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Consumer Brand Marketing through Full- and Self-Service Channels in an Emerging Economy

Rajkumar Venkatesan[a,*], Paul Farris[b,1], Leandro A. Guissoni[c,2], Marcos Fava Neves[d,3]

[a] *Bank of America Research Professor of Business Administration, Darden Graduate School of Business, University of Virginia, 100 Darden Boulevard, Charlottesville, VA 22903, United States*

[b] *Landmark Communications Professor of Business Administration, Darden Graduate School of Business, University of Virginia, 100 Darden Boulevard, Charlottesville, VA 22903, United States*

[c] *Professor of Business Administration, Department of Marketing, Business Administration School of São Paulo, Fundação Getulio Vargas, FGV/EAESP, Rua Itapeva, 474, CEP 01332-000, São Paulo, Brazil*

[d] *Full Professor of Planning and Strategy, School of Economics and Business, FEARP, University of São Paulo, Bloco C, sl 64, CEP 14040-900, Ribeirão Preto, Brazil*

Abstract

A unique characteristic of emerging economies is the wide variety of dominant channel formats. We evaluate the influence of a brand's marketing mix on channel partners and consumer sales in both full and self-service channels in one emerging economy (Brazil). We use monthly stock-keeping-unit (SKU) level sales, and marketing mix data from the beverage category in southeastern Brazil spanning more than four years. In this study, we specify a panel vector autoregression framework with error decomposition to account for endogeneity between sales and marketing mix, cross-sectional heterogeneity among SKUs, seasonality, and the different aggregation of marketing mix elements across the channels. The results show that structural differences in these channels cause differences in the responses to some of the manufacturers' marketing mix elements. Package size variety, price and merchandising have a greater long-term effect on sales in self-service than in full-service channels. Brands' channel relationship programs support price increases in self-service channels without a corresponding decrease in sales. Distribution gains are important in both channels. In the full-service channel, package size variety has the highest long-term effect among all of the modeled marketing mix elements. Our study highlights that marketing mix strategies popular in the self-service dominant channels of the developed economies are not as effective in the full-service formats that remain important in emerging economies.

Keywords: Consumer package goods; Multichannel marketing; Emerging markets; Channel formats; Marketing mix; Channel relationships

Introduction

Emerging economy markets are important to companies in the global economy (Sheth 2011) and will account for most of this century's economic growth (Burgess and Steenkamp 2013). For example, these markets have contributed more than half of the Coca-Cola Company's global revenue since 2006. Eighty-one percent of the company's unit sales were outside the U.S. in 2012, and the three largest contributors were Mexico, China and Brazil, all classified as emerging markets. Despite the interest and potential, many companies are still striving to identify effective marketing strategies for emerging economy markets. Competencies and strategies that have worked well in developed markets cannot necessarily be replicated in developing markets (Sheth 2011; White and Absher 2007).

* Corresponding author. Tel.: +1 434 924 6916.
E-mail addresses: venkatesanr@darden.virignia.edu (R. Venkatesan), farrisp@darden.virignia.edu (P. Farris), leandro.guissoni@fgv.br (L.A. Guissoni), mfaneves@usp.br (M.F. Neves).
[1] Tel.: +1 434 981 7113.
[2] Tel.: +55 11 3799 3472.
[3] Tel.: +55 16 3315 3936. He is also International Adjunct Professor, Purdue University, Center for Food and Agricultural Business. The authors are grateful for the constructive feedback received from participants at the 2012 Theory + Practice in Marketing Conference, the 2012 International Conference on Marketing in Emerging Markets – An Agenda for the Next Decade, and the 2014 Thought Leaders in Marketing Channels Conference. They thank the Special Issue Guest Editor and three anonymous reviewers. Leandro A. Guissoni thanks FGV and Jonny M. Rodrigues for research support.

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Even Coca-Cola, a company with both experience and success in this realm, lists marketing in emerging markets as a major risk factor in achieving growth targets.[4]

Of particular difficulty for consumer packaged goods (CPG) companies in emerging markets[5] is marketing to and through a diverse set of distribution channels (Kumar, Sunder, and Sharma 2014). Traditional full-service (TF)[6] retailers (such as owner-managed grocers and mom and pop stores) compete alongside sophisticated chain self-service (CS) stores such as Wal-Mart and Carrefour. Indeed, in emerging markets, smaller TF-type stores are not disappearing but are growing and, in many cases, providing manufacturers with higher margins (Diaz, Lacayo, and Salcedo 2007).

Several differences between TF and CS stores are relevant for a brand to design its marketing mix strategies. In full-service formats, clerks can exercise more influence on sales by recommending specific products and brands, whereas in self-service, as the term implies, consumers generally browse assortments unassisted. Merchandising aids that support product visibility and call attention to temporary price reductions may therefore be more influential in self-service stores. There are also differences in the effects of marketing mix elements, such as promotion and sales efforts directed at the trade. More professional management is generally found in the self-service channel, and these retailers may respond more to data on sales velocities and gross margins in selecting assortments than less professionally managed retail stores. Such differences in consumer and retail responses to brand marketing activities are important for tailoring marketing mix efforts to each channel.

Marketing mix modeling research has, however, largely been conducted within retail environments that are similar to that found in developed markets (e.g., self-service, sophisticated retail managers and "pull" distribution systems). The heterogeneity in consumer and retail management response in emerging markets has rarely been reflected in published research thus far. This is an important gap, especially since Kumar, Sunder, and Sharma (2014) show that firms can improve the return on marketing efforts in emerging markets by tailoring products and programs to different distribution channels. We build on this important contribution and study how the effects of all four elements of marketing mix (product, price, place and promotion, such as advertising and merchandising) change across channel formats in one emerging economy. Since brand marketing efforts are directed toward channel partners as well as the end consumer, we model the retail and consumer responses to marketing mix decisions.

[4] The Coca-Cola 2012 10-K "...the supply of our products in developing and emerging markets must match consumers' demand for those products. Due to product price, limited purchasing power and cultural differences, there can be no assurance that our products will be accepted in any particular developing or emerging market."

[5] We refer to emerging economy markets and emerging markets interchangeably in the manuscript.

[6] This is intended to include small mom-and-pop operations, where chain self-service is used as a synonym for supermarkets.

Research Questions

Our research aims to address three general questions:

(A) Does the effectiveness of modeled marketing mix elements vary with CS and TF stores (i.e., self-service versus full service formats)?
(B) How do the short- and long-term effects of distribution and in-store attractiveness (merchandising and promotions) differ for the CS and TF channel formats?
(C) How does the relative importance of channel relationship management and brand marketing differ by channel format?

This research focuses on understanding the effects of manufacturer marketing activities that target consumers and retailers in a multichannel environment of an emerging economy. Thus, this research is more concerned with how a brand should seek to market to and through different retail channels than how retailers in different formats should manage their own businesses. To investigate the proposed research questions, we have analyzed data from a large CPG manufacturer in Brazil. Joseph et al. (2008) point out that the role of full-service stores in Brazil is less important than in China or India, but far more important than in the U.S. and Europe. This good mix of retail formats makes Brazil an especially interesting market (among the emerging economies) for a multichannel study.[7] Competing in these markets will require consumer marketers to manage brands that are sold through radically different retail formats and may provide guidance for other emerging markets as the retail mix changes in favor of CS stores.

Contribution

Our research contributes to the small but growing literature on modeling marketing mix effects in emerging economies. The results of our research validate the importance of distinguishing between push and pull marketing effects, especially with regards to self-service and full-service channel partners. The two formats are associated with different retail management styles and sophistication and, as we show, this leads to variations in the effectiveness of marketing activities. Almost all modeled marketing mix elements have higher long-term effects in the self-service channels. Variety in package sizes is shown to have the greatest effect on sales among all the modeled marketing mix elements in the full-service channel, followed by distribution. Thus, in an emerging economy, consumer brands need to carefully monitor distribution intensity and identify the package sizes that are effective in the full- and self-service channels. Our research hence provides managers guidance on managing the traditional full-service channels, a major challenge they usually face in emerging markets. Finally, we contribute to the evolution of marketing mix models by constructing a stock-keeping-unit

[7] Euromonitor International Report (2014), Retailing in Brazil and Nielsen. *Mudanças no mercado brasileiro*. In: Seminário Nielsen Tendências. São Paulo, 2010.

Table 1
Channels' features in emerging markets.

Feature	Chain self-service (CS)	Traditional full-service (TF)
Ownership	- Corporate with more than five stores under the same group	- Independent family owned, located in neighborhood location
Management	- Professionalized buying center - Automated information systems - Distribution centers and area to stock inventory - Large assortment - Data-based decisions	- Non-professionalized buying center since often the owner makes the decisions and manages the relationship with suppliers - Use of heuristics to make decisions - Clerks often recommend products and brands to consumers - Small assortment and no area to stock inventory

Source: Diaz, Lacayo, and Salcedo (2007); Lenartowicz and Balasubramanian (2009); Kalish, Roberts, and Gregory (2010); Guissoni, Consoli, and Rodrigues (2013).

(SKU) specific model of marketing mix effects to capture more granular effects of the distribution and the interactions of product line and distribution.

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

Multichannel Marketing in Emerging Markets

We classify channels in emerging markets as chain self-service (CS) and traditional full-service (TF) stores. Self-service stores often belong to corporate groups, either multinational, national, or regional chains. They typically operate with professional buying centers, distributions centers, checkout lanes, large product assortments and large retail spaces. Independent, traditional full-service stores (also known as "mom-and-pop" stores) are small family-owned grocers, often in neighborhood locations, with a more limited selling and inventory space that restricts available assortments. Table 1 summarizes the features of both channel formats.

Of course, there are differences in how TF and CS stores operate among different emerging markets. For example, India is more highly regulated with respect to foreign investment in the retailing sector, and all retailers in India face less competition from multinational CS competitors. Global retailers have been operating in Brazil for several decades (Carrefour since the 1970s and Walmart since 1995). Further, the largest retailers in Brazil are from Europe (Groupe Casino/GPA, Carrefour) and the U.S. (Walmart). Because of that, we believe that the management practices of the CS format retailers in Brazil are more similar to the management practices of CS stores in developed markets than one might observe in other emerging markets such as India and China.

TF stores, in general, tend to be independently owned and represent the so-called "unorganized" retail sector (Joseph et al. 2008; Kumar, Sunder, and Sharma 2014; Sarma 2005). We also acknowledge that there is substantial heterogeneity in management styles, sophistication in services offered (e.g., credit) and the types of promotions employed across stores within each channel. Our research is, however, concerned with average effects since data on the heterogeneity of stores within the CS and TF channels is not yet available in emerging markets.

Knowledgeable industry observers have predicted that "despite the consolidation, as large modern retailers grow, mom-and-pop stores will represent a significant share of retail sales in Latin America and many other emerging markets for quite some time" (Diaz, Lacayo, and Salcedo 2007, p. 71). Sheth (2011, p. 169) writes that "nontraditional channels and innovative access to consumers may be both necessary and profitable in emerging markets." Further, TF channels are often easier routes for new products into the market. Even in developed markets many American beverage brands, such as Vitaminwater, Snapple and Red Bull, began in cities with a greater concentration of independent stores where "instead of having to woo a national chain, and perhaps hand over a few grand in placement fees, you can talk your way into one store at a time".[8] These comments are reinforced by studies published by McKinsey,[9] Booz & Company[10] and Bain & Company.[11] Thus, we conclude that consumer product manufacturers in emerging markets will need coverage of all retail channels, including smaller independent stores.

We highlight three reasons for the survival of independent stores in emerging markets. First, CPG companies have realized they can achieve higher margins in these smaller format stores even though the cost of servicing them may be higher and shelf space more limited (Diaz, Lacayo, and Salcedo 2007; Kertesz et al. 2011). Second, government regulations and policies restricting foreign direct investment in retail trading (in some countries such as India), protect the interests of local, independent, smaller retailers.[12] Finally, TF stores can offer advantages for time-constrained shoppers, as CS stores are bigger with more aisles for shoppers to browse products and offer larger assortments. Thus, consumers can be motivated to use neighborhood TF stores for specific product needs when their time is limited.

Conceptual Background

Research in marketing-mix models has traditionally investigated the effects of advertising, price, and promotions (Clarke 1976; Dekimpe and Hanssens 1999; Srinivasan, Popkowski Leszczyc, and Bass 2000; Weinberg and Weiss 1982) and

[8] Segal, David (2014), "For Coconut Waters, a Street Fight for Shelf Space," *The New York Times*.

[9] Diaz, Alejandro, Jorge A. Lacayo and Luis Salcedo (2007), "Selling to 'mom-and-pop' stores in emerging markets," *McKinsey Quarterly*.

[10] Booz & Company (2013), "Go-to-Market Strategies for Emerging Markets".

[11] Bain & Company (2014), "Taking the mystery out of developing market brand growth".

[12] 2011 PWC report on Winning in India's Retail Sector: Factors for Success.

distribution (Bronnenberg, Mahajan, and Vanhonacker 2000; Farris, Olver, and de Kluyver 1989; Reibstein and Farris 1995). Recent studies have broadened their approach by including product assortment and have evaluated the effects of all the marketing-mix variables on brand sales, category sales and market share (Ataman, Mela, and van Heerde 2008; Ataman, van Heerde, and Mela 2010; Pauwels 2004; Vanhonacker, Mahajan, and Bronnenberg 2000).

Increasingly, competition among brands is manifested in the task of obtaining distribution and retail support for a full line of SKUs. For example, in the U.S., IRI reports that an astounding 190,000 new UPCs were introduced in 2013, but less than 1% of them (1,800) achieved 30% or more all commodity volume (ACV).

Still, "much less emphasis has been placed on distribution and product line, due in part to a paucity of data" (Ataman, Mela, and van Heerde 2008, p. 1037) and most distribution research has concentrated on relatively homogenous self-service supermarkets in developed economies (Kumar, Sunder, and Sharma 2014). Also, few researchers have investigated the effects of both push and pull activities, i.e., marketing programs directed to retailer and consumers (Vanhonacker, Mahajan, and Bronnenberg 2000). We believe a much-needed next stage in the evolution of marketing mix models is to develop models that allow differentiation by channel (Kumar, Sunder, and Sharma 2014) and include marketing programs directed towards both channels and consumers. Modeling the distribution variable by SKU also can be an important contribution to the literature since there is far less variance for distribution measured at the brand level, and a major challenge that marketers face is the complexity of managing SKU assortments in different trade classes.

Theoretical Framework and Hypotheses

Our research analyzes and compares the effects of a comprehensive set of marketing-mix elements directed to both consumers and retailers by channel format. Fig. 1 depicts the organization of the conceptual development in our research.

We expect the effects of marketing-mix efforts directed to consumers and retailers will potentially differ among channel formats. These efforts are expected to have direct effects on sales through consumer response and an indirect effect on sales through retail distribution breadth and depth. By breadth of distribution, we refer to the percentage of stores that stock a brand or SKU. By breadth, we mean in-store attractiveness such as share of shelf inventory. Marketers may affect both consumers and retailers "pull" efforts, such as advertising across all channel formats. Finally, fueled by both data and perceptions, a feedback-loop exists between sales at the point-of-purchase and retailer decisions on in-store marketing efforts that may affects sales velocity.

In-Store Marketing

We consider in-store marketing to be product availability (breadth of distribution), share of shelf inventory (depth of distribution), retail price, and in-store promotion (e.g., displays, circular advertising). The hypotheses regarding in-store marketing are described in this order.

Distribution. Due to their relatively smaller size, the typical store in this channel has a limited number of brands, fewer SKUs within a brand and less inventory of any given SKU. Hence, there is less in-store brand competition for consumers than in larger assortment retailers (i.e., self-service stores) where shoppers have more choices (Chernev 2003). This implies that a brand or SKU has a higher chance of succeeding once it gains distribution in the traditional full-service format than in the chain self-service format. Thus:

H_{1a}. The immediate effect on sales of an increase in distribution will be higher in traditional full-service than self-service stores.

SKU availability is always the retailer's decision, but it may be influenced by the manufacturer's sales force. As reported by McKinsey,[13] CS stores generally have more professional management. CS stores have information systems and embedded processes to make assortment decisions based on analytics. This means these stores are more likely to accurately identify SKUs that provide higher returns (or sales) from distribution gains and keep these SKUs at their stores than TF formats. Further, in CS organizations, assortment reviews and changes to planograms are expected to be more formal and less frequent.

TF stores in developing economies on the other hand rely more heavily on heuristics to make product and brand availability decisions (Lenartowicz and Balasubramanian 2009; Peterson and Balasubramanian 2002). Changes in assortment composition in TF stores are hence not based on SKU sales performance to the same degree as in CS stores (Peterson and Balasubramanian 2002). Further, TF stores are likely to have higher flexibility in changing their assortment, as they are not dealing with a formal chain structure (e.g., planograms) that is likely to be more difficult to change. As a consequence the owner-operators of small, full-service stores will have increased ability to respond to individual sales representatives on a given sales call. Thus:

H_{1b}. The persistence of distribution effect on sales is higher in self-service than independent traditional full-service stores.

Share of shelf. Given the available data and the objectives of our research, we are focused on the effects of shelf inventory from a manufacturer rather than the retailer's perspective. All stocked products in self-service stores are generally exposed on the shelves for shoppers to inspect and potentially select. However, product visibility is one of the biggest challenges to selling in TF type stores because of limited shelf space (Diaz, Lacayo, and Salcedo 2007).[14] Some products are hence stored behind the counter and cash register to optimize the usage of the more limited store size in TF stores. In contrast, consumers can

[13] Calicchio, Nicola, Tracy Francis and Alastair Ramsay (2007), "How Big Retailers Can Serve Brazil's Mass-market Shoppers," *McKinsey Quarterly*, March, 2007.

[14] The Wall Street Journal (2007), "P&G's Global Target: Shelves of Tiny Stores".

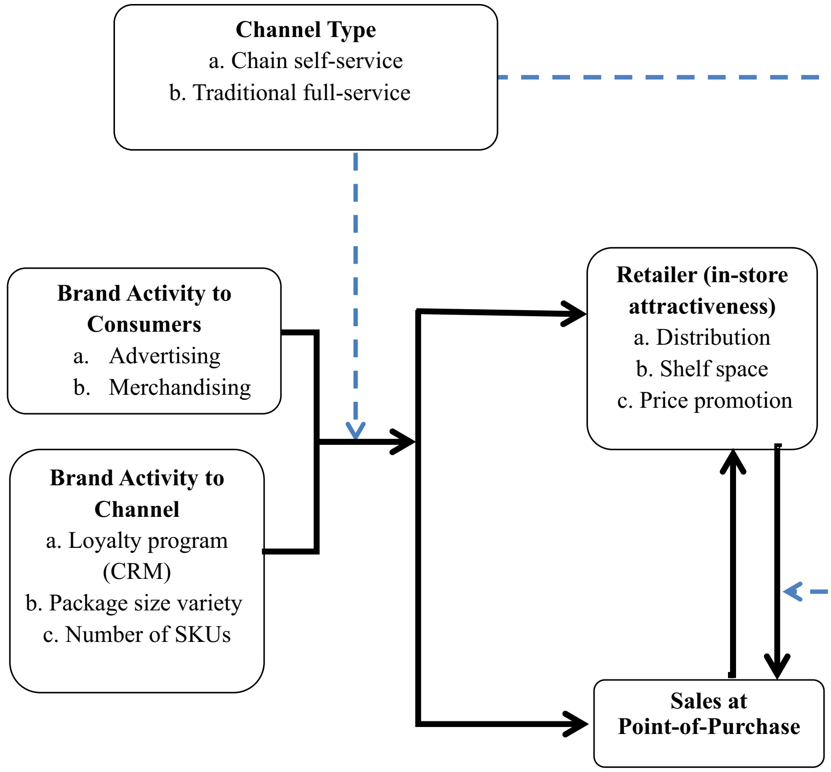

Fig. 1. Brand activity to consumers and channels.

browse all the SKUs available in a store with relative ease in the CS channel. Thus, an increase in share of shelf inventory for a SKU will usually also mean higher visibility in the CS than TF channel. Thus:

H_{1c}. The effect on sales of an increase in share of shelf inventory will be higher in self-service than traditional full-service stores.

Price. According to Kumar, Sunder, and Sharma (2014), price sensitivity will not be highly different across store formats. They are, however, referring to a specific emerging market in which brands are required to have a maximum retail price (MRP) printed on their packages. This ensures that competition across different store formats is minimal. In fact, Kumar, Sunder, and Sharma (2014) also acknowledge that price sensitivity could be significant across store formats for markets where MRP does not apply.

Brazil does not have MRP regulations, and we believe that the salience of price in consumer decisions could change with channel format. Consumers may expect more temporary price reductions and other in-store promotions in CS stores or choose to shop in these stores for products that are highly price and promotion sensitive (e.g., they are willing to stock up or change brands). Further, price comparison is easier in large self-service (CS) stores because consumers can browse for products by themselves. This can make shoppers more price and promotion sensitive. Finally, Diaz, Lacayo, and Salcedo (2007) state that "traditional shop owners normally live in the same neighborhoods as their customers, who are often their close friends." TF stores also offer more personalized service and other conveniences such as credit with little risk of default. Thus:

H_{1d}. Price sensitivity is higher in self-service than traditional full-service stores.

Brand Marketing Activity Directed to Consumers

Marketing pull involves activities directed to consumers. In this research, we included advertising (i.e., out-of-store pull), since it helps consumer brand recognition and unaided recall. A strong advertising effect on consumer preference might not only cause a consumer to create a shopping list or make a special trip to buy a particular brand, but even to select a particular outlet based on prior knowledge that the brand is stocked there. In the latter case, retailers are likely to be aware that consumers are willing to search or plan their shopping to reflect brand preference and be sure to stock the brand or SKU in question.

It has been reported in earlier literature (Collins-Dodd and Louviere 1999; Kaufman, Jayachandran, and Rose 2006; Klink and Smith 2001; Montgomery 1975; Rao and McLaughlin 1989; Völckner and Sattler 2006) that advertising and promotion plans are among the top criteria that grocery buyers used in deciding whether to accept a new product into their assortment. Although these effects have been documented for supermarket buyers in the U.S., we believe they likely also exist in developing markets and for traditional outlets. Presentation of advertising plans by the sales force may be less likely in the TF channel. But if owners see the advertising themselves, we believe that they will be more likely to stock the advertised products.

In addition to the adoption of new products, there is support in the literature for the ability of advertising to influence an existing product's availability in retail stores (Olver and Farris 1989; Völckner and Sattler 2006). For example, Vanhonacker, Mahajan, and Bronnenberg, (2000) show that advertising positively affects a product's retail distribution. In the TF channel, clerks have more contact with consumers than in the self-service format. These stores can have more flexibility and speed in changing their assortments as they are not dealing with the formal embedded processes and systems of a chain structure. Thus, pull efforts might exert greater influence on the demand the trade perceives, affecting retailers' decisions in terms of stocking and availability, whereas self-service (CS) retailers do not have such close relationships with consumers. Therefore, while both CS and TF stores both pay attention to customer needs, they do so in different ways. CS retailers tend to make more data-based decisions with less flexibility in changing assortments than TF stores. Thus:

H_{2a}. Advertising has a higher positive effect on distribution in traditional full-service formats than chain self-service formats.

In addition, the direct effect of advertising on consumers is often significant (Ataman, van Heerde, and Mela 2010) and can take place across channels where the brand/SKU is available. Thus:

H_{2b}. The effect of advertising on sales is significant and positive in both chain self-service and traditional full-service stores.

Finally, consumer purchase intent driven by advertising stimulus can be modified by in-store attractiveness (Chandon et al. 2009; Olver and Farris 1989). In this context, in-store merchandising practices can also play an important role (Chandon et al. 2009; Quelch and Cannon-Bonventre 1983), especially in CS stores where there are no clerks and consumers browse the shelves by themselves. Thus:

H_3. Merchandising has a higher positive effect on sales in chain self-service formats than traditional full-service formats.

Brand Activity to Channel

We measure three channel directed brand activities: retailer directed loyalty programs, the variety of package sizes and the length of the brand's product line.

Loyalty program (CRM). In developed markets, "manufacturers are increasingly questioning whether they can rely on retail sales clerks to push their products at the point of purchase" (Quelch and Cannon-Bonventre 1983, p. 164). However, in emerging markets such as Brazil and India, the relationship between manufacturers and retail sales clerks (who in small channels are sometimes store-owners) is critical to gain distribution, shelf inventory space and sales. Recognizing this, CPG companies have developed programs to help channel partners improve their business profits (Diaz, Lacayo, and Salcedo 2007; Lenartowicz and Balasubramanian 2009).

In TF stores, owners and clerks are more accessible and have a higher level of autonomy. In contrast, CS managers are less reliant on personal relationships with manufacturers and their sales people and depend more on data generated by management information systems. As stated by Lenartowicz and Balasubramanian (2009), as small retailers use heuristics rather than analytics in the decision-making process, these stores are more susceptible to supplier influence.

The marketing literature also supports the idea that relationship programs generate stronger customer relationships that enhance seller performance outcomes (Palmatier et al. 2006). A brand's salesforce often directly interacts with the store owner in the TF channel. This direct relationship can also enhance the sales effect of the brand's relationship programs. Thus:

H_4. Relationship marketing programs have a higher effect on sales in independent full-service stores than chain self-service stores.

Package size variety. We define package size variety as the variance in the different SKU sizes offered by the manufacturer (and stocked by the retailer) in a channel. Our measure refers to the variance in SKU sizes across all stores in a channel. It does not necessarily correspond to variance within an individual store.

Variety in assortment allows retailers to address different customer needs better. TF stores have tighter space constraints than the larger CS stores and will usually be able to stock fewer SKUs. However, each TF store can adjust its own assortment to correspond to its particular customer preferences. So while they may not have many SKUs of the same kind, they could create variety in assortment through better customization.

CS stores have sufficient display space but are constrained by centralized assortment policies and, for some products, warehouse distribution slots. On the other hand, the ability to browse CS assortments may make value of assortment variety more visible and does not require the active intervention of sales clerks to make the different items known to shoppers. As we can find no strong reasons to support a hypothesis that compares the magnitude of variety of package size effects on CS versus TF channels, we propose to empirically investigate this question without a directional hypothesis comparing TF and CS channels.

H_5. Package size variety has a positive effect on sales in both the TF and CS channels.

Number of SKUs

Even though a higher number of SKUs potentially drives brand sales, retailers cannot accommodate all SKUs offered by manufacturers at their stores (Kaufman, Jayachandran, and Rose 2006; Völckner and Sattler 2006). The scope for out-of-stock also increases with an increase in the number of SKUs because of the challenges associated with managing larger assortments and shelf space cannibalization (Shah, Kumar, and Zhao 2014). Thus, a larger number of assortments from a manufacturer's perspective can be beneficial. However, too many might not be beneficial because it can lead to consumer cognitive overload. Therefore, we expect an inverted U-shaped relationship between number of SKUs and sales at each channel as the

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marginal response to a higher level of number of assortments can be negative after a certain (optimal) point.

H₆. Number of SKUs has an inverted "U" shaped effect on sales in both the TF and CS channels.

Research Design and Data

Our research design contains two stages. First, for the comparison of the effectiveness of marketing mix across channel formats, we employed a panel vector autoregression (VAR) analysis of point of sale data and in-store marketing mix across channel formats. Second, we analyze channel relationship (i.e., loyalty program offered from brand to channel), package size variety and the number of SKUs available in each channel, advertising and in-store merchandising by the decomposition of residuals from the panel VAR.

The data covers four years of monthly SKU level data for more than 360 SKUs for all brands of soft drinks in the beverage category in Brazil. The time period of the data spans January 2008 to December 2011. This data comes from store audits compiled by a large global market research firm, and the analysis is restricted to 120 cities in Brazil's Southeastern region, which accounts for more than 15% ACV in food retail in this emerging market. This region has a more urban geography with a mix of retailer formats, which allows us to isolate channel effects better and avoid confounding effects due to regional differences in income.

Latin American countries, including Brazil, have been key markets for carbonated-beverage growth.[15] We believe some specific features of soft drinks make them a particularly appropriate category for our research. First, traditional full-service represents 24% of total global volume sales of soft drinks, whereas this channel represents at least 40% of sales volume in the emerging markets.[16] Further, soft drinks are bought in a broad variety of channels and occasions. The ability to distribute this category through small independent stores is hence vital for consumer penetration.[17] Second, soft drinks are perishable, which implies that brands need to balance distribution (i.e., breadth and depth) and inventory turnover while serving both CS and TF channels. Finally, brands have more flexibility in customizing product size to reach different retailers and consumers in this category. Thus, soft drinks are a particularly interesting category for studying the importance of tailoring SKU assortment to local preferences and channel format. Our data for this category is broken down into two retail formats with greater depth in Table 2.

Fig. 2 shows all CS and TF locations in one Brazilian city located in the same region from which the data is collected. CS stores are not located on the edges of urban areas but are

Table 2
Channels' features in the data[a].

Feature of the stores in the data	Chain self-service (CS)	Traditional full-service (TF)
Ownership	Corporate	Independent family owned
Management	Professional buying center, data-driven decisions	Non-professional buying center and management, heuristics-based decisions
Number of checkout lanes	More than five	No checkout lanes
Number of stores represented in the data	394	4,262
% ACV	62.4%	15%
# of SKUs (across all categories) available in one usual store	4,000 to 50,000 SKUs	Usually less than 1,000 SKUs
Size of one usual store (channel)	7,534 ft^2 to 172,222 ft^2 sales area	Usually less than 538 ft^2 sales area

[a] Convenience stores (gas stations) have 2.3% ACV. Also, in Brazil there is a channel called independent self-service stores, which account for the remaining difference in ACV and carry 1,000 to 4,000 SKUs, with a 538–7,534 ft^2 sales area and operating with 1–4 checkout lanes.

relatively evenly dispersed within the urban areas, making them almost as easy to reach as TF stores. This also implies that TF stores are between all other store formats. So, location is probably not the sole reason for any differences in preferences for CS and TF stores. Further, TF stores may be more convenient than CS stores by the mere fact that there are many more of them.

An important feature of the data is the distribution breadth metrics employed in this study: product category volume (PCV). The marketing literature has evolved from using percent-numeric distribution (Farley and Leavitt 1968; Nuttal 1965) to the use of weighted distribution measures (Ataman, van

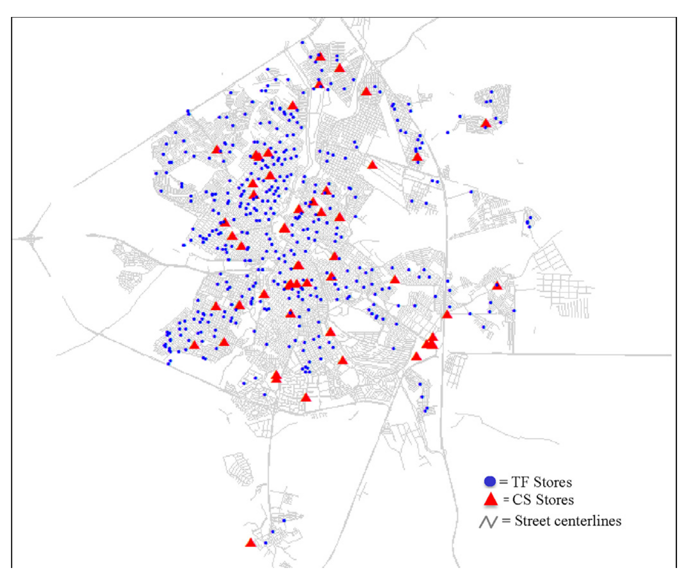

Fig. 2. Geographic analysis – CS stores and TF stores.

[15] Euromonitor International from official statistics, trade associations, trade press, company research, store checks, trade interviews, trade sources.

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

[17] Euromonitor International Report (2013), "Soft Drink: The Evolution of Soft Drinks Distribution".

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Table 3
Variable operationalization and descriptive statistics.

Variable	Operationalization	Chain self-service		Traditional full-service	
		Mean	SD	Mean	SD
Unit sales	Unit sales to consumers (cases of 24 units of 8 ounces) of a relevant SKU	15.713	47.387	10.344	32.729
Product category volume retail distribution (net of out-of-stocks)	Percentage share of category sales made by stores that carry a relevant SKU, adjusted for out-of-stock situations	50.780	4.032	27.663	1.910
Share of shelf inventory	Percentage share of space for a given SKU available on shelves in terms of units (ounces) compared to the total units (ounces) available on shelves for a specific category	0.797	0.065	0.934	0.092
In-store promotion (PCV% on promotion)	Percentage of stores where a given SKU is on promotion which shows activation of promotion at the point of sales	6.385	1.373	0.667	0.533
Relative unit price	SKU price (to consumers and weighted by ounces) divided by the average price in the relevant category (to consumers and weighted by ounces)	184.569	11.215	182.191	9.999
Number of SKUs	Number of manufacturer assortments offered to retailers and purchased at least once by any retailer	72.673	3.584	67.510	4.468
Package size variety	Variance in SKU size offered by brand manufacturer and stocked by retailers	0.662	0.034	0.623	0.049

Marketing pull		Mean	SD
Advertising spend	Dollar amount spent by one manufacturer on advertising in a month	420,538	183,336
Merchandising spend	Dollar amount spent by one manufacturer on merchandising in a month	161,000	98,745

Heerde, and Mela 2010; Farris, Olver, and de Kluyver 1989; Vanhonacker, Mahajan, and Bronnenberg 2000), such as all commodity volume (ACV) and PCV. Similar to Kumar, Sunder, and Sharma (2014), we believe PCV is better suited for multichannel marketing modeling in an emerging market environment. The motivation is that not all channel types have the same degree of sales in a given category. Unlike ACV%, which weights stocking stores by share of "all commodities," the PCV% metric weights stocking stores by the percentage of the relevant product category they sell. So, it is more representative of distribution for a product category and is particularly useful when comparing different retail formats.

Loyalty Points Program

A unique feature of our data is that it covers the implementation of a channel loyalty points program quasi-experiment conducted by the focal brand. This loyalty points program was implemented by the direct sales force of the consumer brand across the two analyzed channels as part of channel relationship management activities.

The points program was implemented as follows: (i) retailers were invited to join the program (more than 200 retailers joined); (ii) the sales force presented the program details to participating retailers and were responsible for reviewing the retailer's performance in the program at each sales visit; (iii) retailers accumulated points based on their sales and in-store execution of the manufacturer's channel strategy; and (iv) participating retailers could redeem prizes earned by their store. The program was implemented in two separate time periods, first from April 2008 to June 2009 and, second, from November 2009 to December 2011. Our data includes the monthly number of retailers participating in the program by each channel format.

Table 3 also describes the data. The proportion of TF and CS stores in the program (24.3%) was representative of the retail population in the analyzed market (see Table 2). The decision to join a loyalty program may be much easier for TF stores to make than CS stores who have more complex organizational decision processes. This is true in spite of the fact that the program was designed to offer rewards relevant to both formats. The brand manufacturer customized the type of reward according to each channel's specific characteristics. For example, while participating TF stores were potentially rewarded with prizes targeted to store owners (such as vacation travels and educational programs to improve business management skills), participating CS stores were offered price and promotion benefits.

Descriptive Analysis

To illustrate the data from the store audits, we show in Fig. 3A–D the historical sales, price, PCV, brand in-store promotion activation at the point of sales, share of shelf and package size variety for the SKUs in the dataset, which we discuss in more detail in subsequent sections. The plots suggest similarity in brand actions for the CS and TF channels.

For example, Fig. 3A shows evidence of seasonality, since sales of soft drinks increase during the summer in Brazil (i.e., December to March) through both channels. In Fig. 3B, our focal brand is shown to be trending down in relative price in both channels due to a decrease of prices for this brand's SKUs relative to competitors' price changes in the same category.

However, the plots also suggest some contrasts across channels. The total PCV metric in Fig. 3C (PCV summed over SKUs) indicates that the average TF store stocks fewer than 20 SKUs in a given period of time. Fig. 3D shows an increase in the number of SKUs sold across all TF retailers (e.g., SKUs purchased at

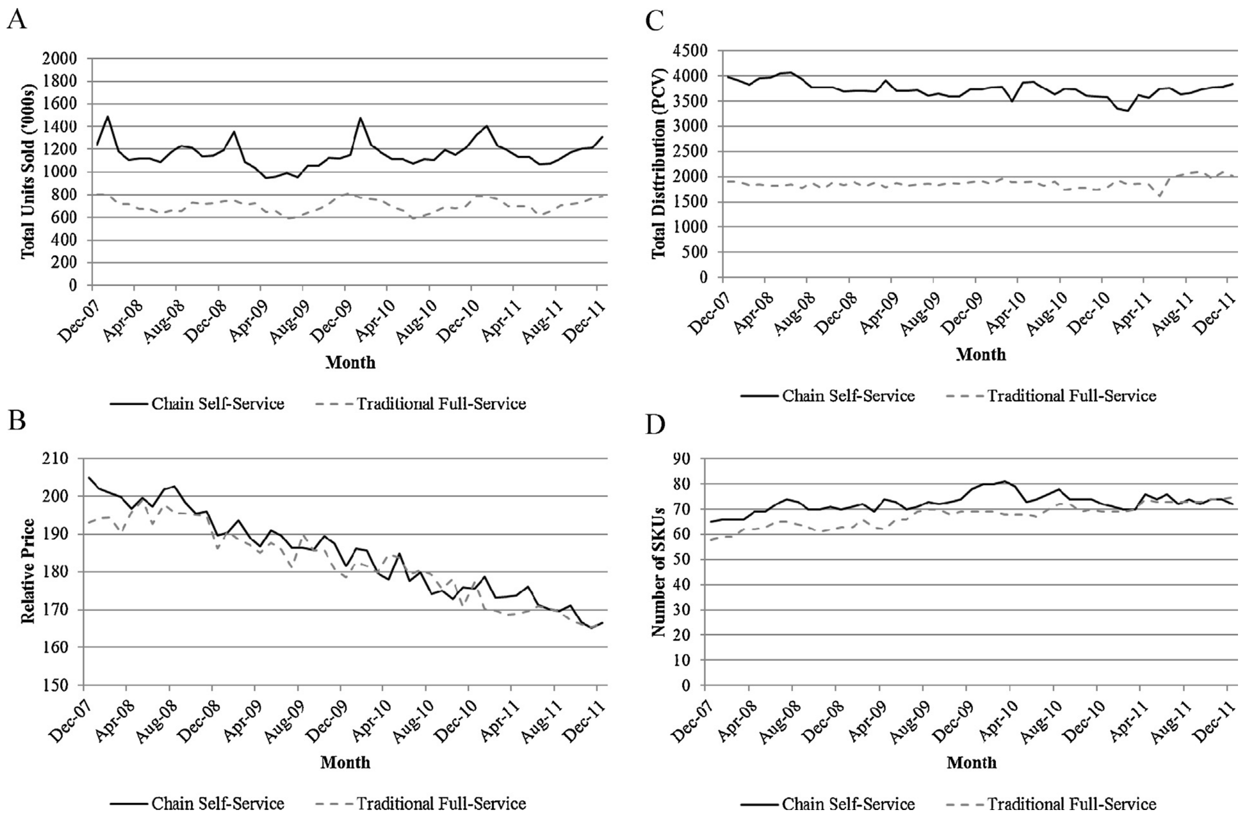

Fig. 3. (A) Total monthly unit sales volume (across all SKUs for focal brand). (B) Average relative unit prices by month (across all SKUs for focal brand). (C) Monthly total distribution (PCV) for focal brand. (D) Average manufacturer number of SKUs offered to retailers and purchased at least once by any retailer (for focal brand).

least once by any retailer). That is, despite the observation from Fig. 3C that, compared to CS stores, the average TF store has half of the number of SKUs stocked, Fig. 3D shows that the focal brand is increasing the variety (number of SKUs) stocked among all TF stores. These differences are not statistically significant and the figures are only suggestive of how the different retailer formats, in the aggregate, respond differently to manufacturer marketing programs. Our research seeks not only to understand the differences in retailer response, but also to understand differences in consumer response between CS and TF formats. The fact that the differences are not significant also implies that the brand manufacturer did not make any systematically different decisions for the CS and TF channels. It also shows that the endogeneity concern is not an issue in our data.

Model Development

We specify a SKU-level model framework for assessing the relationships among in-store marketing factors (distribution, price, share of shelf and promotion) and sales. Our model structure must address several objectives. First, it has to accommodate the (a) contemporary and lagged effects of in-store marketing on sales, (b) the feedback effects of lagged in-store marketing on sales, (c) the reinforcement effect of lagged sales on current sales, and (d) the reinforcement of lagged in-store marketing on current in-store marketing. Second, since the analysis is at the SKU level, the model needs to accommodate heterogeneity across SKUs and account for seasonality. Third, our model must allow for estimation of short- and long-term effects of in-store marketing on sales.

We therefore specify a panel VAR model of sales, distribution, price, share of shelf and promotion. The model structure is specified as:

$$\begin{bmatrix} \mathrm{lSales}_{ijt} \\ \mathrm{lPCV}_{ijt} \\ \mathrm{lPrice}_{ijt} \\ \mathrm{lSOS}_{ijt} \\ \mathrm{lPromo}_{ijt} \end{bmatrix} = \begin{bmatrix} \alpha_{1_i} \\ \alpha_{2_i} \\ \alpha_{3_i} \\ \alpha_{4_i} \\ \alpha_{5_i} \end{bmatrix} + \begin{bmatrix} \gamma_{1_t} \\ \gamma_{2_t} \\ \gamma_{3_t} \\ \gamma_{4_t} \\ \gamma_{5_t} \end{bmatrix} + \begin{bmatrix} \beta_{11_j} & \cdots & \beta_{15_j} \\ \beta_{21_j} & & \beta_{25_j} \\ \beta_{31_j} & & \beta_{35_j} \\ \beta_{41_j} & & \beta_{45_j} \\ \beta_{51_j} & & \beta_{55_j} \end{bmatrix} \times \begin{bmatrix} \mathrm{lSales}_{ijt-1} \\ \mathrm{lPCV}_{ijt-1} \\ \mathrm{lPrice}_{ijt-1} \\ \mathrm{lSOS}_{ijt-1} \\ \mathrm{lPromo}_{ijt-1} \end{bmatrix} + \begin{bmatrix} e_{1_{ijt}} \\ e_{2_{ijt}} \\ e_{3_{ijt}} \\ e_{4_{ijt}} \\ e_{5_{ijt}} \end{bmatrix} \tag{1}$$

lSales_{ijt} is the log of unit sales for SKU i in channel j in month t; lPCV_{ijt} is the log of product commodity volume (retail distribution) for SKU i in channel j in month t net of out-of-stock;

lPrice_{ijt} is the log of relative unit price[18] for SKU i in channel j in month t; lSOS_{ijt} is the log of share of shelf inventory for SKU i in channel j in month t; lPromo_{ijt} is the log of % of stores with promotion activated for SKU i in channel j in month t; and $\{e_{1_{ijt}}, e_{2_{ijt}}, \ldots, e_{5_{ijt}}\}$ is normally distributed random error.

Heterogeneity among the SKUS are accommodated by the SKU fixed effects $\{\alpha_{1_i}, \alpha_{2_i}, \ldots, \alpha_{5_i}\}$ and time fixed effects, $\{\gamma_{1_t}, \gamma_{2_t}, \ldots, \gamma_{5_t}\}$, control for seasonality. Unobserved correlation among the variables is accommodated by specifying a common covariance matrix for the errors. The random errors are normally distributed with zero mean and a common covariance matrix Σ_e. The coefficients $\beta = \{\beta_{11_j}, \beta_{12_j}, \ldots, \beta_{55_j}\}$ estimate the lagged, reinforcement and feedback effects among in-store marketing and sales. For example, lagged effects are captured by including lagged PCV in the equation for sales. Reinforcement effects are captured by the lagged sales variable in the sales equation. Inclusion of lagged sales in the PCV equation captures the feedback effect of sales on managers' in-store marketing decisions. Log transformation of the variables accommodates for the diminishing returns of the marketing mix.

We estimate the Panel VAR model using STATA according to the methodology provided by Love and Zicchino (2006). Fixed effects in our model can be correlated with the lagged dependent variables, and this can lead to biased coefficients. We use the forward mean-differencing procedure to accommodate for this issue (Love and Zicchino 2006). In this procedure, we take the mean of all future observations available for each SKU and month and subtract this value from the dependent variable for each SKU at every month. Our model also allows for month-specific fixed effects. We eliminate these fixed effects by mean centering the forward differenced dependent variable with the mean of the forward differenced dependent variable across all SKUs in each month. We run the Dickey-Fuller unit root tests on the forward differenced and mean centered dependent variable and find that unit root is not an issue in our analysis. Then, to choose the order of the model, we use Akaike's Information Criterion (AIC) and observe that one-period lag provides the best fit.

In the second stage of this analysis, for the brand marketing activity directed to consumers and channels, we model the effects of brand activities to consumers (advertising and merchandising) and channels (loyalty program, package size variety and number of SKUs) on sales and in-store marketing. To model the effects of these activities directed to consumers and channels, we first sum the residuals of sales and in-store marketing from Eq. (1) across SKUs and channels. We do this because the brand did not vary spending on activity to consumers by channel and SKU. By summing the residuals, we get the total effect to develop the brand-level model in the second stage. Our model is equivalent to the decomposition of residuals in the panel VAR model. While it is typical to model variables with different levels of aggregation using a hierarchical model framework, we are unaware of such a framework being used for a panel VAR model. We adopt this two-stage approach, since it is important to model the endogenous relationships among the in-store marketing factors and sales. The decomposition of residuals is therefore provided by:

$$\begin{aligned} E_t = {} & \gamma_0 + \gamma_t + \gamma_1 \times \Delta l\text{AD}_t + \gamma_2 \times \text{PACKAGESIZEVAR}_{tj} \\ & + \gamma_3 \times \text{CRM}_{tj} + \gamma_4 \times \Delta l\text{MERCSPEND}_{tj} + \gamma_5 \\ & \times \text{NUMBEROFSKU}_{tj} + \gamma_6 \times \text{NUMBEROFSKU}_{tj}^2 \\ & + \gamma_7 \times \text{TF}_j \times \Delta l\text{AD}_t + \gamma_8 \times \text{TF}_j \\ & \times \text{PACKAGESIZEVAR}_{tj} + \gamma_9 \times \text{TF}_j \times \text{CRM}_{tj} \\ & + \gamma_{10} \times \text{TF}_j \times \Delta l\text{MERCSPEND}_{tj} + \gamma_{11} \times \text{TF}_j \\ & \times \text{NUMBEROFSKU}_{tj} + \gamma_{12} \times \text{TF}_j \\ & \times \text{NUMBEROFSKU}_{tj}^2 + \varepsilon_{tj} \end{aligned} \tag{2}$$

where $E_t = \{\text{se1}_t, \text{se2}_t, \text{se3}_t, \text{se4}_t, \text{se5}_t\}$ = the vector of the sum of both channels residuals for sales, PCV, SOS, and Price, and Promotion across SKUs, $\Delta l\text{AD}_t$ = First-difference of log Advertising spend in month t, $\text{PACKAGESIZEVAR}_{tj}$ = Variance of SKU sizes in month t for channel j, $\text{CRM}_{tj} = 1$ if there is CRM program in month t in channel j, 0 otherwise, $\Delta l\text{MERCSPEND}_{tj}$ = First-difference of log Merchandising Spend in month t for channel j, NUMBEROFSKU_{tj} = Number of the focal manufacturer's SKUs stocked by any retailer in month t for channel j, and TF = 1 if channel is Traditional Full Service, 0 otherwise.

We capture the time fixed effects in Eq. (2) with γ_t. Each of the γ coefficients is a five dimensional vector that represent sales and each of the in-store marketing factors. For example, $\gamma_0 = \{\gamma_{01}, \gamma_{02}, \ldots, \gamma_{05}\}$ is a vector of five coefficients, where γ_{01} through γ_{05} represent the intercept of sales, PCV, SOS, price and promotion, respectively. We include the linear and quadratic terms for Number of SKUs to capture the inverted "U" shaped effect.

Sales, product availability (PCV), price, and promotion could affect a brand's advertising and merchandising spend decisions. This poses an endogenous relationship that can bias the estimates in Eq. (2). We hence first evaluate the effect on advertising on lagged advertising and lagged sales. The coefficient of lagged advertising was close to one, and lagged sales had a positive and significant effect on advertising.[19] These issues were, however, not evident when we considered first difference of advertising instead of the level of advertising at each period. Specifically, lagged difference in advertising and lagged sales did not affect the first difference in advertising. Similar results were observed for merchandising. We hence include difference in advertising and merchandising in Eq. (2). Firms take more time to change package size variety and number of SKUs than advertising and merchandising. This was also evident from the fact that lagged sales did not have a significant effect on package size variety and number of SKUs.

[18] For the relative unit price, the units are ounces.

[19] Dickey Fuller unit root tests rejected the null hypotheses of no unit roots in the advertising and merchandising time series.

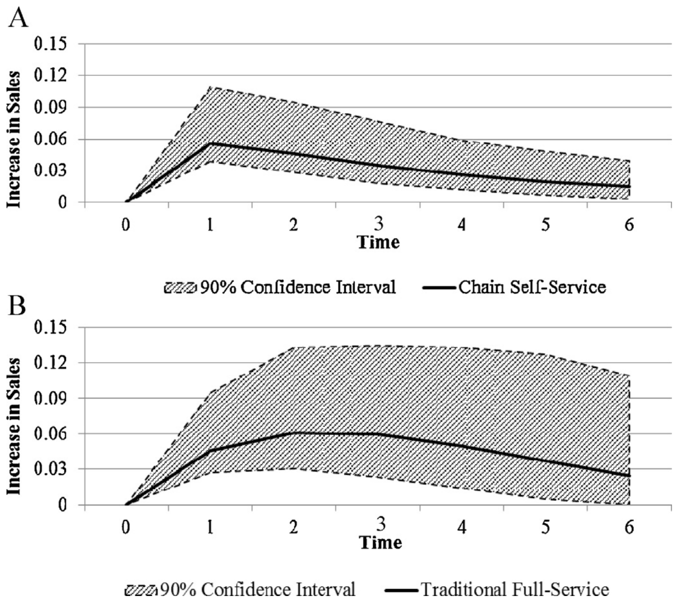

Fig. 4. (A) Impulse-response functions for PCV on sales (CS). (B) Impulse-response functions for PCV on sales (TF).

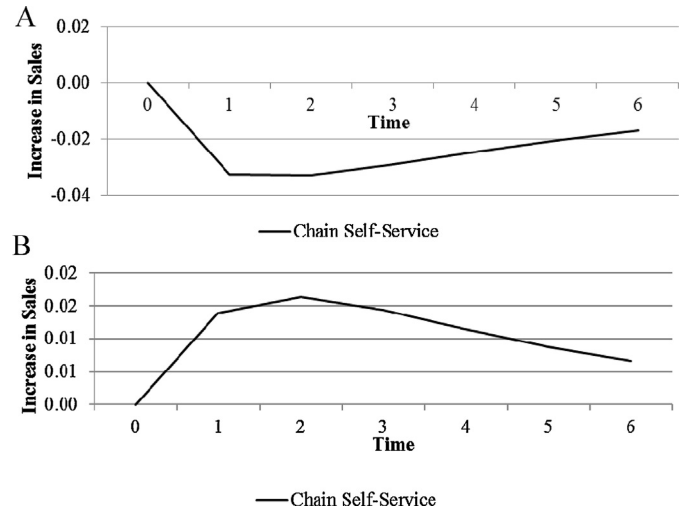

Fig. 5. (A) Impulse-response functions for price on sales. (B) Impulse-response function for in-store promotion on sales.

Discussion of Results

In this section, we first discuss the results based on estimates from the panel VAR model. Then we present the long term effects of the marketing mix elements using the impulse response functions. Finally, we report the results from the decomposition of panel VAR residuals.

Table 3 provides the operationalization and summary statistics for this data. The data with variables used in the first stage of our model are based on within-channel data. For example, TF PCV for a particular SKU includes only the category sales within TF stores. The table highlights the different marketing-mix investments and outcomes in the two channel formats. For example, we see higher mean unit sales and number of SKUs in CS than TF stores. Further, the means of PCV and in-store promotion (PCV–weighted promotion at retail, meaning the activation of in-store promotional activities for a relevant SKU at the point of sales) are even higher in the CS channel. The data show little difference in the means of relative unit price and share of shelf inventory in either channel. More stores in the TF channel participated in the CRM program.

Table 4a provides the parameter estimates of the direct effects of in-store marketing-mix on sales. In the Appendix, we present the estimates for the other endogenous variables in the panel VAR model. Table 4a indicates there are both differences and similarities between the channels. Distribution has a significant and positive effect on sales in both the TF ($\beta_{122} = 0.147$, $p < 0.1$) and CS ($\beta_{121} = 0.142$, $p < 0.1$) channels. As shown in Fig. 4A (CS) and Fig. 4B (TF), the impulse-response function allows us to see that availability is important in both channels. The confidence interval of the impulse response curves between the two channels (Fig. 4A and B) shows that the effect of distribution is similar in both CS and TF stores. Thus, we could not find support for hypotheses H_{1a} and H_{1b}. In retrospect, using PCV as the metric for distribution breadth means that the full adjustment for category sales potential is contained in the measure itself.

Share of shelf inventory does not have a significant effect on sales in either TF or CS stores. Because of this, we could not see the impulse-response function to test hypothesis H_{1c}. In the discussion section, we explore some possible implications and rationale for not observing a significant effect of share of shelf inventory. Table 4a indicates price is significant and negatively affects sales ($\beta_{131} = -0.117$, $p < 0.1$) in the CS channel. Our results also support hypothesis H_{1d} since the effect of price is not significant in TF. In CS, immediate loss in sales from a unit price increase was −0.032%, and the corresponding long-term effect is −.157% (see Fig. 5A). In-store promotion showed only significant effects on sales in CS stores ($\beta_{151} = 0.025$, $p < 0.1$). Short-term elasticity of in-store promotion is 0.013% and long-term is 0.071% (see Fig. 5B).

Independent Self-Service Channel (IS)

In Brazil, there is a channel format called small independent self-service (IS). This channel represents 20% of ACV of the total market, and it has characteristics from both CS (self-service – no retail clerks to assist the sales) and TF (small independent owned and managed). The store size (see Table 2) shows that IS stores are often in-between CS and TF stores. Even though our research does not have a focus on this channel format, we show the results from the VAR model (first stage) for IS format. The reason is based on the wisdom that CS and TF are more common in emerging markets and have more extreme contrasts, which makes it interesting to compare for the purposes of this study, whereas the IS channel format is "in the middle." So, the rationale behind the expected effects is not as clear as in the CS or TF formats.

Table 4b shows the results of the direct effects of in-store marketing-mix on sales for the IS channel. Distribution (PCV) is also important and significant ($\beta_{123} = 0.079$, $p < 0.1$) in this channel, following the same pattern for CS and TF. Similarly,

Table 4a
Estimation results (CS and TF).

Equation	Coefficient	Chain self-service ($j=1$)		Traditional full-service ($j=2$)	
		Mean	Standard error	Mean	Standard error
Sales	lagged sales (β_{11j})	0.697***	0.070	0.574***	0.133
	lagged pcv (β_{12j})	0.142***	0.024	0.147***	0.037
	lagged price (β_{13j})	−0.117*	0.070	n.s.	n.s.
	lagged sos (β_{14j})	n.s.	n.s.	n.s.	n.s.
	lagged promo (β_{15j})	0.025**	0.011	n.s.	n.s.

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

Table 4b
Estimation results (IS).

Equation	Coefficient	Independent self-service ($j=3$)	
		Mean	Standard error
Sales	lagged sales (β_{11j})	0.657***	0.067
	lagged pcv (β_{12j})	0.079***	0.027
	lagged price (β_{13j})	−.072***	0.028
	lagged sos (β_{14j})	0.400***	0.124
	lagged promo (β_{15j})	n.s.	n.s.

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

price is significant but the coefficient is lower ($\beta_{133} = -0.072$, $p < 0.1$) than in CS. Price comparison among products on the shelves in IS stores is as easy as in the CS format because consumers browse by themselves. However, the lower coefficient in IS might be evidence that consumers are less price sensitive in this channel. Further, in-store promotion activation is not significant, which could be evidence that consumers are not willing to stock up or change brands due to in-store promotional efforts in this channel. The same pattern was found in TF. Finally, share of shelf inventory is significant and directly affects sales ($\beta_{143} = 0.400$, $p < 0.1$). Products are often on the shelves and visible to consumers (and not behind the counter as in TF). However, store size is more limited than in CS, which can make the competition for visibility in the store more important to drive sales. We believe that these results corroborate the knowledge that this channel has some features from both CS and TF.

Estimates from the Decomposition of Residuals

Table 5 shows the estimated coefficients from the decomposition of sales residuals, PCV, SOS, price and promotion. This allows us to compare the effects of package size variety, number of SKUs, advertising spending, merchandising spending and the relationship program for each channel on variation in consumer (sales) and retailer (PCV, SOS, Price and Promotion) decisions, which is unexplained by the endogenous relationship between in-store marketing mix and sales.

Advertising is not significant for sales and PCV in both channels; therefore, we were not able to support hypotheses H_{2a} and H_{2b}. Table 5 also shows the positive and significant effect of merchandising on sales ($\beta_{151} = 29.086$, $p < 0.1$) and PCV ($\beta_{251} = 10.017$, $p < 0.1$) in CS. The negative and significant coefficient of the interaction between merchandising and the dummy variable for the TF channel ($\beta_{152} = -27.426$, $p < 0.1$) indicates that the effect of merchandising on sales is smaller in the TF and CS channels. The net effect of merchandising on sales in the TF channel is still positive. The results highlight the importance of in-store merchandising practices especially in CS the channel where there are no clerks influencing sales (as expected in H_3).

The relationship program does not have a significant effect on any variable in the second stage in the TF channel. Hence, we do not find support for H_4. We also observe (see Table 5) that the loyalty program results in higher prices in CS stores without significant reductions of sales or PCV ($\beta_{461} = 15.850$, $p < 0.1$). This would mean the brand could increase profits in CS using CRM by maintaining a higher price and ensuring retailers improve execution.

The estimation results also reveal that the effect of variety of package sizes is significant in both channels, which supports H_5. In CS this variable has a significant and positive effect on sales (0.840, $p < 0.1$) and PCV (0.868, $p < 0.1$). However, the coefficient of the interaction between package size variety and the TF dummy variable on sales (−2.648, $p < 0.1$) and PCV (−2.647, $p < 0.1$) is negative. This result indicates that the effect of package sizes is smaller in the TF than CS format. We believe it might be possible these results highlight that people often go to larger assortment stores for major shopping trips (Bell, Corsten, and Knox 2011), which can lead to a more diverse shopping list.

Fig. 6 presents the inverted U-shaped relationship between number of SKUs and sales using the estimates from Eq. (2).[20] Taking the first derivative of Eq. (2) with respect to number of SKUs and equating it to zero provides us the formulation for the optimal number of SKUs (NUMBEROFSKU*) by each channel. The derivation of the optimal number of SKUs for CS

[20] Please note that the *x*-axis presents the index of number of SKUs with 60 SKUs as the base, 100 in the *x*-axis refers to 60 SKUs, 110 refers to 66 SKUS or 110% of 60 SKUs.

Table 5
Estimation results for the residuals of sales, PCV, SOS, price and promo.

Coefficient	Residual of sales $i=1$		Residual of PCV $i=2$		Residual of SOS $i=3$		Residual of price $i=4$		Residual of promo $i=5$	
	M	SE	M	SE	M	SE	M	SE	M	SE
Package Size Variety (β_{i11})	1327.36***	248.29	538.353***	102.09	−437.79***	123.48	344.91***	67.12	706.54***	169.81
Number of SKUs (β_{i21})	493.43***	107.31	124.31***	43.81	n.s.	n.s.	51.28*	26.27	231.39***	73.74
Number of SKUs^2 (β_{i31})	−3.28***	0.71	−0.83***	0.29	n.s.	n.s.	−.34**	.17	−1.54***	.490
Advertising Spending (β_{i41})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Merchandising Spending (β_{i51})	29.09***	10.40	10.02**	4.28	n.s.	n.s.	n.s.	n.s.	12.30*	7.11
CRM (β_{i61})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	15.85***	4.566	n.s.	n.s.
TF × Package Size Variety (β_{i12})	−819.70**	362.66	−324.14**	149.10	n.s.	n.s.	n.s.	n.s.	−429.23*	248.03
TF × Number of SKUs (β_{i22})	−412.80***	150.59	−152.65**	61.05	n.s.	n.s.	n.s.	n.s.	−328.57***	103.97
TF × Number of SKUs^2 (β_{i32})	2.80***	1.05	1.07**	0.42	n.s.	n.s.	n.s.	n.s.	2.31***	.72
TF × Advertising Spending (β_{i42})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
TF × Merchandising Spending (β_{i52})	−27.43***	14.60	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
TF × CRM (β_{i62})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.

Notes: n.s. = not significant at 10%. M = Mean; SE = Standard error.
* Significant at $\alpha = 10\%$.
** Significant at $\alpha = 5\%$.
*** Significant at $\alpha < 1\%$.

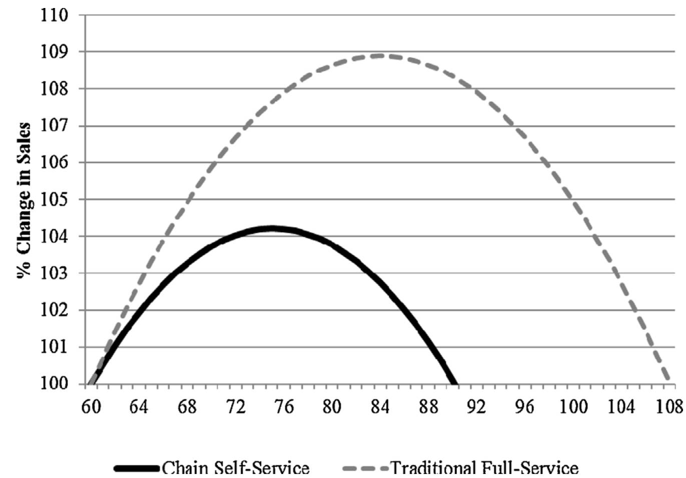

Fig. 6. Optimal number of SKUs.

is provided by:

$$E_{Sales_t} = \gamma_5 \times \text{NUMBEROFSKU} + \gamma_6 \times \text{NUMBEROFSKU}^2$$
$$\frac{\partial E_{Sales_t}}{\partial \text{NUMBEROFSKU}} = \gamma_5 + 2 \times \gamma_6 \text{NUMBEROFSKU}$$
$$\text{NUMBEROFSKU}^* = \frac{-\gamma_5}{2 \times \gamma_6} = \frac{-(493.42)}{2 \times (-3.28)} \cong 75 \quad \text{SKUs} \tag{3}$$

Similarly, the optimal number of SKUS for the TF channel is 85. In the TF channel the optimal number of SKUs is greater than in CS. This result comes from the second stage of our model, which is a brand level analysis. It may not be intuitive that the optimal number of SKUs would be greater for TF than CS (especially given the smaller footprint of the former). It should be recalled, however, that the number of SKUs variable is for the channel, not individual stores. Our interpretation is that there is a greater variety of store locations, clientele, and shopping occasions within the TF channel than the CS format. So the optimal total number of SKUs offered by the manufacturer to the TF channel could be larger than for CS formats.

Therefore, from the decomposition of residuals we conclude that a brand's trade activities such as merchandising, number of SKUs and package size variety provide the brand with positive outcomes in CS and TF stores. Further, the optimal number of SKUs is greater in TF than CS. The results also support the important role of a relationship program that compensates the channel in the case of CS.

Discussion and Implications

Our study contributes to the emerging literature on effectiveness of brand activities directed to consumers and retailers across different channel formats in emerging markets. We show that effectiveness of marketing mix elements can vary with channel format. We extend the findings of Kumar, Sunder, and Sharma (2014) and show that marketing mix strategies prevalent in developed nations, such as mass advertising, are less effective

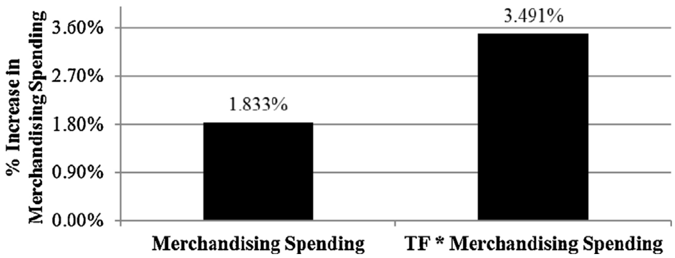

Fig. 7. Merchandising spending required to generate 1% increase in sales.

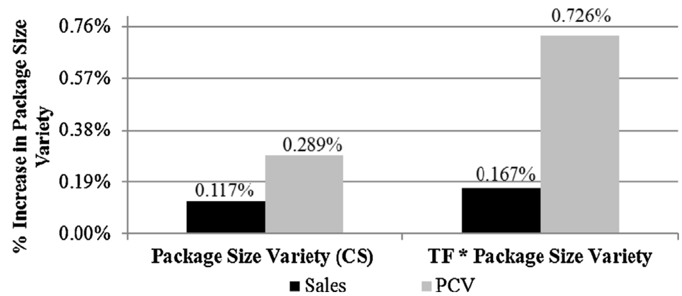

Fig. 8. Package size variety required to generate 1% increase in sales and PCV.

in directly generating sales in a channel that is more prevalent in emerging markets (i.e., TF stores). Managers in emerging markets on the other hand should be concerned about designing the optimal product line. The significant effects of package size variety and number of SKUs implies that to succeed in this emerging market, brands need to focus on customizing their assortments in each channel. The product line decisions need to be combined with effective in-store merchandising and a retailer relationship program, at least in the CS channel. However, the effect on sales of expanding share of shelf appears limited in both channels. This could be possible because of low variation in share of shelf over time (see Table 3). Further, Chandon et al. (2009) found that gaining in-store attention (i.e., shelf space) is not always sufficient to drive increases in sales.

Marginal Marketing Return on Investment

Our research can support managers in their efforts to increase sales and improve profitability in different channels. To this end, by using the estimates from the VAR and error decomposition, we calculate the increase in merchandising spending and variety of package sizes required to provide a 1% gain in some outcomes such as sales and PCV. The impulse response functions from the VAR model are then used to transform the percent increase in sales shock from merchandising and product size variety to the long-term effects on sales. Results are significant for both channels, which allows us to contrast the long term effect by channel. Then, we present the sales lift attributable to merchandising and package size variety.

As shown in Fig. 7, in terms of merchandising spending, a lesser percentage increase in spending is required to generate a 1% gain in sales. Specifically, in CS stores, a 1% increase in sales requires a 1.833% increase in merchandising spending. In TF stores, a 1% increase in sales requires a 3.491% increase in merchandising spending.

Further, the direct effect of package size variety offered by manufacturers and stocked by retailers on sales is higher than its indirect effect on sales through PCV (see Fig. 8). When comparing the two channels, it requires less change in a product's line package variety to increase sales (0.117%) and PCV (0.289%) in CS than in TF (0.167% for sales, 0.726% for PCV). Finally, the estimation of Eqs. (1) and (2) allows us to specify the sales lift (e.g., the sales impact of a 1% increase in marketing support) as:

$$lSalesLift_j^x = \%Increase_j^x \times \hat{\eta}_j^k \times E_{tj} \quad (4)$$

where $lSalesLift_j^x$ is the lnsales lift due to x in channel j, x is the marketing support activities of merchandising and package size variety, $\hat{\eta}$ is the cumulative impulse response over time of a shock on k ={*Sales, PCV, Share of Shelf Inventory, Promotion and Price*}, $E_{tj} = \{se1_{tj}, se2_{tj}, se3_{tj}, se4_{tj}, se5_{tj}\}$ = the vector of the sum of the residuals for sales, PCV, SOS, Price, and Promotion across SKUs.

Then, to calculate the marginal marketing ROI (MROI) of advertising and CRM, we use:

$$\text{Marginal MROI}_j^x = \frac{\text{Average Manufacturer Revenue}_j^x \times \text{SL}_j^x \times \text{Average Manufacturer Margin}_j^x}{\%\ \ \text{Increase}_j^x \times \text{Average Merchandising Spent}} - 1 \quad (5)$$

Eq. (4) represents how we calculate the cumulative implications of an increase in marketing support activities (merchandising and package size variety) on lnsales over a time window of 6 periods ahead. We use 6 periods because the long-term effects from the impulse response function $\hat{\eta}_j^k$ beyond six months were close to zero, as derived from Eq. (1). This shock in marketing has a direct impact on sales, but also an indirect impact through some significant variables previously described (see Tables 4 and 5). Such indirect effects are also accommodated in Eq. (4). For example, an increase in merchandising spend has a significant effect on PCV in the CS channel. Further, PCV has a significant effect on sales. To calculate the marginal MROI according to Eq. (5), we used data from one of the brands: its monthly average sales, revenue and margin in CS and TF stores, as well as average spending on merchandising.

The sales lift attributable to a 1% increase in merchandising spending is higher in CS (0.446%%) than TF (0.097%) stores. Further, the marginal MROI is higher in CS (10.456%) than TF (−0.055%%) stores. Finally, the sales impact of a 1% increase in variety of package sizes is higher in CS (6.804%) than TF (2.404%) stores. Our finding that the product line's size variety has a larger effect than other marketing instruments is similar to Ataman, van Heerde, and Mela (2010), who found that product line length has the greatest effect on sales over time.[21]

[21] We also estimated a model with product line length but did not find a significant effect.

Therefore, despite the importance of TF channels in emerging markets, our research findings show it is not easy to manage brands in order to obtain sales lift from marketing activities. Traditional marketing mix tools used in developed markets do not provide brands with the same pattern of outcomes across different channels in an emerging market environment. Package size variety, optimizing product line length, and distribution seem to be the main tools to improve sales in the TF channel.

Limitations and Further Research

Clearly, there are many distribution channels through which marketers sell consumer products. These range from hypermarkets and club stores to kiosks and gasoline station convenience stores. Our research has only addressed the differences between two types of channels in greater depth: traditional full-service (mom-and-pop) versus chain self-service stores in emerging markets. Also, we acknowledge the management practices of full-service stores may be different in developed markets, as well as among different emerging markets, since Brazil, India and China, for example, present different demographics, political and economic environments that can lead to different practices developed by store owners in the TF channel.

Also, we have developed a SKU-based marketing mix model to capture the different responses between the TF and CS channels, an important issue for emerging markets. Future research may well address differences in these responses among different emerging markets. A brand model that incorporates interactions of individual SKUs might have different characteristics. Inherently, the effects on consumers of some variables, such as variety and shelf-share, might be easier to assess with a brand model. Integrating brand and SKU models with respect to managing and forecasting the effects of marketing mix models on retailers' decisions with respect to distribution, merchandising and promotion will be valuable extensions that will support the shopper marketing initiatives. Further, this work has shown that aggregate product variety offered to consumers can be greater in the individually managed TF formats than CS stores, even though the former on average stock far fewer SKUs. Finally, one can imagine there are valuable interactions to model among channel policies that we have not captured. For example, minimum advertised price policies may support some less price competitive channels while being less favorable to aggressive discounters. The CS results are similar to the findings in the literature regarding developed economies. The theory behind CS and TF is generalizable and the modeling approach presented can be used by other brands. Future research can test differences across emerging economies. Our objective is to alert researchers of this important issue. Given scarce prior research in this area, we believe our study will contribute to the development of cross-channel marketing mix models appropriate for emerging economies.

Appendix. Estimation results for PCV, share of shelf inventory, relative unit price and promotion

Equation	Coefficient	Chain self-service ($j=1$)		Traditional full-service ($j=2$)	
		Mean	Standard error	Mean	Standard error
Retail distribution (PCV)	lagged sales (β_{21j})	n.s.	n.s.	0.428*	0.249
	lagged pcv (β_{22j})	0.122***	0.037	0.769***	0.066
	lagged price (β_{23j})	0.290**	0.122	0.173**	0.072
	lagged sos (β_{24j})	n.s.	n.s.	0.180**	0.079
	lagged promo (β_{25j})	n.s.	n.s.	n.s.	n.s.
Relative unit price	lagged sales (β_{31j})	n.s.	n.s.	n.s.	n.s.
	lagged pcv (β_{32j})	n.s.	n.s.	n.s.	n.s.
	lagged price (β_{33j})	0.685***	0.133	0.560***	0.099
	lagged sos (β_{34j})	n.s.	n.s.	n.s.	n.s.
	lagged promo (β_{35j})	0.020***	0.011	n.s.	n.s.
Share of shelf inventory	lagged sales (β_{41j})	0.095***	0.031	n.s.	n.s.
	lagged pcv (β_{42j})	0.034***	0.007	n.s.	n.s.
	lagged price (β_{43j})	n.s.	n.s.	n.s.	n.s.
	lagged sos (β_{44j})	0.443***	0.103	0.427***	0.081
	lagged promo (β_{45j})	n.s.	n.s.	n.s.	n.s.
Promotion	lagged sales (β_{51j})	n.s.	n.s.	n.s.	n.s.
	lagged pcv (β_{52j})	0.119***	0.035	n.s.	n.s.
	lagged price (β_{53j})	n.s.	n.s.	n.s.	n.s.
	lagged sos (β_{54j})	n.s.	n.s.	n.s.	n.s.
	lagged promo (β_{55j})	0.423***	0.030	0.242***	.0056

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

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