Marketing-Mix Strategies Effectiveness: Results from In-Store Consumer Market

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ABSTRACT

Marketing mix strategies are very important for brands in order to generate greater market share and participation. This theme is discussed in different manners in marketing field. In our paper, we aimed to analyzed two marketing mix variables (product category volume and price) and their relations with the brand sales. We conduct a vector autoregressive model and vector error correction model with the data from a major brand in Brazilian cookie category. Between the results generated by the tests, our model suggested that the sales are explained by distribution.

Keywords: marketing-mix, consumer package goods, vector error correction.

1. INTRODUCTION

Neil H. Borden proposed the term "marketing mix" for the first time in his speech at the American Marketing Association in 1953 (Dominici, 2014). The author used this term to refer to the marketing executive as "mixer of ingredients," who is constantly engaged in fashioning creatively a mix of marketing procedures to produce a profitable enterprise (Borden, 1964). Borden (1964) proposed 12 elements to the marketing mix: 1) Product Planning, 2) Pricing, 3) Branding, 4) Channels of Distribution, 5) Personal Selling, 6) Advertising, 7) Promotions, 8) Packaging, 9) Display, 10) Servicing, 11) Physical Handling and 12) Fact-Finding and Analysis. After Borden, many approaches to the marketing mix were proposed; however McCarthy's became the standard with 4 elements being proposed: Product, Price, Advertising and Distribution (van Waterschoot & Van den Bulte, 1992).

In literature, the marketing mix has long been explored in the context of B2C. Additionally, it has been an interesting approach to measuring firm performance in several metrics. Some author studies the effect of the marketing mix on brand sales (Ataman, Mela, & van Heerde, 2008; Ataman, Van Heerde, & Mela, 2010; Slotegraaf & Pauwels, 2008); others study this effect in the market share of the firm (Bronnenberg, Mahajan, & Vanhonacker, 2000), others in financial measure (e.g., top- and bottom-line performance) (Pauwels, Silva-Risso, Srinivasan, & Hanssens, 2004; R. Srinivasan, Lilien, & Rangaswamy, 2004) and others in choice (Jedidi, Mela, & Gupta, 1999; Mela, Gupta, & Jedidi, 1998; Mela, Gupta, & Lehmann, 1997).

Despite the interest from academics on the subject, usually, studies have been covering the effect of only some aspects of the marketing mix. Prior literature has focused almost solely on the effects of advertising and sales promotion on brand equity (Sriram, Balachander, & Kalwani, 2007). However, some authors found that distribution (e.g., distribution breadth) and product (e.g., product innovation) can have a significantly bigger effect on brand equity and sales than the other elements of the mix (Ataman et al., 2010; Sriram et al., 2007). It can be argued that the main reason for distribution and product innovation not often being incorporated into marketing mix models is because the necessity of longer data periods being needed to uncover the long-term effects of these elements (Srinivasan, Vanhuele, & Pauwels, 2010).

In this paper we explore how the modeled marketing-mix elements impact the sales of brands. To explore this issue, we have employed a vector autoregression (VAR) to analyze the weighted distribution and price effect on sales.

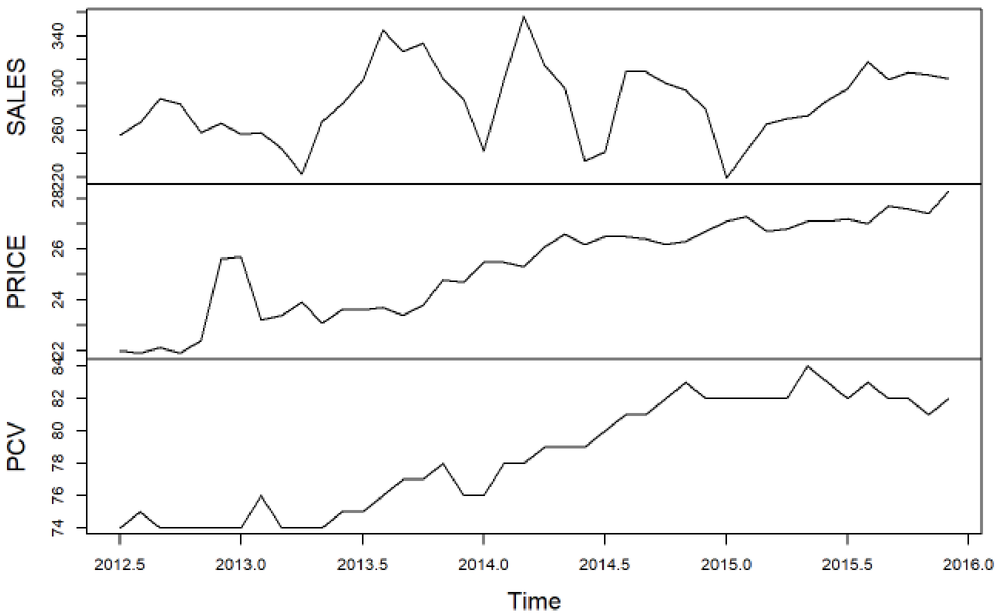
2. RESEARCH DESIGN AND DATA

The data covers three years of monthly brand-level data for a major brand in the cookie market in Brazil. The time period of the data spans from July 2012 to December 2015, corresponding to 42 observations. The data comes from in-store audit research compiled by a large global research firm. Three variables were selected to develop the model. Sales were operationalized as unit sales to consumers in kilos. Price was operationalized as the average brand price at a certain time period. Weighted distribution was operationalized as the product commodity value (PCV%) as the share of the brand category sold by the stores in which the brand has been sold. Table 1 summarizes the variables operationalization and descriptive statistics and Figure 1 presents the effect of the variables over time.

Table 1. Variable operationalization and descriptive statistics

Variable	Operationalization	Mean	SD
Sales	Sales of the brand to consumers in volume (kilos)	283,400	32.15516
Product Category Volume (PCV%)	Share of the brand category sold by the stores in which the brand has been sold.	78.48	3.437513
Price	Average brand price to consumers in reais	25.33	1.864101

Figure 1. (SALES) Total monthly sales volume for the focal brand. (PRICE) Average unit price for the brand. (PCV) Montly total distribution for focal brand.



3. MODEL DEVELOPMENT

We specified a brand-level model framework for assessing the relationships among in-store marketing factors (distribution and price). Since the analysis is at the brand level and we are working with only one brand, the model does not accommodate heterogeneity across brands. The model structure is specified as

$$\begin{bmatrix} SALES_t \\ PCV_t \\ PRICE_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_{11}^1 & \beta_{12}^1 & \beta_{13}^1 \\ \beta_{21}^1 & \beta_{22}^1 & \beta_{23}^1 \\ \beta_{31}^1 & \beta_{32}^1 & \beta_{33}^1 \end{bmatrix} \times \begin{bmatrix} SALES_{t-1} \\ PCV_{t-1} \\ PRICE_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11}^p & \beta_{12}^p & \beta_{13}^p \\ \beta_{21}^p & \beta_{22}^p & \beta_{23}^p \\ \beta_{31}^p & \beta_{32}^p & \beta_{33}^p \end{bmatrix} \times \begin{bmatrix} SALES_{t-p} \\ PCV_{t-p} \\ PRICE_{t-p} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix}$$

$SALES_t$ is the unit sale for the focal brand in month *t*; PCV is the product commodity value (retail distribution) for the focal brand in month *t*; Price is the unit price for the focal brand in month *t*.

3.1. Test for unit root

First, we conduct the Augmented Dickey-Fuller test (ADF test) to test for a unit root in the time series. We can reject the null hypothesis of a unit root in 5% in the price series (p-value = 0.03439). However, the PCV and price series cannot be rejected. Thus, we are assuming that PCV and price are integrated variables. We check the order of integration by differencing the series and doing the tests again. On all three differenced series, we were able to reject the null hypothesis of a unit root (p-value < 0.1). Thus, we can affirm that the variables are integrated of order 1.

We also conduct the Johansen cointegration trace and eigenvalue test, which helped us to identified zero cointegrating relations (test = 40.23 > 41.07 at 1pct). Furthermore, we estimated the statistic regression and assess whether its residuals are stationary.

3.2. Equilibrium correction using OLS & Model specification

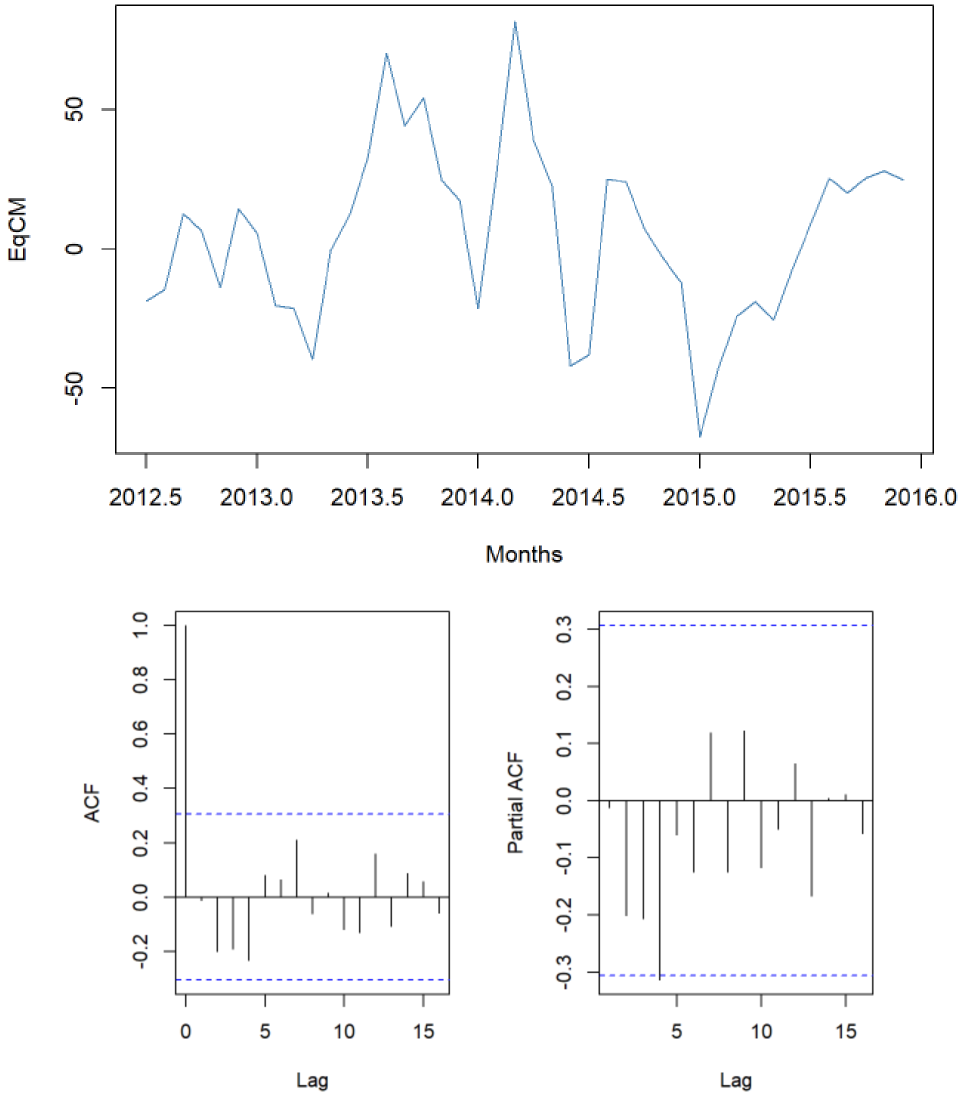
The Equilibrium Correction Model links the long-run equilibrium relationship implied by cointegration with the short-run dynamic adjustment mechanism that describes how the variables react when they move out of long-run equilibrium (Engle & Granger, 1987). We employed a two-step residual-based testing procedure based on regression techniques developed by Engle & Granger (1987). First, we regressed Price and PCV on Sales to find the parameters. Table 2 presents the regression output.

Table 2. Regression output

	Dependent variable:
	Sales
Price	-6.464
PCV	5.631
Constant	1.060
Observations	42
R^2	0.07224
Adjusted R^2	0.02342
Residual Std. Error	28.44 (df = 38)
F Statistic	1.48 (df = 2; 38)
Note:	*p<0.1; **p<0.05; ***p<0.01

Second, we have plotted the residuals of the regression and the autocorrelation function (ACF) and partial autocorrelation function (PACF). The plot of the residuals shows data around the mean, the ACF tails off at lag 2 and PACF cuts of at lag 1. Finally, we applied the ADF test to test for a unit root in the residuals. Based on the augmented dickey fuller test results, we can reject the null hypothesis and confirm that the residuals are stationary for the regression $SALES_t = \beta_1 \times PRICE + \beta_2 \times PCV_t + \epsilon_t$.

Figure 2. Residuals of the regression; ACF and PACF



We also conduct the Johansen cointegration trace and eigenvalue test, which helped us to identified two cointegrating relations. For the case of r <= 2, we confirm that the calculated test statistic of 4.48 is below the critical values of 7.52, 9.24, and 12.97. On the other hand, for the case of r <=1 and r = 0, the test statistic is above the critical values.

Finally, to choose the optimal lag length of the model, we used different criteria such as Akaike (AIC), Schwarz (SC), Hannan-Quinn (HQ), and final prediction error (FPE). Based on all of these criteria, the seven-period lag provides the best-fit.

4. ANALYSIS AND DISCUSSIONS OF RESULTS

4.1. VAR Model Estimation

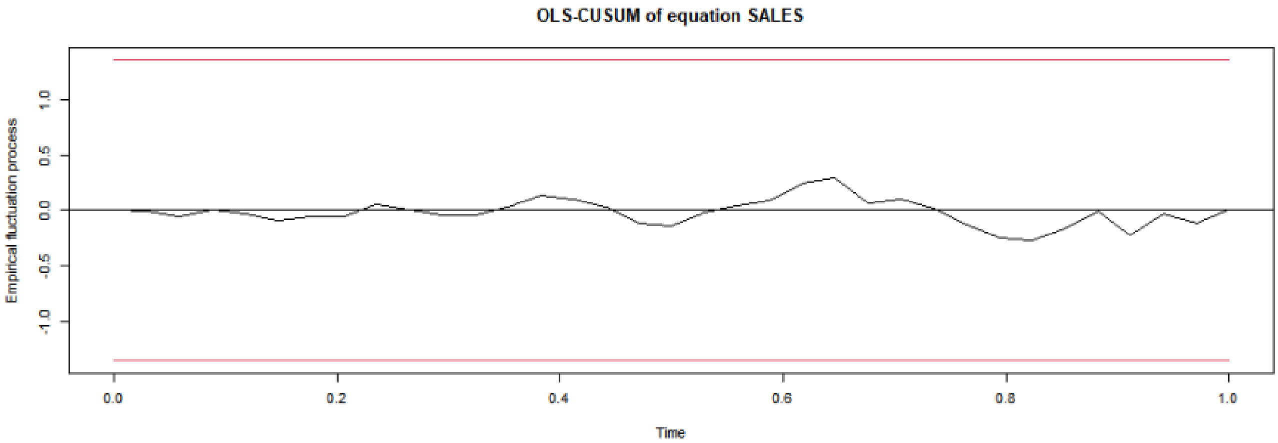
Furthermore, we have estimated the VAR model. Table 3 provides the parameters estimates of the direct effects of in-store marketing mix on sales. Distribution has a significative negative effect on sales for the focal brand (β_{12}^{2} = -12.590, p-value < 0.05 and β_{12}^{7} = -21.978, p-value < 0.05), price has also a significative negative effect on sales for the focal brand (β_{13}^{6} = -16.000, p-value < 0.05), and we have found that lagged sales also had a small negative effect on sales (β_{11}^{2} = -0.651, p-value < 0.05.

To test for robustness on our model, we have employed four tests Serial Correlation Test (Portmanteau Test), Heteroscedasticity (Arch Test), Normality (JB-Test, Skewness, and Kurtosis). We have found that our model rejected the null hypothesis of the Portmanteau Test. Therefore, our model has a serial correlation in the errors. Autocorrelation is not a desired trait. It biases the estimators and makes them less efficient. On the other hand, the other robustness tests provide good results, as no heteroscedasticity (p-value = 0.612), and also the that the residuals are normally distributed (JB-Test: p-value = 0.9521, Skewness: p-value = 0.7348, Kurtosis: p-value = 0.9542).

Table 3. VAR Estimation results

	Dependent variable:		
		y	
	SALES	PRICE	PCV
SALES.l2	-0.651**	0.011**	-0.003
	(0.278)	(0.004)	(0.011)
PCV.l2	-12.590*	0.077	-0.235
	(6.754)	(0.109)	(0.278)
SALES.l3	-0.525*	0.003	-0.008
	(0.259)	(0.004)	(0.011)
SALES.l4	-0.617*	0.007	-0.022*
	(0.289)	(0.005)	(0.012)
PRICE.l6	-16.000*	0.048	-0.430
	(8.806)	(0.141)	(0.362)
SALES.l7	-0.068	-0.002	-0.017*
	(0.206)	(0.003)	(0.008)
PCV.l7	-21.978**	0.142	-0.337
	(9.580)	(0.154)	(0.394)
const	30.915**	-0.091	0.502
	(11.461)	(0.184)	(0.471)
Observations	34	34	34
R^2	0.745	0.638	0.557
Adjusted R^2	0.300	0.004	-0.218
Residual Std. Error (df = 12)	26.002	0.418	1.069
F Statistic (df = 21; 12)	1.673	1.007	0.718
Note:	*p<0.1; **p<0.05; ***p<0.01		

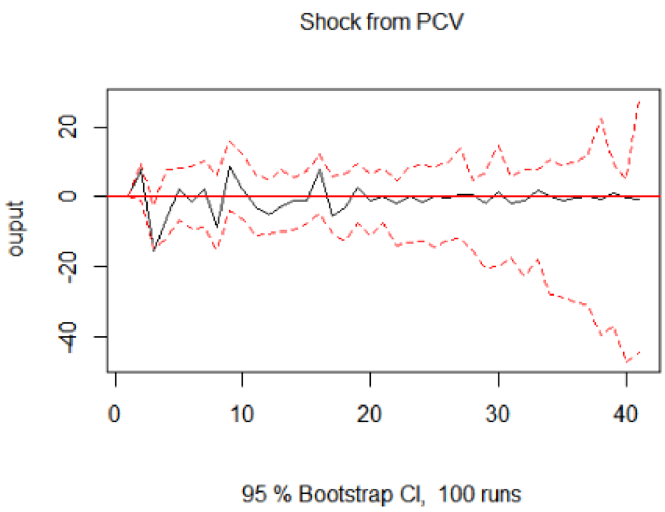
Figure 3. OLS-CUSUM of Sales



4.2. Granger-Causality Test and Impulse Response Function

The granger-causality test was conducted pairwise for variables in different lag-lengths. To conduct this test, we choose the optimal lag defined previously, which is seven. Thus, the results show that sales are granger-caused by the lags of distribution (p-value = 0.004359). As shown in Fig. 4, the impulse-response function allows us to see the response of sales for the impulse from PCV. Since a significative portion of the line is below zero, we could argue that the PCV will have a negative shock on sales.

Figure 4. Impulse Response Function



5. CONCLUSION

This paper presents a preliminary analysis of the in-store marketing-mix strategy effect on sales. More specifically, it investigated the effectiveness of in-store marketing strategies on sales. To do this investigation, we have employed a VAR(7) model and have found significant relationships of some lagged values. In contrast, what has been largely proved in literature, distribution has shown a negative effect on sales. Meanwhile, price presented a negative effect on sales, which was expected since an increase in the price of a product will likely decrease the number of sales of a certain product.

Moreover, our model has passed on all robustness tests, except for the serial correlation. This problem in addition to the negative effect of PCV on sales is significant indicators that the model is not appropriate for the available data. We present some assumptions on these points. First, the available data is from a short time period (42 months of data); therefore, the statistical results may be limited. Second, we had access to only a certain brand and product line. Thus, the effects on the available period may not be enough to reflect the expected results, as presented by several studies in the literature. Third, our model lacks control variables and other important variables that are usually analyzed using in the marketing-mix model (e.g., investments in advertising, word-of-mouth, promotions, display). Fourth, the operationalization of our variables may not be ideal for the proposed model. There are several other options to operationalize in-store marketing. For instance, for the price, researchers may use the relative price metric in order to normalize the price in the category. Moreover, we have employed product commodity value, where other weighted distribution variables may create different results. PCV accounts for the total category sales of outlets carrying the brand by total category sales of all outlets. Therefore, we can argue that the category we analyzed may not suffer significant changes in distribution strategies, which may limit the results of our model. Additionally, in negotiations with retail outlets, manufacturers do not employ single strategies for each product category. Nevertheless, other products should have been analyzed in this model.

For future research, we argue that a greater time period should be selected and that the model should be applied for several products. This strategy may capture significant effects that were not found in our model. Furthermore, future studies may try to use control variables and analyze the effects for different channel types, which may also contribute to the model estimation.

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