European Economic Letters
ISSN 2323-5233
Vol 14, Issue 3 (2024)
http://eelet.org.uk

Co-integration and Fundamentals in Indian FMCG Sector: A Time Series Econometric Analysis

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ABSTRACT

This study investigates the long-run equilibrium relationship between the volume of shares traded and key fundamentals of companies in the Fast-Moving Consumer Goods (FMCG) sector of the Indian economy using time series econometric analysis. Monthly data from January 2012 to March 2017 was collected from the National Stock Exchange (NSE) for the volume of shares traded (VOL) and its determinants, including current market price (C.M.P.), earning per share (EPS), price-earnings ratio (P/E), price-to-book ratio (P/B), and dividend yield (YIELD). The stationarity of the data variables was tested, and after confirming co-integration, the short-run relations were examined using the vector error correction (V.E.C.M.) model. Both the Trace and Lmax tests revealed the existence of one co-integrating equation in the system, indicating a long-run equilibrium relationship between the volume of shares traded in the FMCG sector and the price, EPS, P/E, P/B, and yield variables. The findings suggest that FMCG investors should consider long-term investments or aim for short-term gains of at least one year, depending on the quarterly EPS, P/E, and P/B dynamics, as these factors drive the market in the long run. This study is unique in exploring the long-run equilibrium relationship between the volume of shares traded and key fundamentals of companies in the Indian FMCG sector.

Key Words: FMCG, Co-integration, Indian Economy, Stock Exchange

Introduction

The significant role of rural markets in the growth of India's FMCG sector suggests that companies should focus on developing targeted strategies to penetrate and expand their presence in these areas. This may involve tailoring products, pricing, and distribution channels to meet rural consumers' specific needs and preferences, potentially leading to increased market share and revenue growth for FMCG companies operating in India.To capitalize on this opportunity, FMCG companies should consider conducting extensive market research to understand rural consumers' unique characteristics and demands. This research could inform product development efforts, resulting in innovations catering to rural lifestyles and preferences. For instance, companies might develop smaller package sizes or more affordable variants of their products to align with rural income levels and purchasing patterns. Furthermore, companies may need to adapt their marketing and advertising strategies to effectively reach rural audiences. This could involve leveraging local media channels, organizing community events, or partnering with influential local figures to build brand awareness and trust. Additionally, FMCG firms should explore innovative distribution models to overcome infrastructure challenges often present in rural areas. This might include collaborating with local retailers, implementing mobile sales units, or utilizing e-commerce platforms that are gaining traction in rural India.

Investing in rural market expansion could also have broader socioeconomic implications. As FMCG companies increase their presence in these areas, they may contribute to job creation, skill development, and overall economic growth in rural communities. This, in turn, could lead to increased purchasing power among rural consumers, further driving demand for FMCG products and creating a positive feedback loop for both the industry and rural development. However, companies must also be mindful of potential challenges in rural market expansion, such as logistical difficulties, diverse regional preferences, and price sensitivity. Overcoming these obstacles will require a deep understanding of local contexts, flexible business models, and a long-term commitment to rural market development. By successfully navigating these challenges and capitalizing on the growth potential of rural markets, FMCG companies can position themselves for sustainable growth and competitive advantage in India's evolving consumer landscape.

The Indian FMCG sector is a significant component of the economy, with rural markets playing a crucial role in its growth. The sector has been experiencing a higher growth rate in rural areas than in urban regions, with rural India

accounting for a substantial portion of FMCG consumption, particularly in personal care, hot beverages, and fabric care (Kumar & Gogoi, 2013). This trend is supported by the increasing purchasing power in rural communities, driven by economic growth and the green revolution (Kumar & Gogoi, 2013). Interestingly, while the overall sector is growing, specific areas, such as tourist destinations, present unique marketing opportunities for FMCG companies, as seen in the Vellore District (Sudarvizhi A, 2023). Additionally, consumer preferences for natural and eco-friendly products influence the sector's growth, particularly in states like Kerala (Pillai & Jothi, 2020). The Ayurvedic FMCG market, for instance, is expanding rapidly, with a significant CAGR, indicating a shift towards natural products (Sharma et al., 2019). However, the industry faces challenges such as irregularity and the need for companies to adapt to consumer caution towards proprietary products (Sharma et al., 2019). In summary, the Indian FMCG sector is demonstrating robust performance, particularly in rural markets, with a notable shift towards natural and eco-friendly products. The sector's growth is also influenced by unique consumer behaviors in different regions and market niches, such as tourist destinations and the Ayurvedic market. Despite the challenges, the sector's potential is underscored by its significant contribution to the economy and the evolving consumer preferences (Sudarvizhi A, 2023; Kumar & Gogoi, 2013; Pillai & Jothi, 2020; Sharma et al., 2019).

Literature Review:

The Error Correction Model (E.C.M.) is a powerful technique for calculating immediate and enduring trade response elasticities. E.C.M.s excel in economic studies due to their capacity to track the dynamic shifts of a dependent variable in response to changes in independent variables over time, while also taking into account the equilibrium relationship between these factors (Alemu et al., 2003; Benmehaia, 2021; Erhabor et al., 2013; Hadi et al., 2019; Hendershott et al., 2000; Hendershott et al., 2002; Lim & Yoo, 2016; Lukyanenko & Oliskevych, 2014; Okoroafor et al., 2011; Taghvaee & Hajiani, 2014). Notably, although E.C.M.s are extensively utilized across various industries, including agriculture, real estate, and energy, the results often indicate differing sensitivities to economic stimuli or price fluctuations. For example, research shows that Korean gasoline demand exhibits relatively high elasticity to price and income changes, with increased elasticity over time (Lim & Yoo, 2016). In contrast, the UK property market demonstrates much lower demand elasticities for space in terms of price and income, especially in London (Hendershott et al., 2000; Hendershott et al., 2002). Likewise, in the agricultural sector, while crop supply does respond to price incentives, the long-term elasticities are generally low (Alemu et al., 2003; Benmehaia, 2021). In conclusion, the ECM approach is invaluable for determining trade elasticities, considering both short-term variations and long-term equilibrium conditions.The widespread use of ECM in diverse studies highlights its adaptability and power in modelling the intricate relationships within economic systems. Research outcomes from these investigations emphasize the necessity of examining both immediate and enduring influences when evaluating how trade reacts to economic factors (Alemu et al., 2003; Benmehaia, 2021; Erhabor et al., 2013; Hadi et al., 2019; Hendershott et al., 2000; Hendershott et al., 2002; Lim & Yoo, 2016; Lukyanenko & Oliskevych, 2014; Okoroafor et al., 2011; Taghvaee & Hajiani, 2014).

Various studies have examined the connection between share trading volume and fundamental company metrics, yielding diverse results. In the energy sector, Zhussipova et al. (2023) discovered a reciprocal relationship between trading volume and price formation in Kazakhstan, while Kurniawan et al. (2024) found no influence of trading volume on share prices in Indonesia. Nassirzadeh et al. (2015) emphasized the importance of liquidity and performance indicators on trading volume in Tehran, whereas Rahmisyari (2022) noted that Internet Financial Reporting had minimal effect on stock returns and trading volume in Indonesian banking firms. Muna and Khaddafi (2022) observed that stock split events in Indonesia significantly impacted stock trading volume, suggesting that corporate actions can affect trading activity. These findings present some contradictions. For example, the conclusion by Kurniawan et al. (2024) that trading volume does not impact share prices conflicts with Zhussipova et al. (2023)'s observation of a mutual interaction between trading volume and price formation. Furthermore, Rahmisyari's (2022) finding of the minimal impact of Internet Financial Reporting on trading volume contrasts with Nassirzadeh et al. (2015) emphasis on the significance of financial indicators. The connection between share trading volume and a company's fundamental indicators is intricate and varies based on specific circumstances. While certain research indicates notable correlations between trading activity and financial metrics (Nassirzadeh et al., 2015), other studies show little to no effect (Kurniawan et al., 2024; Rahmisyari, 2022). These conflicting findings imply that the influence of fundamental factors on trading volume may differ across various markets, industries, and corporate events (Muna & Khaddafi, 2022). Additional investigation is required to elucidate these relationships and comprehend the underlying factors that influence trading volume in response to a company's fundamental indicators (Kurniawan et al., 2024; Muna & Khaddafi, 2022; Nassirzadeh et al., 2015; Rahmisyari, 2022; Zhussipova et al., 2023).

The use of the Error Correction Model (ECM) to evaluate Fast-Moving Consumer Goods (FMCG) sector performance is

not directly addressed in the provided literature. ECM, a statistical approach, typically measures how quickly a dependent variable regains equilibrium following changes in other variables. In theory, it could be employed to examine the connection between macroeconomic factors and company performance or to predict electricity usage in production processes within the FMCG sector, as these areas might exhibit equilibrium relationships (Anupama et al., 2022 Yeşil & Bolat, 2019). Notably, while Anupama et al. (2022) recognize that various factors, including liquidity, solvency, and profitability ratios, influence firm performance in India's FMCG sector, they do not mention ECM or any econometric models. Yeşil and Bolat (2019), focusing on electricity consumption forecasting using Artificial Neural Networks (ANN), propose a different methodological approach that ECM could potentially complement to understand energy demand adjustment dynamics. In essence, although the papers offer valuable insights into various aspects of FMCG sector performance, such as IoT impact, strategic partnerships, consumer behavior, and systematic performance evaluation, they do not specifically discuss E.C.M. application in this context (Akhmetova et al., 2023; Olatunji & Awolusi, 2020; Sagar et al., 2018; Siam et al., 2023). Implementing ECM in the FMCG sector would require identifying long-term equilibrium relationships between relevant variables and then utilizing E.C.M. to analyze short-term dynamics around this equilibrium. Collectively, the papers underscore the complexity and multifaceted nature of FMCG sector performance but do not provide a direct basis for ECM application.

Research by Bharti and Verma (2024) suggests that the FMCG industry plays a crucial role in India's economy, with its growth driven by evolving lifestyles and increasing incomes. These factors may indirectly affect trading volumes by influencing company performance and investor sentiment. However, Anupama et al. (2022) present contrasting findings, indicating that non-commercial aspects like Corporate Social Responsibility (C.S.R.) have no bearing on firm performance, implying that not all fundamental factors equally impact share trading volumes. Furthermore, Andrade et al. (2020) emphasize the significance of optimizing product assortment for FMCG manufacturers, which could substantially influence stock trading if investors consider product strategies in their decision-making process. In conclusion, while the cited studies do not explicitly demonstrate a long-term equilibrium relationship between FMCG companies' share trading volumes and key fundamentals in India, they highlight various factors affecting firm performance. These include financial ratios, production and distribution efficiencies, and product assortment strategies (Andrade et al., 2020; Anupama et al., 2022). Although investors may take these fundamentals into account when trading shares, further empirical research is necessary to establish a definitive long-run equilibrium relationship between these factors and share volume.

3. Data & Methodology:

3.1 Scope and Data

This study examines the Fast Moving Consumer Goods (FMCG) sector companies with high trading volumes and turnover on the CNX Nifty, India's national stock exchange. The research focuses on three prominent players in the Indian FMCG industry: Jubilant Food Works Ltd, ITC Limited, and Hindustan Unilever Limited. While Jubilant Food Works Ltd entered the Indian stock market in February 2010, ITC Limited and Hindustan Unilever Limited have been listed since 1995. The analysis covers monthly data from 2012 to 2017, resulting in 189 observations for each company. Key variables examined include trading volume, current market price (CMP), earning per share (EPS), price-to-earnings ratio (P/E), price-to-book value (P/B), and earnings yield. Data was obtained from the Centre for Monitoring Indian Economy (CMIE) Prowess database, and the econometric software EViews was utilized for analysis. To assess their economic performance, the research investigates the connections between price, volume, and other fundamental indicators in the selected FMCG companies. Both long-term and short-term relationships are explored to understand how volume and price interact with other crucial variables like yield and P/E, aiming to justify capital investments in FMCG companies based on their fundamental relationships.

3.2 Econometric Modeling

Engle and Granger (1987) is a seminal paper in econometrics, particularly in time series analysis and cointegration. The paper's full title is "Co-Integration and Error Correction: Representation, Estimation, and Testing," published in Econometrica. Understanding co-integration is crucial for analyzing long-term economic and financial data relationships, particularly when dealing with non-stationary time series.

The Engle-Granger causality technique and Johansen co-integration procedure are econometric methods for analyzing time series relationships. The Engle-Granger causality technique, developed by Nobel laureates Robert F. Engle and Clive W. J. Granger, is primarily employed to ascertain if one time series can predict another. This method is particularly

European Economic Letters
ISSN 2323-5233
Vol 14, Issue 3 (2024)
http://eelet.org.uk

beneficial in identifying lead-lag relationships between economic variables. The procedure encompasses several critical steps: Stationarity testing, Cointegration testing and Error correction model estimation. The Johansen co-integration (1991) procedure, introduced by Søren Johansen, is a more sophisticated technique for testing cointegration in multivariate time series. This method offers several advantages over the Engle-Granger approach: Multiple cointegrating relationships detection and no a priori variable specification requirement.

The vector autoregressive (V.A.R.) model is frequently employed to predict interconnected time series systems and examine how random disturbances dynamically affect a set of variables. By treating each variable in the system as endogenous and dependent on the lagged values of all other endogenous variables, the V.A.R. approach eliminates the need for traditional structural modelling. This study utilizes the V.A.R. framework to investigate the connections between volume, price, and other company fundamentals.

$$VOL_t = C_1 + \sum_{i=1}^{k} a_{1i} VOL_{t-i} + \sum_{i=1}^{k} b_{1i} CMP_{t-1} + \sum_{i=1}^{k} c_{1i} EPS_{t-1} + e_{1t}$$

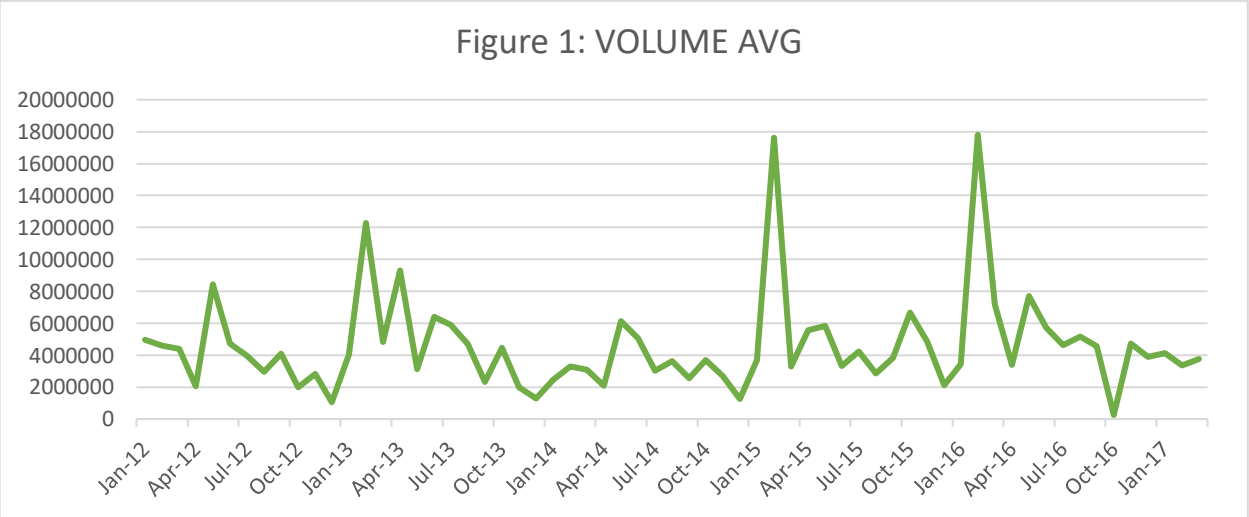
$$CMP_t = C_1 + \sum_{i=1}^{k} a_{1i} VOL_{t-i} + \sum_{i=1}^{k} b_{1i} CMP_{t-1} + \sum_{i=1}^{k} c_{1i} EPS_{t-1} + e_{1t} \ldots\ldots \text{etc}$$

Where VOL is the volume of shares traded each month, C.M.P. is the current market price, EPS is the earnings per share and e1t,e2t ...etc. are the stochastic error terms called as “Impulses or Innovations.” The Vector Auto Regression (V.A.R.) model determines the direction of causality running between the variables. The presence of a co-integrating relation forms the basis of the vector error correction model (V.E.C.M.) specification. VECM-Error correction mechanism used to see the short run behavior of volume and price with the key fundamentals of the company.

4. Results and Discussion

4.1 Trend of volume, price and other indicators

Figure 1 illustrates the trading volume pattern for FMCG stocks. From January 2012 to January 2015, share trading remained relatively stable. However, between April 2015 and April 2016, trading volumes peaked at 16 million shares, followed by a decline that brought levels back to their starting point. Figure 2 depicts the price trend, which, despite fluctuations in volume, showed an overall steady increase from 330 in January 2012 to 685 in July 2015. Subsequently, the price dropped to 498 before resuming an upward trajectory. Notably, periods of low trading volume corresponded with significant price increases, and vice versa. The earnings per share (EPS) trend was positive, ranging from a low of 40 to a high of 60. The profit-to-earnings ratio fluctuated between 20 and 25, while the profit-to-book value ratio varied from 15 to 25. On average, the yield ranged from a minimum of 1 to a maximum of 3 during the study period.



European Economic Letters
ISSN 2323-5233
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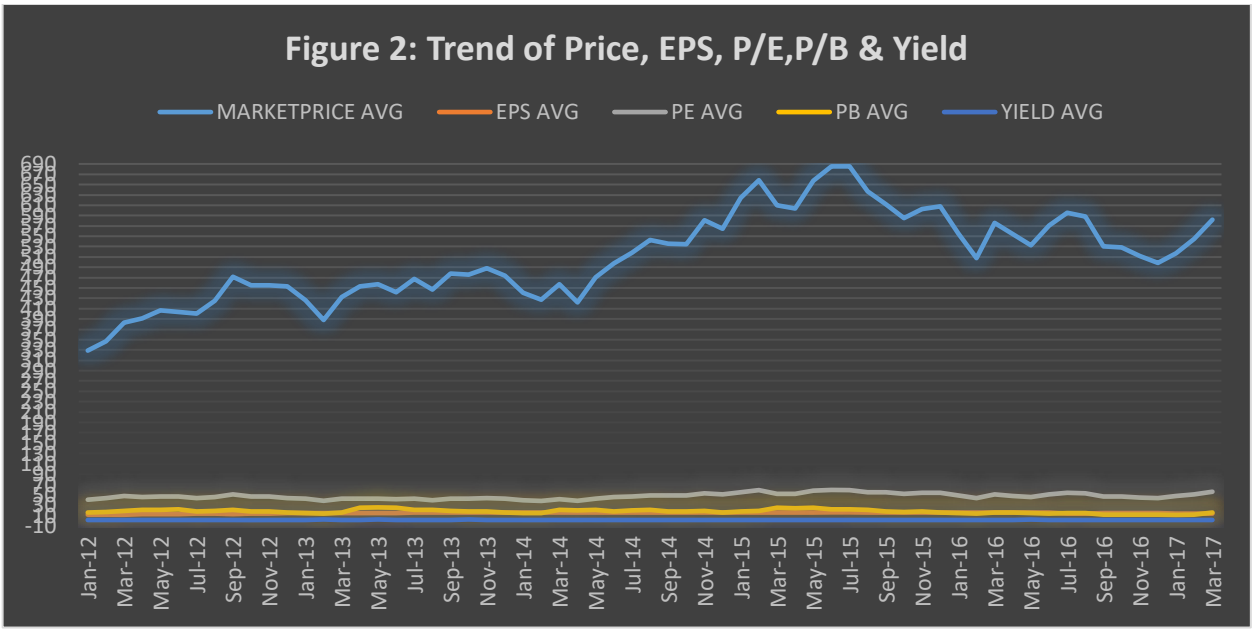
http://eelet.org.uk



4.2 ADF Tests for Stationarity

Table 1: Stationarity sample size 185; unit-root null hypothesis: ρ = 1

Variables In Log Level	Test	ADF Test–P Values	Variables In First Difference	Test	ADF Test–P Values
l_Vol	without constant with constant with a constant and trend	0.9999 0.4343 0.5252	d_l_Sharestraded	without constant with constant with a constant and trend	0.0000 0.0000 0.0000
l_Price	without constant with constant with a constant and trend	0.9965 0.2831 0.5955	d_l_Price	without constant with constant with a constant and trend	0.0000 0.0000 0.0000
l_EPS	without constant with constant with a constant and trend	0.7894 0.2252 0.5465	d_l_EPS	without constant with constant with a constant and trend	0.0000 0.0000 0.0000
l_PE	without constant with constant with a constant and trend	0.6857 0.5181 0.4952	d_l_PE	without constant with constant with a constant and trend	0.0000 0.0000 0.0000
l_PB	without constant with constant with a constant and trend	0.8465 0.1763 0.1672	d_l_PB	without constant with constant with a constant and trend	0.0000 0.0000 0.0000
l_Yield	without constant with constant with a constant and trend	0.8967 0.7060 0.4247	d_l_Yield	without constant with constant with a constant and trend	0.0000 0.0000 0.0000

To implement the VAR-VECM framework, time series data must be stationary. If variables are not stationary in their level form, they can be transformed into stationary data by taking the first difference or integrating it into order one. In this study, all data variables are expressed in natural logarithmic form to mitigate heteroscedasticity effects. The Augmented Dickey-Fuller (A.D.F.) test examines the variables for stationarity. This test assumes a null hypothesis of non-stationarity, with the alternative hypothesis being stationarity. Table 1 displays the p-values of A.D.F. statistics, which are not significant for level form variables but significant for first difference variables. This indicates acceptance of the unit root hypothesis, confirming that the data variables are non-stationary in log-level form but stationary in their first difference form.

4.3 Test for Co-integration

Once it is verified that the data variables are integrated of order one, the subsequent step involves determining whether these variables are co-integrated, indicating a long-term equilibrium relationship among them. This research examines the connections between volume, price, and other fundamental ratios. The Johansen procedure for multivariate co-integration analysis necessitates an adequate number of time lags. The findings reveal that all three criteria - AIC, BIC, and HQC - yield minimum values at the same lag length. Consequently, at the chosen lag length of one, the data variables are evaluated for co-integration, and VAR is employed to ascertain the direction of causality. The results of the lag length selection are presented in Table 2.

Table 2 Lag Selection

VAR system, maximum lag order 10					
The asterisks below indicate the best (that is, minimized) values					
of the respective information criteria, AIC = Akaike criterion,					
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.					
lags	loglik	p(LR)	AIC	BIC	HQC
1	590.19230		-6.125054*	-5.377175*	-5.821795*
2	614.73239	0.07172	-5.997010	-4.608093	-5.433815
3	639.77684	0.05947	-5.874602	-3.844646	-5.051471
4	664.73593	0.06141	-5.751239	-3.080246	-4.668173
5	701.23015	0.00026	-5.756761	-2.444729	-4.413759
6	739.76478	0.00008	-5.785081	-1.832011	-4.182142
7	767.52913	0.01983	-5.693063	-1.098954	-3.830188
8	789.45955	0.17264	-5.535861	-0.300713	-3.413050
9	839.34985	0.00000	-5.691060	0.185126	-3.308313
10	909.38264	0.00000	-6.071314	0.445910	-3.428631

Table 3 Johansen's Co-integration Test

Johansen's Co-integration Test

A. Co-integration rank Tests				
Unrestricted co-integration rank tests, Trace & Maximum Eigen (Lmax) value				
No.of co integrating Equations or Rank	Eigenvalues (λ_i)	Trace Test	P-value	Lmax Test P-value
0	0.43022	161.68 [0.0000]	105.75 [0.0000]	
1	0.12692	55.926 [0.3835]	25.517 [0.3630]	
2	0.087433	0.409 [0.6998]	17.202 [0.5727]	

3	0.04698	13.207 [0.8801]	9.0476 [0.8254]
4	0.02162	4.1593 [0.8845]	4.1100 [0.8417]
5	0.00026	0.04937 [0.8242]	0.049371 [0.8242]

*Both the Trace test and Lmax test indicates one co-integrating equation at both 5% and 1%

B. Normalized co-integrating β and adjustment α coefficients (standard errors in parenthesis)

l_Voll_Price	l_EPS	l_PE	l_PB	l_Yield	Constatnt
β Coefficients:	1.00(0.00)	2.44 (0.62)	-1.04* (0.78)	-1.85**(0.84)	-0.19*(0.24)	-1.24 (0.21)	15.99 (1.42)

d_ l_Vol	d_l_Price	d_l_EPS	d_l_PE	d_l_PB	d_l_Yield
α Coefficients:	−0.83*	0.01	0.007	0.007	0.001	-0.004
P-values:	0.00	0.36	0.39	0.29	0.93	0.85	

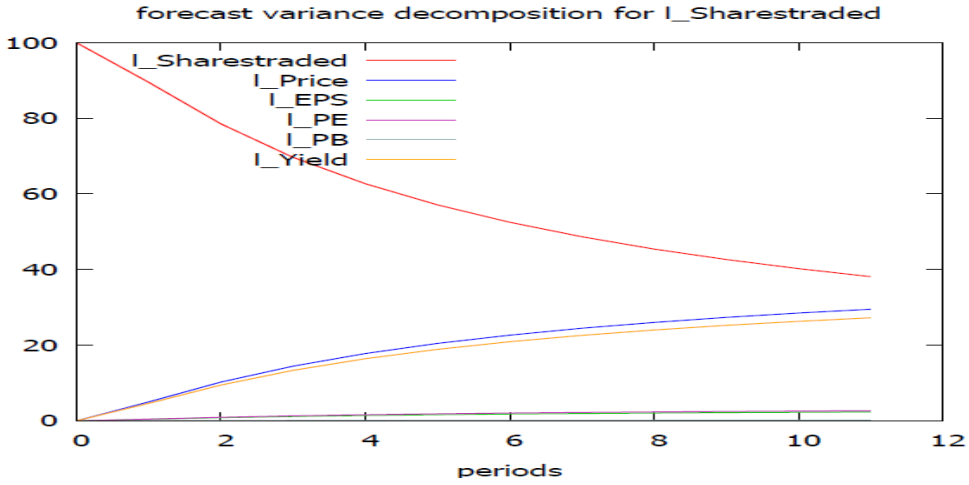
* at 5% & **at 1% level of significance

Table3 gives the results of Johansen's co-integration test for determination of co-integration rank based on trace test and Maximum Eigen (Lmax) value. The trace statistics test the null hypothesis that there are at most "r" co-integrating relations against the alternative of "m" co-integrating relations where r = 0, 1, 2….m-1. Whereas the maximum Eigen value test the null hypothesis of "r" co-integrating relations against the alternative of "r+1" co-integrating relations. Both the Johansen trace test and maximum Eigen values support the rejection of the null hypothesis that there are no co-integrating relations in the system. Both the Trace and Lmax test indicates there exits one co-integrating equation in the system meaning that the volume of shares traded in FMCG sector having a long run equilibrium relation with the price, EPS, PE, PB and yield variables. If the variables are co-integrated then we can measure the short run relationship by using Vector Error Correction Model (VECM).

From the above co-integrating equation it is concluded that a 1 percent change in current market price causes the volume of shares traded to decrease by about 2.44 percent as a correction in profit booking, a 1 percent change in earnings per share causes the volume of shares traded to increase by about 1.04 percent meaning that the almost the equal effort of gaining the cost of the stock as the volume increase at the same pace. A 1 percent change in price-earnings ratio causes the volume of shares traded to increase by about 1.85 percent meaning that the cost recovery happening so fast so that the volumes are increasing. A 1 percent change in price-book ratio causes the volume of shares traded to increase by about 0.19 percent meaning that the stability of the price causes volumes to go up as long as the earnings are positive. A 1 percent change in dividend yield causes the volume of shares traded to increase by about 1.24 percent causing good financial returns on investment boost volumes to go up as long as the investment decisions lies in the grey areas of risk. The endogeneity model of volume of shares traded for FMCG stocks shows that the error correction term (-0.83) is negative and significant which means that there exists a long run causality running from all the remaining variables viz..Current market price, earnings per share, price to earnings, price to book and dividend yield. However in the short run there is no significant causal relationship exists in the system. The residual and diagnostic checks of VECM model is found to be satisfactory.

4.4 Innovations

Figure 3 Forecasting the Variance Decomposition



The innovations contributed from within may found from decomposition of error variance, Figure 3 gives the details of forecasting of volume of shares traded for FMCG stocks over a period of 12 months it is found that own innovations or shocks will reduce the volume to 40%, the price and dividend yield will increase moderately about 30%, there is no much change in the other variables for the next 12 months period. The results are verified with the current data from April 2017 to March 2018 to confirm the results, the results found to be satisfactory.

5 Conclusion

The endogeneity model for studying the volume of stocks traded in FMCG sector by using the key fundamentals of the company shows both the long run and short run relationship between the variables. A long run stable relationship exists between the volume of shares traded, current market price, earnings per share, price to earnings, price to book and dividend yield. The short run coefficients or error correction terms are less than zero indicates the speed of adjustment to the equilibrium relation takes time as it is evident from the variance decomposition. Investors in FMCG sector should look for long term investment or look for at least for the period of one year for short term gains depending on the quarterly results of EPS, P/E and P/B dynamics as they drive the market in the long run more profitable than for short term. The own drive of volume does not guarantee the healthy run for the FMCG stocks, it requires both the short price movements and long run fundamentals.

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