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An Econometric Measurement of the Impact of Marketing Communication on Sales in the Indian Cement Industry

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Abstract

This study analyzes the relationship between net sales revenue and Integrated Marketing Communications (IMC) viz. advertising, sales promotion, personal selling and direct marketing. It attempts to find the existence of a long-term relationship between the two variables and goes on to analyze the impact of one variable on the other and its possible implications. Seven year quarterly data of ten firms in the Indian Cement industry when analyzed reveals that there is no evidence of cointegration between the above mentioned variables, but the Vector Autoregression (VAR) model suggests that although past sales do not influence current advertising, advertising and sales promotion have a significant effect on the sales of cement after one year. The Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) also support this view.

Keywords: Advertising, Cointegration, Forecast Error Variance Decomposition, Impulse Response Function, Net sales, Sales Promotion, Vector Autoregression.

1. Introduction

Intense competition has led to brand extensions and line extensions and with ever proliferating brands, the challenge of getting the attention of and remaining in the mind of the consumer has steadily increased. Advertising agencies have started being entrusted with the responsibility of creating unique ads and slowly but surely, the marketing communication budget of the major competing firms in most industries have skyrocketed. It is in this backdrop that firms have started to realize the importance of marketing metrics, and have became serious about the returns that their marketing communications are bringing back to them. All marketing communications have a purpose, a purpose to seek a cognitive, affective or behavioural response from the target audience. A marketing communications manager may choose from various tools of the marketing communications mix such as advertising, sales promotion, public relations, personal selling, direct marketing, special events, and so on (Shah and D'Souza, 2009). An optimum combination of the different marketing communication mix elements is what firms strive to achieve so as to create the much needed synergistic effect. Integrated Marketing Communications, a concept that recognizes the added value of a comprehensive plan, can thus produce stronger message consistency and help to build brand equity and create greater sales impact (Kotler, Keller, Koshy, and Jha, 2009).

The most important function of marketing communication apart from communicating the message is generation of sales revenue. Marketing communications in the form of advertising and sales promotion help firms in generating sales in the long run and short run respectively. Since advertising takes time to build a favourable image in the mind of the consumer, its impact is generally felt after a certain time period is elapsed, while sales promotion, mainly consumer promotions generate immediate sales for the firms. Firms therefore judiciously select a mix of both and allocate their marketing communication budget accordingly so as to get maximum purchase out of every penny that they spend. Thus it becomes imperative for organizations to measure the effectiveness of marketing communications campaigns on generation of sales revenue so as to interpret their marketing performance.

2. Review of literature

There are quite a few studies that have investigated the nexus between marketing communications, viz. advertising and sales promotion and sales in different points in time. A brief review of the same is presented below.

In one of the earliest studies involving the relationship between advertising and sales, Hollander (1949) found a carryover effect of advertising on sales in the sales of an ethical drug. The relationship between advertising and aggregate demand was studied by Verdon et al (1968) where they found that advertising has a positive relationship with aggregate demand. Clarke (1976) concluded that the cumulative effect of advertising on sales lasts only for few months rather than years. Baghestani (1991) took annual advertising and sales data from the Lydia Pinkham Company from 1907 to 1960 and found that both are cointegrated and share a long-term relationship. Zanias (1994) also analyzed the Lydia Pinkham data set and found bivariate granger causality between advertising and sales. The two series were also found to have a valid long-term relationship. Dekimpe and Hanssens (1995) found out that advertising has a strong effect on sales for a chain of home improvement stores. Lee et al (1996) found causality to run in both directions for the Lydia Pinkham Company as opposed to other findings of unidirectional causality. Leong et al (1996) found cointegration between advertising expenditure and sales and suggested therefore that a strong positive relationship exists between the two variables. Leach and Reekie (1996) tested Granger causality between advertising expenses and sales and found only unidirectional causality from advertising expenses to sales. Metwally (1997) studied the growth rates of advertising expenditure of consumer goods and services in Australia during the period 1975-1995 and found that the growth in advertising expenditure is strongly correlated with the growth in sales. Graham and Frankenberger (2000) calculated the asset value of advertising expenditure and found that changes in advertising result in earnings up to five years after the year of expenditure and that asset value is more in consumer and industrial products and less in sales and service industry. Elliot (2001) found cointegration between advertising and sales for food industry but did not find the same for soft drinks industry. Pagan et al (2001) studied the effectiveness of advertising on sales for oranges and found that increase in advertising expenditure leads to increase in the sales with a one month lag. Esteve and Requena (2006) established a long run relationship between advertising and sales across different markets over the period 1971 – 2001 in the UK car industry and found out two structural breaks during the recession periods. Agyapong et al (2011) found strong relationships between marketing communication and sales performance of Vodafone in Ghana. Banerjee et al (2012) found evidence of cointegration between marketing communication and sales in the personal care industry in India. The Vector Error Correction model suggested that that the speed of adjustment of advertising budget to a fall in sales will take almost a year and thus during recession, organizations may do well to increase their promotions instead of decreasing.

As is evident from the above review, many studies have found out positive correlation between marketing communication and sales revenue and also suggested that there is some kind of long run relationship between the two variables in some cases. In the authors' earlier work on the personal care industry in India, which is primarily a business to consumer segment, cointegration was found between advertising and sales promotion and sales revenue. Thus, it is well worth studying, whether similar long term relationship between the two variables, also do exist in a predominantly business to business segment like cement.

3. Research objectives

This study analyzes time series data pertaining to advertising, sales promotion, direct marketing and personal selling expenditures, collectively referred to as Integrated Marketing Communications (IMC) and its causal nexus with Net Sales revenue of some Indian firms operating in India in the Cement industry as categorized by Capitaline database. The present study tests the stationarity of the variables of IMC like Advertising, Sales Promotion expenses etc. (hereinafter referred to as ASP expenses) and Net Sales revenue. The study tries to determine whether ASP expenses and Net Sales revenue are cointegrated in the long run. The present research work has been designed to construct a Vector Auto Regression (VAR) model to see the impact of one variable over the other. Finally, the Impulse Response Function (IRF), which shows the time path of a variable to a shock or innovation from itself and all other variables, and the Forecast Error Variance Decomposition (FEVD), which shows the proportion of movement or variation in a variable, explained by shocks from it and other variables in the system are then analyzed.

4. Research methodology

The data for the above empirical study is secondary in nature sourced from the Capitaline database of Capital Market Publishers India Pvt. Ltd. Quarterly time series data pertaining to selling and administrative expenses and net sales revenue for 10 firms in the Cement industry spanning over a period of seven years (June, 2004 – March, 2011), i.e. 28 observations have been mined from the said database for the purpose of the research. The choice of the industry is due to the fact that this is an industry in India where the Herfindahl Index (HI) is very low historically (Das, 1987).

HI, a measure of the industry concentration, is equal to the sum of the squared market shares of the firms within the industry, where the market shares are expressed as fractions, and indicates the amount of competition between them. A low HI implies low market power and high competition which invariably leads to substantial monetary expenditure on marketing communications, including both above-the-line and below-the-line tools, from the firms' side. Thus, it is pertinent to study the impact that such marketing communications have on the sales revenue in the cement industry. After accounting for missing values, only ten firms in the Cement industry had quarterly data for the above period.

The methodology used is to first check whether the variables in the time series are stationary or not. If not, we go on to check whether the time series are cointegrated or not. Two or more time series are cointegrated if, to a limited degree they share a certain type of behaviour in terms of their long-term fluctuations. If the time series are found to be cointegrated, then depending on the rank of the cointegrating vector, the Vector Error Correction (VEC) model or the Vector Autoregression (VAR) model need to be undertaken for the analysis. The logic for using the VAR framework is that time series data pertaining to ASP expenses and Net Sales show problems of endogeneity and carryover effects. Endogeneity problem occur when the current advertising and sales promotion budget depend on the sales of previous periods. Carry over effect takes place when previous advertising expenditure has an effect on current and future sales. Such a situation makes it difficult to distinguish the variables as exogenous and endogenous and it is in this spirit that Sims (1980) introduced the VAR framework which is appropriate in such circumstances when we have to work with different time series and capture the evolution and interdependencies between multiple time series. The unrestricted VAR framework is then transformed to a moving average representation to obtain the impulse response function. The current and past innovations in the IRFs are orthogonalised using the Cholesky decomposition so that the innovations become uncorrelated. The FEVD is also analyzed along with the IRFs.

The authors have used the software packages Gretl, and EViews to analyze the data.

The natural logarithms of the two variables ASP expenses and Net Sales instead of their absolute values are used after suitable transformation. Log transformation reduces unnecessary variances in data which may give biased results, which is why this procedure is widely used. Almost any study in time series starts with the tests of stationarity. For this purpose, the various stationarity tests like Augmented Dickey-Fuller (ADF) test, Philips-Perron (PP) test and the Kwiatkowski-Philips-Schmidt-Shin (KPSS) tests were undertaken. A series is said to be stationary if the mean and covariance are constant over time and the auto-covariance of the series depends only on the lag between two time periods and not on the actual time at which the co-variance is calculated. Engle and Granger (1987) argued that a non-stationary series is integrated of the order "d" if it can be made stationary by differencing the series "d" times. The ADF test without trend and with intercept is represented by the following equation

$$\Delta Y_t = a_0 + b_1 Y_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-1} + \varepsilon_t \dots\dots\dots (2)$$

where, $\Delta Y_t = \Delta Y_{t-1}$ etc. ε_t is the white noise error term, Y_t is the variable of interest and k is the number of lags chosen by the Schwarz Bayesian Criterion (SBC). The null hypothesis of $b_1 = 0$ i.e. presence of unit root or non-stationarity of Y is tested against the alternative hypothesis of $b_1 < 0$ and if the tau statistic of the coefficient from the ADF tests is significantly less than the critical values, then the null hypothesis is rejected which implies the series is stationary. The Philips-Perron (1989) test is simultaneously performed along with the ADF test to check the stationarity of the series. It is based on the ordinary least square (OLS) estimator α^* of α in the model,

$$Y_t = \beta + \alpha Y_{t-1} + \varepsilon_t \dots\dots\dots (3)$$

where ε_t is the error term and Y_t is the variable of interest and the null hypothesis is that of non-stationary against the alternative hypothesis that the series is stationary. Finally the KPSS (Kwiatkowski et al., 1992) test is conducted which has a null hypothesis opposite to that of the earlier two tests. Here, the null hypothesis is that of stationarity against the alternative hypothesis of non-stationarity. The KPSS test statistic is represented as

$$\rho = \frac{\sum_{t=1}^{T} S_t^2}{T^2 s^2} \dots\dots\dots (4)$$

where $\frac{1}{T^2}\sum_{t=1}^{T} S_t^2$ is the normalized sum of squared partial sums and S^2 is the consistent estimate of the long-run variance, σ^2. If the value of the test statistic is higher than the critical value, the null hypothesis is rejected implying the non-stationarity of the series. After checking for the stationarity of the variables, the time series are tested for cointegration to make it clear whether they share any long term relationship among them. Before proceeding with the cointegration test, the lag order of the two time series need to be determined. We apply the VAR lag order selection method to select the appropriate lag length which uses the minimum of Akaike Information Criterion (AIC), SBC, and probability of Likelihood Ratio p(LR) for its purpose. Once the lag order selection is done we go ahead with the Johansen cointegration test. According to Johansen (1988), a p-dimensional VAR model with k lags can be defined as

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_k Y_{t-k} + \varepsilon_t \ldots\ldots (5)$$

Where Y_t is a (p x 1) vector of p endogenous variables, $\Pi_1, \Pi_2, \ldots$ are (p x p) matrices and ε_t is the error term. Johansen and Juselius (1990) show that such a cointegration test may lead to three possibilities:

i. The rank of Π can be zero in which case there is no cointegration among the time series in question and the VAR model is applied in first differences after making the series stationary.
ii. The rank of Π can be full in which case the series are stationary and a VAR in levels can be done.
iii. The rank of Π can be anything between 1 and (p-1) in which case the VECM needs to be applied.

The cointegrating equation above can then be expressed in a VEC model as

$$\Delta Y_t = c + \Pi_k Y_{t-k} + \sum_{i=1}^{k-1} \theta_i \Delta Y_{t-i} + \varepsilon_t \ldots\ldots\ldots (6)$$

where Δ denotes difference operator, Π & θ are (p x p) matrices, k is the appropriate lag length and ε_t is the error term and Π_k contains the vector of loading matrices which denotes the speed of adjustment from disequilibrium. As a bivariate VAR model assumes that both the variables as endogenous, the cross-equation feedback relationships are natural. So, the IRF and FEVD may give a better picture of the reaction of the variables to various shocks. To conduct the said analysis, the VAR has to be represented in moving average (MA) form. To borrow Hamilton (1994), a VAR (p) model in MA form may be written as

$$Y_t = \alpha + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \ldots + \phi_p \varepsilon_{t-p} + \ldots\ldots\ldots (7)$$

where $\phi_s = \frac{\delta Y_{t-s}}{\delta s_t'}$, i.e. row i, column j element of ϕ_s identifies the consequences to a one unit increase in the j^{th} variable's innovation at time t(ε_{jt}) for the value of the i^{th} variable at time t+s ($Y_{i,t+s}$), holding all other innovations at all times constant. A plot of row i, column j element of ϕ_s; $\frac{\delta Y_{t-s}}{\delta s_t'}$ as a function of s is called the IRF. It describes the response of $Y_{i,t+s}$ to a one time impulse in Y_{jt} with all other variables at t or earlier held constant.

5. Findings and analysis

The two time series in contention, ASP and Net Sales (hereinafter referred to as NT_SALES) were first transformed to their logarithmic counterparts and then subjected to time series plot. The LNASP (log transformation of ASP) and LNNT_SALES (log transformation of NT_SALES) are non-stationary but their first differences, DLNASP and DLNNT_SALES, hover around a constant mean. Unit root tests viz. ADF test, PP test and KPSS tests were then conducted on the variables LNASP and LNNT_SALES, the results of which are summarized in *Table 1*. The ADF and PP tests indicate the stationarity of both the time series at first differences as it rejects the null hypothesis of non-stationarity at 1% level of significance, while the KPSS test rejects the null hypothesis of stationarity conducted at the levels of both the series at 5% level of significance. Thus both the series, LNASP and LNNT_SALES are integrated of order one, i.e. I (1), and hence a long-term relationship may be conjectured between them. The test of cointegration used for the purpose is the Johansen cointegration test. A prerequisite of any cointegration test is to know the appropriate lag length, which has been determined here by the VAR lag selection procedure. An optimum lag order is where most or all of the criterions, viz. AIC, SBC, Hannan-Quinn (HQC) are minimized and the p(LR) is significant. *Table 2* summarizes the results of VAR lag selection which indicate, on the basis of AIC, SBC, HQC criterions, that optimum lag would be four. Once the optimum lag order is calculated, the Johansen cointegration test is performed with constant but no deterministic trend on LNASP and LNNT_SALES. The test results in *Table 3* indicate that at 5% level of significance, there is no cointegration, as suggested by the trace test as well as the maximum eigenvalue test respectively. Since there is no cointegration vector, a long-term relation cannot be conjectured between LNASP and LNNT_SALES. As the rank of the cointegrating vector is zero, the appropriate model would be a VAR model in first differences after making the variables stationary. Thus LNASP and LNNT_SALES were both differenced once to make them stationary and then were subjected to Vector Autoregression by assuming both as endogenous variables at lag four as selected by the VAR lag selection criterion. The result of the VAR is summarized in *Table 4* below. The adjusted R-square and the F statistic are significant for both equations 4(a) and 4(b) and the Durbin-Watson coefficients in both the equations are close to '2', suggesting that both the regressions are free of autocorrelations. The result of VAR equation 4(b) indicates that there is unidirectional causal relationship from DLNASP at lag 4 to DLNNT_SALES as suggested by a high t-statistic 2.780 and a significant p-value of 0.0148. But DLNASP at one, two or three period lags do not seem to impact DLNNT_SALES much. Thus it is evident that marketing communications of four time periods back i.e. one year back (as the research work is with quarterly data), have a significant effect in generation of sales revenue in the cement industry in India. This finding may be corroborated from that fact that advertising takes its own time to build favourable image in the mind of the consumers, and it is only after that time period, in this case one year, that its impact is visible. Moreover, cement is a product which is marketed mostly in the business to business arena, where sales promotion tools are mostly in the form of trade promotions. According to the 95th Report on Performance of Cement Industry, published by the Department of Industrial Policy and Promotion under the Ministry of Commerce and Industry, Government of India in February 2011, the 'housing', 'industrial' and 'commercial and institutional' sectors account for 64%, 6% and 13% of the cement market respectively. The 'housing' market is dominated by small, medium and large real estate firms which construct and deliver readymade apartments to people where individual customers have almost no decision making power regarding the brand of cement used in the construction activity. Thus this huge market of about 83% is mainly a business to business segment where marketing communication are carried out more in the form of trade promotions. So, the typical short term impact that consumer promotions have on sales revenue is absent for a product like cement. The coefficient of DLNASP (-4) is positive and less than unity suggesting that a positive change in promotional expenditure one year back, has a positive effect on DLNNT_SALES, and although less than proportionate, an increase in ASP increases NT_SALES. Thus it can be said that advertising and sales promotion are significantly responsible for increase in sales in the cement industry apart from other factors like product quality, price, brand image and availability. On the other hand, equation 4(a) suggests that DLNASP of preceding quarter is inversely proportional to DLNASP in current quarter, which means if promotional expenditures are stepped up in one quarter they are relaxed in the next. But more important is the fact that lagged values of DLNNT_SALES have no significant effect on DLNASP in the cement industry in India. In other words, brand managers do not fix promotional budget by taking into account the previous quarter or year's sales figures. What therefore follows is that cement companies in India do not go for top down approach of advertising budget allocation like percentage of sales method, but follow a bottom up approach in general, where advertising goals are first set and accordingly the budget allocation is done. Since causal relationships are studied better by IRF and FEVD, the same is carried out on the VAR model concerning the two variables, NT_SALES and ASP. The IRF tracks the impact of a shock on any variable on itself and the others after few time periods, while the FEVD shows what proportion of these variations in the future time period is explained by those shocks. In our analysis the IRFs are orthogonalised using Cholesky decomposition so as to make the error terms uncorrelated as without orthogonalisation it would be impossible to shock one variable without affecting the other variables. *Figure1* below shows the orthogonalised IRFs. The IRF suggests that a one standard deviation innovation in LNASP has a positive effect on LNNT_SALES which peaks after four time periods, i.e. a year, as is evident from the figure. On the other hand a one standard deviation innovation to LNNT_SALES has no significant impact in LNASP in the subsequent periods as the curve hovers around the zero line. Coming to the FEVD analysis, as obtained from *Figure 2*, it may be seen that only about 20% of variation in LNASP is explained by LNNT_SALES, whereas about 60% of variation in LNNTSALES after four quarters, is explained by LNASP, which strengthens our earlier proposition that advertising takes time to build image and hence its impact is felt some time periods later, i.e. one year in this scenario.

6. Conclusion

The study of marketing communication and sales revenue in the cement industry in India presents certain insight into the relationship shared between the two variables. On the one hand it shows that net sales have no impact on the advertising and sales promotion expenditure allocated in the next quarter. This suggests that bottom up approaches of advertising budget allocation are generally followed in the cement industry in India. On the other hand it shows that changes in advertising budget allocation for marketing communications have a significant effect on generation of sales revenue in subsequent periods of time, more specifically, after one year. Both these propositions are simultaneously justified by the IRF and FEVD analysis conducted in the study. Thus, marketing managers in the cement industry should be prudent to invest in above-the-line tools like advertising and below-the-line tools like building relationship with the clients, strengthening dealer networks by giving buying allowances, cash rebates and then wait patiently for the returns.

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Table 1: Unit root tests on LNASP and LN_NTSALES (Constant without trend)

Series	ADF test statistic(max. lag 1)	PP test statistic	KPSS test statistic
LNASP (levels)	-0.378211	0.444601	0.668677**
LNASP (first differences)	-6.779254***	-6.094588***	0.248609
LNNT_SALES (levels)	-0.323160	0.472933	0.657406**
LNNT_SALES (first differences)	-7.080310***	-5.398477***	0.400000

**** and ** represent rejection of null hypothesis at 1% and 5% level of significance respectively*

Table 2: VAR lag selection (maximum lag order 6)

Endogenous variables: LNASP and LNNT_SALES				
Lags	p(LR)	AIC	SBC	HQC
1		-4.592986	-4.295429	-4.522891
2	0.59478	-4.355848	-3.859920	-4.239022
3	0.00002	-5.209039	-4.514740	-5.045483
4	0.00108	-5.677043*	-4.784372*	-5.466756*
5	0.40772	-5.494650	-4.403608	-5.237633
6	0.19238	-5.407922	-4.118508	-5.104174

** indicates minimum values*

Table 3: Johansen cointegration test - No deterministic trend (restricted constant)

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.240135	8.127301	15.49471	0.4519
At most 1	0.037262	0.987322	3.841466	0.3204
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.240135	7.139979	14.26460	0.4727
At most 1	0.037262	0.987322	3.841466	0.3204

Trace test indicates no cointegration at the 0.05 level; Max-eigenvalue test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at 5% level; **MacKinnon-Haug-Michelis (1999) p-values*

Table 4: VAR system, lag order 4

Vector Autoregression Estimates		
Included observations: 23 after adjustments		
Standard errors in ( ), t-statistics in [ ] and p-values in italics		
Determinant of residual covariance	4.2674157e-006	
Log-likelihood	76.920602	
AIC	-5.1235	
BIC	-4.2349	
HQC	-4.9000	
	DLNASP	DLNNT_SALES
Equation	**4(a)**	**4(b)**
DLNASP(-1)	-0.730612	-0.166670
	(0.292567)	(0.218958)
	[-2.497]	[-0.7612]
	0.0256 **	*0.4592*
DLNASP(-2)	0.128423	0.459737
	(0.382744)	(0.286446)
	[0.3355]	[1.605]
	0.7422	*0.1308*
DLNASP(-3)	0.0724280	0.363919
	(0.335697)	(0.251236)
	[0.2158]	[1.449]
	0.8323	*0.1695*
DLNASP(-4)	0.362319	0.668126
	(0.321157)	(0.240354)
	[1.128]	[2.780]
	0.2782	*0.0148* **
DLNNT_SALES(-1)	0.461030	0.297111
	(0.337192)	(0.252354)
	[1.367]	[1.177]
	0.1931	*0.2587*
DLNNT_SALES(-2)	-0.399782	-0.638657
	(0.373624)	(0.279621)
	[-1.070]	[-2.284]

	0.3027	*0.0385* **
DLNNT_SALES(-3)	-0.416947	-0.213069
	(0.405258)	(0.303295)
	[-1.029]	[-0.7025]
	0.3210	*0.4939*
DLNNT_SALES(-4)	0.413999	-0.00969936
	(0.395200)	(0.295768)
	[1.048]	[-0.03279]
	0.3126	*0.9743*
C	0.0587547	0.00940503
	(0.0433544)	(0.0324465)
	[1.355]	[0.2899]
	0.1968	*0.7762*
R-squared	0.760182	0.775688
Adj. R-squared	0.623143	0.647509
Sum sq. resids	0.076116	0.042633
S.E. equation	0.073735	0.055184
F-statistic	5.547192	6.051628
Log likelihood	33.04075	39.70654
Durbin-Watson	1.942780	2.179376
Akaike AIC	-2.090500	-5.123531
Schwarz SC	-1.646176	-2.225810
Mean dependent	0.056197	0.054972
S.D. dependent	0.120112	0.092947

*** denote statistical significance at 5% level.*

Figure 1: Orthogonalised Impulse Response functions of LNNT_SALES and LNASP

Source: Authors' analysis using EViews

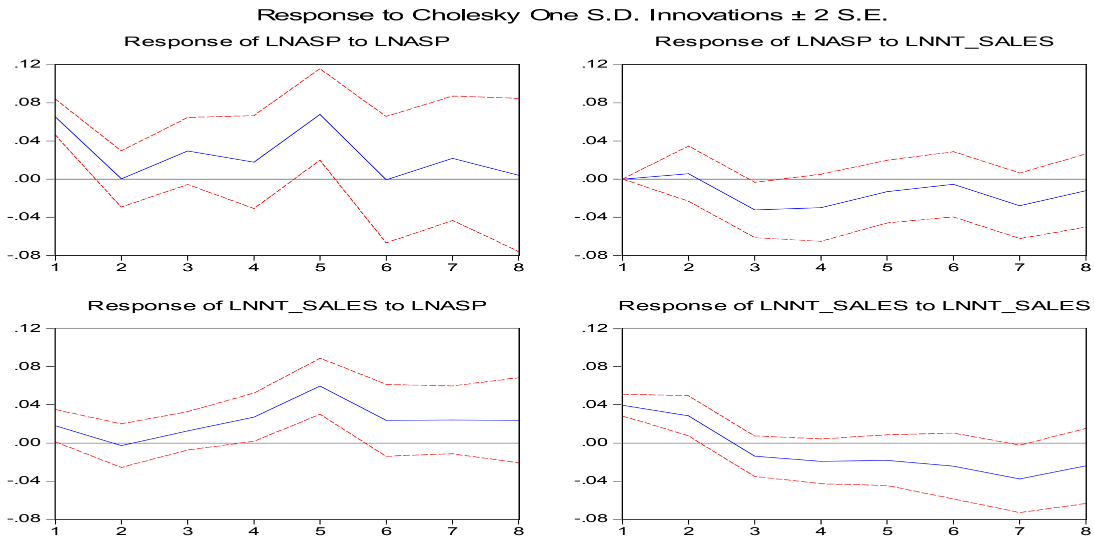

Figure 2: Forecast Error Variance Decomposition of LNNT_SALES and LNASP

Source: Authors' analysis using EViews