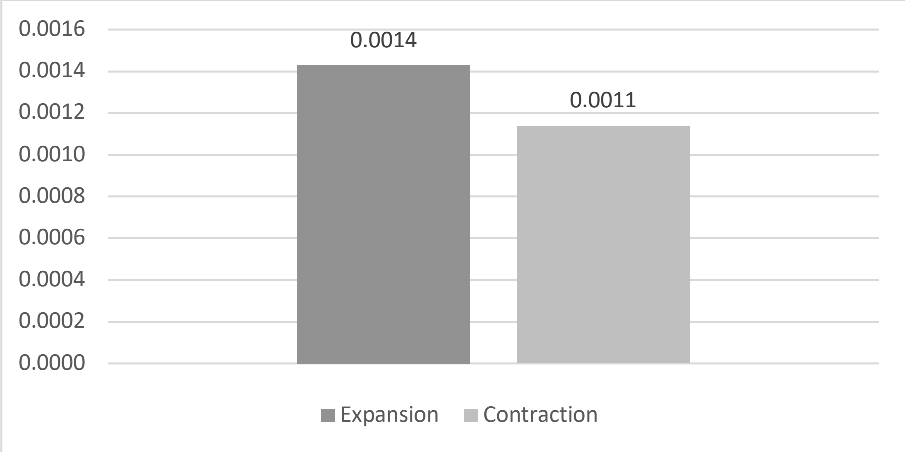
Source: Author

Figure 24 – Immediate effect of distribution convexity for high-share brands



Source: Author

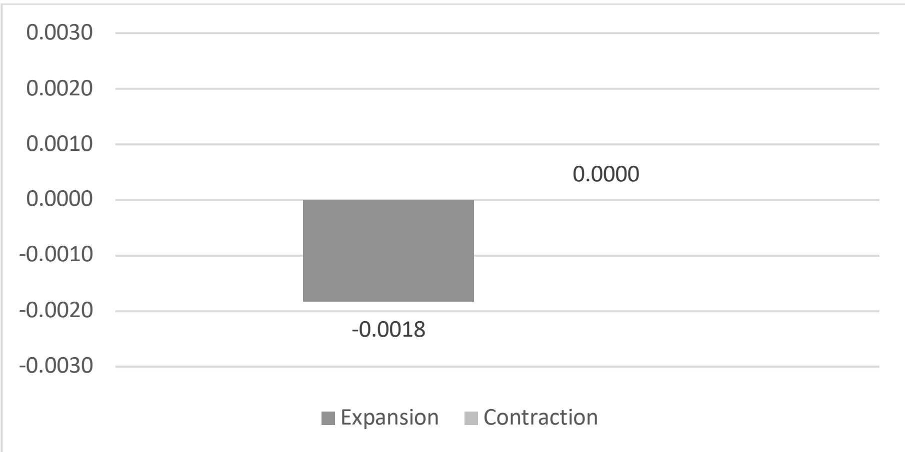
Figure 25 – Immediate effect of distribution convexity for small-share brands



Source: Author

In economic upturns, the high-share brands lose share when they choose to increase full-service channel rather than PCV in self-service channel (-.0018). In an expansion, consumers are less price sensitive (Kumar et al. 2015) and go to places with more availability of products. Then, high-share brands do not have incentive to go to full-service channel rather than increase their participation in self-service channel. Indeed, the results were not significative for small-share brands. Figure 26 displayed this situation:

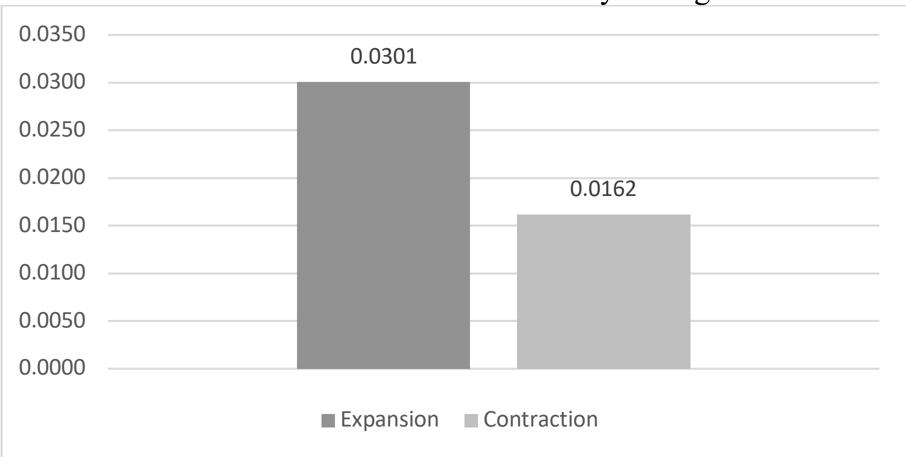
Figure 26 – Effect of cross-numeric distribution elasticity for high-share brands



Source: Author

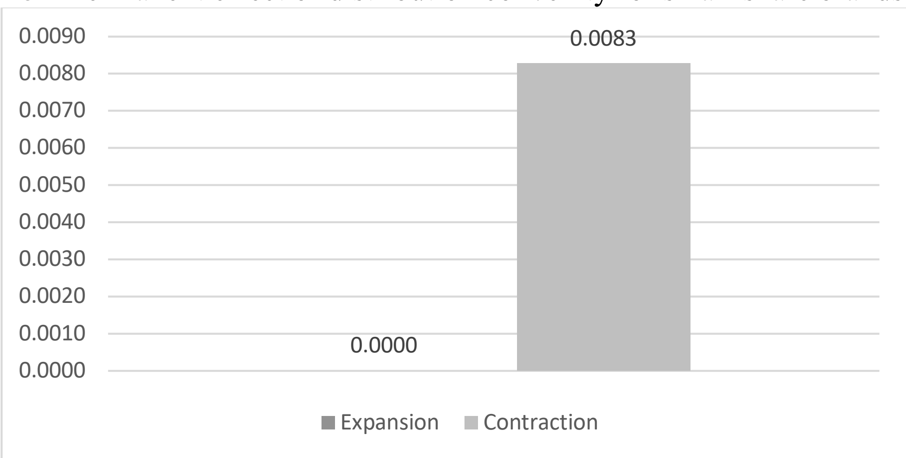
The last two figures 27 and 28 presented an opportunity to small-share compete with the “double jeopardy”. In economic downturns, the high-share brands decreased the distribution convexity, whereas the small-share brands gained in velocity. Hence, small-share brands need to be kept in the stores shelves in contraction periods to gain preference of consumers. The high-share brands need to distribute more to “close” the space in the shelf for these small-share brands. In fact, this study could not find any paper that discussed how local and small-share brands could compete with the “double jeopardy” and how to gain share being small.

Figure 27 – Permanent effect of distribution convexity for high-share brands



Source: Author

Figure 28 – Permanent effect of distribution convexity for small-share brands



Source: Author

The last chapter brings the final remarks of this research.

7 CONCLUSIONS, LIMITATIONS, AND OPPORTUNITIES FOR FUTURE STUDIES

This study contributed to the idea of tailoring distribution strategies to different channels and geographic regions in one emerging economy, based on the analyses of the relationship between two different distribution measures and market share. It also collaborated with insights on how distribution-share relationship changes depending on business cycles.

Specifically, this research demonstrated that a weighted measure of distribution used in previous studies, e.g., PCV (Reibstein & Farris, 1995; Wilbur & Farris, 2014; Venkatesan et al.; 2015; Kumar et al., 2015) remains important, however, it is not enough by itself to support distribution decisions that target market share as the outcome in a more fragmented retail market such as an emerging economy. Consumer goods companies should also consider numeric distribution, which simply indicates how many outlets stock a product (Ailawadi & Farris, 2017).

Furthermore, the importance of both distribution measures varied with structural differences in terms of retail formats (i.e., self-service and full-service stores), regions and products with different market dynamics.

Overall, the quality of distribution accounted by weighted measures such as PCV matters as companies in an emerging economy need to manage their channel strategies across different store formats and regions with different levels of retail concentration. In full-service stores, it was observed that in a region with a more fragmented retail market (i.e., northeast), the gain of ND was not significant to influence market share increase, but the weighted measure of PCV was.

Thus, being available at more stores might not benefit the product in terms of market share unless it is distributed through the most relevant stores for a particular category. Consequently, distribution strategies in this case should be more selective to make a better use of their spending on sales force and logistics to reach full-service stores. Then, CPGs should consider the relative importance of the category in such fragmented retail environment (i.e., northeast TF).

However, in the same channel (i.e., TF) but in another region that the retail environment was more concentrated (i.e., southeast), numeric distribution was important to influence market share until a certain extent (24% of ND). It was found the same pattern but in the other region and channel analyzed (i.e., northeast CS). In this region, the optimal point was higher (43% of ND).

These results showed that although reaching a number of outlets that stock a supplier's product is important until a certain extent and its influence on market share varies within both channel and regions, the level of numeric distribution was greater in a more fragmented retail region such as the Northeast. Further, the ND was not significant in its relationship with market share in the case of an extremely fragmented retail environment in terms of both region and channel characteristics (i.e., northeast TF).

Furthermore, findings also indicated that the importance of the quality of distribution (i.e., PCV) mainly changes depending on product category specificities (i.e., beverage type) as opposed to the variation in terms of retail format or region. Categories such as carbonated soft drink and juices that are more fragmented with greater market coverage (i.e., ND and PCV) and that are preferred less (i.e., lower share per PCV) benefit less from an increase in PCV than less fragmented categories, such as energy drinks and tea.

Overall, the importance of reaching (i.e., market coverage through ND) was greater for beverages such as carbonated soft drinks and juices. Some specific characteristics such as the Herfindahl-Hirschman (HHI) Index and Value Density were significant to account for the distribution-market share relationship and the importance of numeric distribution was greater with a more concentration in market share (i.e., higher HHI). PCV is overall more important than ND with higher value density (i.e., product value).

Indeed, results suggested that manufacturers that target market share gains through their distribution strategy and make use of sales force and logistics resource to support their distribution strategy should also take product's characteristics into account before choosing the most appropriate distribution measure to target market share.

Additionally, it is believed that structural differences in channels and geographic regions in such markets can lead to the use of measures that are not so popular to support distribution decisions in a more concentrated retail market in developed economies.

Besides the previous literature support to research opportunities for the analysis of distribution-market share relationship, the idea for this study also came from the field. Conversations with industry experts including CPGs and market research firms in Brazil also motivated the interest in contrasting the two different distribution measures of weighted (PCV) and numeric distribution (ND).

Many companies reported numeric distribution as the most important distribution measure they target to increase market share through marketing push activities and sales force efforts. The results show that both measures are important, and their relevance varies with region, channel, and product specificities.

Companies should also pay attention to weighted measures in emerging markets even when they target growth in a more fragmented retail region such as the northeast of Brazil. Thus, knowledge of this relationship and also that numeric distribution is an interesting metric to target depending on the region and until a certain extent may help manufacturers to avoid unprofitable distribution decisions.

These results shown in chapter 6 did not imply that the relationships portrayed in both graphs and models are solely due to the effect of distribution on market share. Instead, it would rather portray them as the quasi-equilibrium of share and distribution resulting from consumer's preference (in part due to manufacturer's pull), manufacturer's distribution efforts and resources, and retailer's stocking decisions.

The overall theme that numeric distribution is very important to convenience products should be considered for future channel studies in emerging markets. Numeric distribution metrics may capture dimensions of visibility and availability in markets that are not captured by PCV and other weighted metrics. Furthermore, for managing logistics and channel service, surely one of the determinants of distribution, numeric distribution can be a good indicator of the resources required. Thus, companies need to carefully balance their efforts when they direct their sales force and logistics to target ND through reaching and PCV through quality of distribution (PCV) depending on the region, channel, and product specificities.

As an additional contribution, business cycles change the pattern of effectiveness in an emerging market. The managers need to be alert to economic upturns and downturns. In business cycles fluctuations, the degree of convexity between distribution and share brought the necessity to plan the distribution strategy over time.

7.1 Conclusions concerning the hypothesis analysis

Table 30 - Hypotheses and implications

	Hypothesis	Results	Implication
H_1	*The pattern of distribution/market share relationship varies with different regions and channel types.*	Confirmed	Managers need to consider different channels and regions in order to make better decisions of distribution. Researchers need to control the endogeneity of distinct channels and regions and the possible bias that they can generate.
H_{2a}	*The gain of numeric distribution is more important than PCV to increase SKU market share in a region with less retail concentration (i.e., Northeast) than in a region with more retail concentration (i.e., Southeast) for both channel self-service and full-service formats.*	Refuted	Numeric distribution performance is important even in concentrated regions. Managers need to consider more stores to keep their brands and SKU's as a good strategy. Researchers can use more this metric and the effectiveness of varied distribution strategies.
H_{2b}	*The degree of convexity between PCV and market share is greater in the more concentrated retail region (e.g., Southeast) than in the less concentrated retail region (e.g., Northeast) for both self-service and full-service channel formats.*	Refuted	For managers, knowing the speed of the category does not depend on how concentrated the market they operate is.
H_{3a}	*Numeric distribution is more important to gain share in traditional full-service than self-service stores.*	Refuted	For managers, the speed of the category is not directly proportional to the concentration of the market that they act, but of more variables. For researchers, this is an indicative that consumer preference may not be related to market concentration.
H_{3b}	*PCV is more important to gain share in self-service stores than traditional full-service.*	Confirmed	Managers need to know that even in emerging markets the quality of distribution is one of the keys for success. For researchers, the discussion on differences of consumer behavior in these stores can be relevant.
H_4	*The degree of convexity between PCV and market share is greater in categories with more concentration in sales.*	Confirmed	For managers, the HHI knowledge is fundamental to survive in concentrated markets. For researchers, the entropy between the players needs more studies, but the HHI can be a good introduction in the theme.
H_{5a}	*The pattern of PCV/market share varies over business cycles fluctuations.*	Confirmed	Brands can lose share in contraction, and, therefore, managers need to have plans on how to increase distribution in these periods. For researchers, there is a gap in how brands can fend off these downturns and survive in the marketplace.
H_{5b}	*The degree of convexity between PCV and market share varies over business cycles fluctuations.*	Confirmed	Because distribution and share relationship varied over business cycles fluctuations, more studies are necessary in emerging markets for distribution and other marketing variables. The manager can use this information to make a better decision.

H_{6a}	*The pattern of distribution and market share is greater in economic upturn than economic downturn.*	Confirmed	Managers will need less distribution to access the same market share, so there is a need for planning during contractions to properly prepare the distribution strategy. For the researcher, there are still only few studies on the behavior of consumer in expansion periods and retail.
H_{6b}	*The degree of convexity between PCV and market share is greater in economic upturn than in economic downturn.*	Confirmed	When the economy warms up, the brands with the most distribution tend to accentuate their share difference compared to the brands that are not so distributed. Therefore, managers can prepare a strategy to block the competitor or prepare for a possible difficulty in regaining share when the economy grows again.
H_7	*ND is more important to gain share in contractions scenarios than in expansions scenarios.*	Confirmed	Consumers change the place to buy their product in contraction. Then, managers need to understand this pattern to make the right decision about where to distribute.
H_{8a}	*The pattern of distribution permanent effect is more important to gain share than immediate effect.*	Confirmed	Managers need to keep their products on the shelves, because the real gains of market share come from the long-turn, and quick changes in distribution strategy can penalize companies.
H_{8b}	*The degree of convexity of distribution permanent effect is more important to gain share than immediate effect.*	Confirmed	An insight to managers is to keep the product in the store shelf, because it can increase, in a long-turn, the preference of consumer.
H_{9a}	*The pattern of distribution and share relationship is lower to small-share brands than high-share brands over business cycles*	Confirmed	The business cycles intensify the “double jeopardy” effect. Small-share brands have more difficulty to compete with high-share brands. Managers of small-share need to have a marketing-mix strategy to support the loss of marketing share and the impossibility to gain more distribution quickly.
H_{9b}	*The degree of convexity between distribution/share is lower to small-share brands than high-share brands over business cycles*	Confirmed	For researchers, this is an opportunity to study the ways a brand can gain share over “double jeopardy”. The path to small brands may be the gain of preference during market contractions.

Source: Author

7.2 Limitations

This research presented some limitations. First, on the methodological aspect, the use of instrumental variables can be questioned. Sometimes, researchers understand IV method as a form of sensitivity analysis. That is, estimates of causal effects using standard regression methods are compared with estimates based on IV procedures. If the estimates are not appreciably different, then some conclude that endogeneity bias is not a problem.

While this procedure is certainly more sensible than abandoning regression methods altogether, it is based on the implicit assumption that valid instruments are employed. If the instruments are not valid, then the differences between standard regression style estimates and

IV estimates do not have any bearing on the existence or extent of endogeneity bias (Rossi, 2014).

Second, despite the wide use and relevance of GDP as an economy indicator, it can be criticized because it does not consider important factors such as life expectation and education, present in measures such as the human development index.

Additionally, this study only addressed fast-moving consumer goods. The effects could probably be much stronger for retailers selling durables and apparel as consumers reduce spending in these categories during recessions (e.g., Deleersnyder et al., 2004). Furthermore, these sectors are more heavily affected by online players (Hunneman et al., 2015).

Lastly, on the theoretical point, the role of corporate social responsibility and sustainability was not studied. These aspects influence companies' decisions and can also shape distribution strategies.

7.3 Opportunities for future studies

This study also points to some interesting revenues for future research. One important topic concerns the mechanisms underlying the effects found. Experimental or extensive survey-studies are needed to test these mechanisms. Similar studies should also be conducted in other countries to understand the role of culture (e.g., Deleersnyder et al., 2009).

In general, more research is required to assess the effects of the economy on consumer decision-making in service industries and retailing (Hunneman et al., 2015). Another economic indicator can be used: human development index. In addition, future studies can investigate other product categories, without focusing on fast consumer-goods, in order to verify whether the effects of distribution hold and how business cycles can play a role.

Future research can also test numeric distribution when modeling marketing-mix variables in an emerging market in order to compare with results derived from this study. Finally, corporate responsibility and sustainability may be used as control variables in further studies.

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APPENDIX

Table A1 - Extended business cycle model for high-share brands

Variable	Param. Est.	t-stat	p-value	
Δs_{mt-2}	-0.0798	-1.97	0.049	**
Distribution immediate effect				
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	-0.0029	-4.07	0.000	***
$contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	-0.0014	-2.86	0.005	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0043	3.68	0.000	***
$expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	0.0027	3.97	0.000	***
Distribution permanent effect				
$contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	-0.0008	-1.98	0.049	**
$contraction_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	-0.0006	-1.77	0.078	***
$expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	0.0017	2.57	0.011	**
$expansion_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	0.0013	2.37	0.019	**
Competitors cross elasticity				
$contraction_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right)$	0.0106	0.41	0.686	
$contraction_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	-0.0460	-1.92	0.056	*
$expansion_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right)$	-0.0543	-1.25	0.214	
$expansion_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	0.0015	0.03	0.979	
Distribution strategies cross elasticity				
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\widehat{\%ND_t^{cb}}\right)$	-0.0060	-3.14	0.002	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\widehat{\%ND_t^{cb}}\right)$	-0.0013	-0.78	0.438	
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right)$	0.0000	0.5	0.620	
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right)$	0.0000	-1.91	0.057	**
trend	0.0000	-0.31	0.758	
constraint	0.0001	0.26	0.798	

*p<0.10; **p<0.05; ***p<0.01

Source: Author

Table A2 – Permanent effect of high share brands over business cycles

Variable	Param. Est.	T-stat	p-value	
$contraction_t \times \Delta\left(\widehat{\%PCV}_{t-2}^{cb}\right)$	0.0096	1.65	0.100	***
$contraction_t \times \Delta(\widehat{\%PCV}_{t-2}^{cb})^2$	0.0073	1.46	0.145	
$expansion_t \times \Delta\left(\widehat{\%PCV}_{t-2}^{cb}\right)$	-0.0210	-1.67	0.097	*
$expansion_t \times \Delta(\widehat{\%PCV}_{t-2}^{cb})^2$	-0.0167	-1.63	0.105	
$contraction_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	0.5767	1.46	0.144	
$expansion_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	-0.0182	-0.03	0.979	

*p<0.10; **p<0.05; ***p<0.01

Source: Author

Table A3 - Extended business cycle model for small-share brands

Variable	Param. Est.	t-stat	p-value	
Δs_{mt-2}	-0.0937	-2.21	0.028	**
Distribution immediate effect				
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	-0.0016	-3.68	0.000	***
$contraction_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	-0.0007	-3.3	0.001	***
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right)$	0.0022	3.19	0.002	***
$expansion_t \times \Delta(\widehat{\%PCV_t^{cb}})^2$	0.0010	3.3	0.001	***
Distribution permanent effect				
$contraction_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	-0.0005	-1.93	0.054	*
$contraction_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	-0.0003	-2.58	0.010	**
$expansion_t \times \Delta\left(\widehat{\%PCV_{t-2}^{cb}}\right)$	0.0002	0.4	0.686	
$expansion_t \times \Delta(\widehat{\%PCV_{t-2}^{cb}})^2$	0.0002	0.67	0.507	
Competitors cross elasticity				
$contraction_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right)$	0.0038	0.39	0.700	
$contraction_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	-0.0086	-0.92	0.359	
$expansion_t \times \Delta\left(\%PCV_{comp_t}^{cb}\right)$	-0.0070	-0.53	0.595	
$expansion_t \times \Delta\left(\%PCV_{comp_{t-2}}^{cb}\right)$	0.0128	0.6	0.548	
Distribution strategies cross elasticity				
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\widehat{\%ND_t^{cb}}\right)$	-0.0020	-1.44	0.152	
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\widehat{\%ND_t^{cb}}\right)$	-0.0031	-1.38	0.170	
$contraction_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right)$	0.0000	-0.47	0.641	
$expansion_t \times \Delta\left(\widehat{\%PCV_t^{cb}}\right) \times \Delta\left(\%PCV_{trad_t}^{cb}\right)$	0.0000	-2.07	0.039	**
trend	0.0000	-1.12	0.266	
constraint	0.0001	1.01	0.312	

*p<0.10; ***p<0.05; ***p<0.01

Source: Author

Table A4 – Permanent effect of low share brands over business cycles

Variable	Param. Est.	T-stat	p-value	
$contraction_t \times \Delta\left(\widehat{\%PCV}^{cb}_{t-2}\right)$	0.0049	1.86	0.065	*
$contraction_t \times \Delta(\widehat{\%PCV}^{cb}_{t-2})^2$	0.0028	1.94	0.054	*
$expansion_t \times \Delta\left(\widehat{\%PCV}^{cb}_{t-2}\right)$	-0.0026	-0.41	0.68	
$expansion_t \times \Delta(\widehat{\%PCV}^{cb}_{t-2})^2$	-0.0020	-0.66	0.51	
$contraction_t \times \Delta\left(\%PCV^{cb}_{comp_{t-2}}\right)$	0.0917	0.94	0.348	
$expansion_t \times \Delta\left(\%PCV^{cb}_{comp_{t-2}}\right)$	-0.1362	-0.52	0.606	

*p<0.10; ***p<0.05; ***p<0.01

Source: Author