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Dynamic Linkages of Stock Market Sectors: Evidence from the Kenyan Stock Market

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Abstract This paper undertakes an empirical investigation into the dynamic linkages of the Nairobi Securities Exchange's sectors. Using weekly indices for the 9th June 2008 to 14th February 2019 period, it examines the dynamic linkages of the Investment, Manufacturing and Allied, and Banking sectors. The study finds out the presence of one cointegrating relationship in the long run. A Vector Error Correction Model is fitted to estimate the temporal relationships of the three indexes. Results of Granger Causality testing, which are based on the VECM output, indicate the presence of bidirectional granger causality between the Manufacturing and Allied & Banking sectors as well as the Banking & Investment sectors. However, there is no granger causality between the Investment & Manufacturing and Allied sectors. Impulse response analysis show that shocks to the Manufacturing and Allied Sector are least significant in terms of their ability to invoke responses from other sectors, while shocks to the Banking sector are most influential as far are the tendency of elevating the volatility of other sectors' indexes is concerned. Forecast Error Variance Decomposition (FEVD) analysis further indicate that shocks to the banking sector are most influential in terms of their explanatory power of other sectors' forecast variances. The study therefore concludes that the banking sector has the highest tendency to influence other sectors' volatility, while the Manufacturing and Allied Sector is least significant in terms of its ability to influence other sectors' volatility. Therefore, it is recommended that that stocks that are listed under the Manufacturing and Allied Sector should be considered for diversification purposes due to the low scale of linkages that this sector has with other sectors. But, better still; investors should seek inter-market diversification opportunities in order to tap fully into the benefits of portfolio diversification.

Keywords: *dynamic linkages, sectoral indexes, cointegration, impulse response analysis, forecast error variance decomposition*

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1. Introduction

There has been a surge in the level of integration within various sectors of security markets around the world in the recent past [1]. Inasmuch as this has enhanced seamless transfer of information across the sectors and hastened the pace of conducting business, a major drawback of stock market integration is that it also has perpetuated the cross transmission of sectoral shocks, thereby leading to elevation of systemic volatility across entire markets [2].

Hurditt [3] opines that in individual security markets, it is crucial to understand propagation of shock and volatility transmission across market sectors in order to determine their persistence, significance and direction over time. This is because large shocks in the highly crucial sectors could generate waves of volatilities and aftershocks that can be highly detrimental to other sectors. Furthermore, awareness of dynamic inter-sector linkages could help investors and policy makers to take interventionist actions on time thereby mitigating the adverse effects of this transmission.

Therefore, it is important for investors to comprehend the interrelationships among different indexes of any economy before portfolio selection and allocation. Additionally, the decision on whether to include securities drawn from different sectors of the economy in a portfolio or not depends on a number of reasons including how, and to what extent, are various sectors related in terms of the tendency of shocks and volatility to spillover over from one sector to another [4]. While studies on dynamic sectoral interrelationships have been extensively conducted in developed countries, they are scanty in the developing nations, especially in Sub Saharan Africa. With increased interest in African securities markets by international investors who are keen on geopolitical diversification of their holdings, the dearth of research on sectoral linkages needs to addressed. This should enhance the information set available to international investors thereby enriching their decision making processes.

Further, an investigation into the dynamic linkages of the NSE's sectors is important due to its desirable implications to various stakeholders, such as regulatory authorities, researchers, investors, and portfolio managers. To attain this aim, the study examines the extant granger causality relations - whether available values on a given market sector can be used to forecast future values about other sector(s) - amongst the NSE's sectors. Moreover, impulse response analysis is undertaken to investigate how asset values - and hence volatility - in each NSE sector react to their own exogenous shocks and those of other sectors. Finally, the forecast error variance decomposition methodology is utilized to appraise the extent to which future volatility in each NSE sector can be attributed to its own shocks and also to shocks of other sectors.

The rest of the paper is structured as follows: The next section presents a concise overview of the Nairobi Securities Exchange, followed by a brief review of literature. Next, the methodology is articulated; after which the section on data analysis and empirical results is outlined. Finally, the conclusion and recommendations of the study are elucidated.

2. Literature Review

Ewing [4] utilized monthly data from January 1988 to December 1997 and a generalized forecast error variance decomposition methodology to examine the dynamic linkages of five (capital goods, financials, industrials, transport and utilities) S&P sectoral indexes. The results found strong interrelations amongst the five sectors in that unanticipated shocks to each sector's returns had a significant influence on the volatility were readily impactful on other sectors' returns.

Hassan and Malik [5] investigated the shock and conditional volatility transmission patterns in six sectors of the US economy. Using a BEKK MGARCH model, their results yielded evidence of highly persistent and statistically significant transmissions of volatility amongst all 15 pairs of the 6 sectors. Shock transmission was significant amongst 11 pairs but with a lower level of persistent as compared to volatility transmission.

Using log-normalized daily returns for the Sep 2000 to Aug 2007 period, Al-Fayoumi, Khamees, and Al-Thuneibat [2] used a Vector Error Correction (VECM) model to investigate multivariate cointegration and causal linkages of four (general, financial, industrial and services) sectoral equity indices of the Amman Stock Exchange in Jordan. The four indices were found to be linked via one cointegrating vector. After fitting the Vector Error Correction Model (VECM) and running granger causality tests, results showed strong unidirectional granger causality effects from general, financial, and Industry sectors to the service sector. These results were triangulated with variance decomposition and impulse response analyses and there was a concurrence of the output. The financial sector was inferred to be the most influential sector in terms of shock and volatility transmission, while the services sector had the least transmission linkages with other sectors. As such, the service sector could offer give the best diversification opportunity of all sampled sectors.

Using a DCC MGARCH model and daily sectoral returns for the January 2, 2008 to September 30, 2010 period, Righia and Ceretta [6] modelled conditional variances and dynamic correlations of the firms listed in the financial and consumer sectors of the BM & F BOVESPA stock exchange in Sao Paulo, Brazil. This research yielded evidence of bidirectional transmission of shocks and volatility between the two sectors. The volatility spillover relationship between the New York Stock Exchange (NYSE) and the JSE was investigated by Yonis [7]. This study concluded the existence of persistent and statistically significant unidirectional volatility transmission from the NYSE to the JSE.

Salman, Rizvi and Parweiz [8] investigated the spillover effects originating from the Banking sector to the Banks, Oil and Gas, Construction, Chemical, Food Producer, Fixed Line Telecommunication, Electricity and Personal Goods sectors of the Pakistan Stock Exchange. This study used daily data of 251 firms that are categorized under these eight sectors and the data collection period was January 2008 to December 2012. Weighted (by market share) average returns were computed from the daily firm-level returns to get the sectoral returns. The study used the BEKK MGARCH model and yielded evidence that volatility in the banking sector tended to spillover to all other sectors of the equity market.

Kalu and Ali [9] examined domestic spillover effects between sectors of the Nigerian economy using a BEKK MGARCH methodology. The central focus was to evaluate the nature and direction shock and volatility transmission between the banking sector, the consumer goods sector and the Shariah compliant equities sector of the Nigerian Stock Exchange. Results indicated the existence of unidirectional shock and volatility transmission from the banking sector to the consumer goods sector and the Shariah compliant equities sector, and bidirectional shock and volatility transmission between the consumer goods and the Shariah compliant equities sectors of the Nigerian Stock Exchange. These findings were deemed to have crucial implications for domestic portfolio selection and management through the hedging opportunities available in the Nigerian Stock Exchange sectors.

Wang, Kutan, and Yang [10] used a generalized forecast error variance decomposition methodology and daily data for the 1994 - 2001 period to investigate the impact of information flows on sectoral returns within and across the sectors of two (Shanghai and Shenzhen) stock exchanges in China. Their proposition was that information flows are tantamount to shock flows and market volatility is driven by arrival of new positive or negative information. The study found out that in both markets, there was a high level of integration and sectoral prices reflected information from other sectors. Additionally, in both markets, shocks to the Industry sector were found to have the highest tendency to influence the returns of other sectors in both markets. The study also found the finance sector of the Shenzhen stock exchange to have the least level of integration and hence the tendency to transmit its shocks and conditional volatility to other sectors of the same market. This result is rather intriguing given the fact that this sector is the one that is quite interlinked with other sectors in the sense that it provides capital to build other sectors. In other markets, the general tendency is for shocks to the finance sector to be readily transmitted to other sectors.

The present paper therefore sought to enhance the literature by providing empirical evidence on the dynamic linkages that are extant amongst the sectors of the NSE.

3. Methodology

3.1. Data

The study was based on three sectors of the Nairobi Securities Exchange: Investment (INV), Manufacturing and Allied (MAA), and Banking (BNK) sectors. Data comprised of these sectors' daily capitalization-weighted index values for the 9th June 2008 to 14th February 2019 period. The final dataset had 3 time series with each having 2680 observations. For each of the sampled sectors, the daily index, $\psi_{i,t}$, was computed as per Equation 1 below:

$$\psi_{i,t} = \frac{\sum_{s=1}^{n} P_{s,t} CAP_{s,t}}{\sum_{s=1}^{n} CAP_{s,t}} \tag{1}$$

Where:

- $P_{s,t}$ is closing price of stock *s*, one of the constituents of sector *i*, as at end of day *t*
- $CAP_{s,t}$ is market capitalization of stock *s*, one of the constituents of sector *i*, as at end of day *t*
- *n* is the number of stocks that are listed under sector *i*
- $i = 1,2,3$ sectors
- $t = 1, 3, ..., 2680$ days

3.2. Specification Tests

The main aim of the study was to investigate the dynamic linkages of the NSE's Investment, Manufacturing and Allied, and Banking sectors. In order to specify the most suited empirical model for the envisaged analysis, the study undertook tests for stationarity and cointegration.

3.2.1. Unit Root Testing

Unit Root Testing revealed the weekly index data of the three sampled firms to be non stationary at levels. This is as per Table 1 which indicates the results of Augmented Dickey Fuller (ADF) Unit Root tests for level indexes and their 1st differences. However, the first differences are stationary at the 1% level, thereby implying that the sectoral indexes are integrated of order one.

3.2.2. Testing for Cointegration

The Johansen cointegration test was utilized to test for cointegration in the study's raw data. As evident in Table 2, both trace and maximum eigenvalue tests indicated the presence of 1 cointegrating equation at the 5% level of significance. This output informed the choice of fitting a vector error correction model which is able to account for dynamic linkages amongst cointegrated variables that are not covariance stationary.

3.3. Empirical Model

Since Augmented Dickey Fuller Unit Root tests revealed that all three series were not stationary at levels and the Johansen test for cointegration indicated the presence of one cointegrating equation, the study fitted a Vector Error Correction model to investigate the dynamic interrelationships between the Investment, Manufacturing and Allied, and Banking sectors of the NSE. Based on the output of the VECM model, Granger Causality Testing as well as Impulse Response Analysis and Forecast Error Variance Decomposition procedures were undertaken to appraise the objective of the study.

Table 1. Augmented Dickey Fuller Tests for Stationarity

	INV		MAA		BNK	
	Level	1st Difference	Level	1st Difference	Level	1st Difference
ADF Test Statistic	-1.26	-44.41***	-1.23	-32.36***	-0.81	-30.73***

(***) denotes significance at the 1% level

Table 2. Johansen Cointegration Test

	Trace Test			Max-Eigen Test		
Hypothesized No. of CE(s)	Trace Statistic	0.05 Critical Value	P-value	Max-Eigen Statistic	0.05 Critical Value	P-value
None *	35.14	29.80	0.01	22.47	21.13	0.03
At most 1	12.67	15.49	0.13	10.04	14.26	0.21
At most 2	2.63	3.84	0.10	2.63	3.84	0.10

Table 3. Descriptive Statistics

	Mean	Max	Min	S Dev.	Skewness	Kurtosis	Jarque-Bera	P value
INV	34.79	83.05	14.65	15.09	0.66	2.57	215.59	0.000
MAA	437.02	696.21	276.72	95.69	0.41	2.31	126.44	0.000
BNK	559.91	949.76	261.85	165.18	0.34	2.42	89.79	0.000

4. Data Analysis and Empirical Results

4.1. Descriptive Statistics

As evident in Table 3, the Banking sector has the highest mean for the daily index values, followed by the Manufacturing and Allied sector while the investment sector's index has the least mean. Moreover, the Banking sector's index has the largest maximum closing values but the Manufacturing and Allied sector's index has the largest minimum closing value. The investment sector's index has the least maximum value and also the least minimum value. Further, the banking sector's index has the highest standard deviation, followed by the Manufacturing and Allied sector's index, and the Investment sector's index has the least standard deviation. These results reflect the fact that the Banking sector's stocks have the highest on share prices, followed by the Manufacturing and Allied sector; while stocks of the investment sector have the least aggregate market value. All three indexes have positive skewness, implying that their distributions are asymmetrical with fat left tails. Furthermore, the three indexes are platykurtic since their levels of kurtosis are less than three. Finally, all Jacque Bera Statistics are strongly significant, thereby implying that the null hypothesis of normality is rejected for all three indexes. It is noteworthy that the values of the indexes depend on the actual market prices of the stocks that are listed under them; and whether such stocks have been subjected to share splits or not. Therefore, these values are not indicative of the relative performances of the various sectors at all.

4.2. Correlation Analysis

The study undertook correlation analysis between the sampled sectors, in order to evaluate their contemporaneous interactions. Table 4 shows that the three indexes have very high levels of pairwise correlation. Arbelaez, Urrutia and Abbas [11] note that sectors that high levels of correlation between any pair of sectors is an indication of the existence of substantial contemporaneous linkages between them. Such linkages cause the pertinent sectors to have similar and simultaneous reactions to exogenous shocks.

Table 4. Correlation Matrix of Sampled Sector's Daily Indexes

	INV	MAA	BNK
INV	1		
MAA	0.8920*	1	
BNK	0.8260*	0.8515*	1

(*) denotes significance at the 5% level

4.3. Trend Analysis

It can be inferred from Figure 1 that there is a systematic decline in all indexes as from the second quarter of 2008. Ostensibly, this can be attributed to the fact that as at the start of the data collection period, the NSE's equities were still reeling from the bear run of 2008 that was brought about by the global financial crisis and Kenyan post election strife of 2007/2008.

From the time plots, it's clear that there are three distinct periods of market appreciation: there is a general upward trend in all indexes as from the second quarter of the 2009 until the end of the second quarter of 2010 when all indexes start to go on a downward trend again. For all three indexes, the most prominent bull run commences around the start of 2012 and peaks in the second quarter of 2014. After this period, the three indexes enter in a period of extreme decline until the second quarter of 2017, after which they start recovering marginally, before getting into a downward trend again in the third quarter of 2018. Figure 1 clearly shows that the three indexes have a high degree of cointegration. This can be attributed to the influence of market-wide systemic influences as well as dynamic linkages which could be extant amongst them.

4.4. Optimal Lag Length Selection

Optimal lag order selection was undertaken using the sequential modified LR test Likelihood, final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion. Table 5 shows the optimum number of lags for an unrestricted VAR model is 4, as per the final prediction error and Akaike information criterion. Becketti [12] notes that the optimal lag order for a VECM model is less than that of its corresponding VAR model by one degree of freedom. Therefore, the VECM model was fitted using three lags.

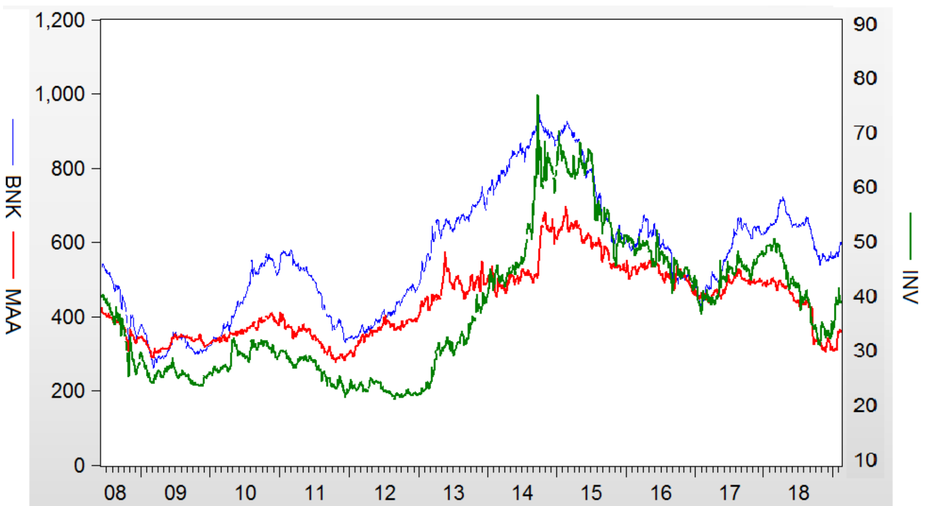

Figure 1. Trend Analysis

Table 5. Optimal Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-40509.94	NA	2.97e+09	30.32405	30.33067	30.3264
1	-19145.58	42664.74	338.9585	14.33951	14.36596	14.349
2	-19033.49	223.5942	313.7869	14.26235	14.30864*	14.2791
3	-19007.23	52.32430	309.7590	14.24943	14.31556	14.273*
4	-18992.79	28.74716	308.4994*	14.24535*	14.33133	14.2764
5	-18986.57	12.35676	309.1431	14.24744	14.35325	14.2872
6	-18983.82	5.473830	310.5913	14.25211	14.37777	14.2975
7	-18972.28	22.87417*	310.0033	14.25021	14.39571	14.3028
8	-18967.26	9.953660	310.9275	14.25319	14.41853	14.3130

4.5. VEC Granger Causality Testing

In the presence of cointegration and first order integration, granger causality analysis is based on the output of a VECM and is augmented by including a single lagged error correction term (ECT) in each causality model. For each variable, the coefficient of the ECT represents its speed of adjustment towards the long run equilibrium relationship which it has with other cointegrating variables (Engle and Granger, 1987; Granger, 1988). After undertaking VEC analysis, the study undertook granger causality testing amongst the sample sectoral indexes, using Block exogeneity Wald tests. Table 6 summarizes the results of granger causality tests. The results indicate the presence of bidirectional granger causality between the Manufacturing and Allied & Banking sectors as well as the Banking & Investment sectors. The central role of the banking sector in the NSE is illustrated by the fact that its index values can be forecasted in the short run on the basis of the other two sectors' lagged index observations while, conversely, each of these two sectors is also granger-caused by the banking sector. Additionally, the study found no evidence of granger causality between the Investment & Manufacturing and Allied sectors. The economic implication of these findings is that fluctuations of the banking sector index can be predicted, to a certain degree, on the basis of lagged fluctuations of the investment and manufacturing and allied sectors. Likewise, the movements of the banking sector's index can be partly used to forecast future movements of the Investment and Manufacturing & Allied sectors' indexes. The results further imply that one cointegrating relation exists between the Investment and Banking sectors, and that the Investment sector has a higher speed of adjustment towards the long run equilibrium relationship than the Banking sector. On the other hand, the Manufacturing sector doesn't have any cointegrating relation with any other sector and hence its error correction term is divergent.

4.6. Impulse Response Analysis

The study undertook impulse response analysis to evaluate how each of the three sectoral indexes would respond to an exogenous shock. Figure 2 shows the impulse response analysis plots. It can be seen that on average, the Investment sector is least responsiveness to impulses, followed by the Manufacturing and Allied sector. The Banking sector has the highest aggregate responses to impulses. This observation can be attributed to fact that Investment sector is the smallest in terms of market capitalization while the Banking sector had the highest market capitalization. Therefore, the banking sector's index is most susceptible to disruption by exogenous shocks. Furthermore, it is evident that each index is most responsive to its own shocks. On the response to cross shocks, it can be noticed that the investment sector is more responsive to shocks from the Banking sector than the Manufacturing and Allied Sector. Furthermore, Shocks to the Investment sector evoke a higher response in the Banking sector as compared to the Manufacturing and Allied Sector's shocks. Finally, the Manufacturing and Allied Sector is noticed to be more reactive to shocks from banking sector *vis-à-vis* the investment sector. In a nutshell, shocks to the Manufacturing and Allied Sector are least significant in terms of their ability to invoke responses from other sectors, while shocks to the Banking sector are most influential as far are the tendency of elevating the volatility of other sectors' indexes is concerned.

Table 6. Summary of Granger Causality Tests based on VECM output

	Short Run Lagged Differences			
Dependent Variables	ΔINV	ΔMAA	ΔBNK	ECT_{t-1}
	Wald χ^2 Statistics			t-statistics
ΔINV	-	1.543	26.439***	-0.00476***
ΔMAA	2.857	-	27.389***	0.044948***
ΔBNK	51.653***	24.682***	-	-0.03679***

(***) denotes significance at the 1% level

4.7. Forecast Error Variance Decomposition

Forecast Error Variance Decomposition (FEVD) analysis shows the prognosis of a sector's Forecast Error Variance over a definite time horizon, in terms of how own and cross shocks drive sectoral variability at each time horizon. Ostensibly, for each sector, own shocks account for all volatility at a 1-day horizon. However, as the horizon lengthens, the impact of cross shocks from other sectors starts to become more and more influential on the volatility of the pertinent sector. Table 7 indicates the FEVD output for 1-day, 2-day, 4-day, 6-day, 8-day and 10-day horizons.

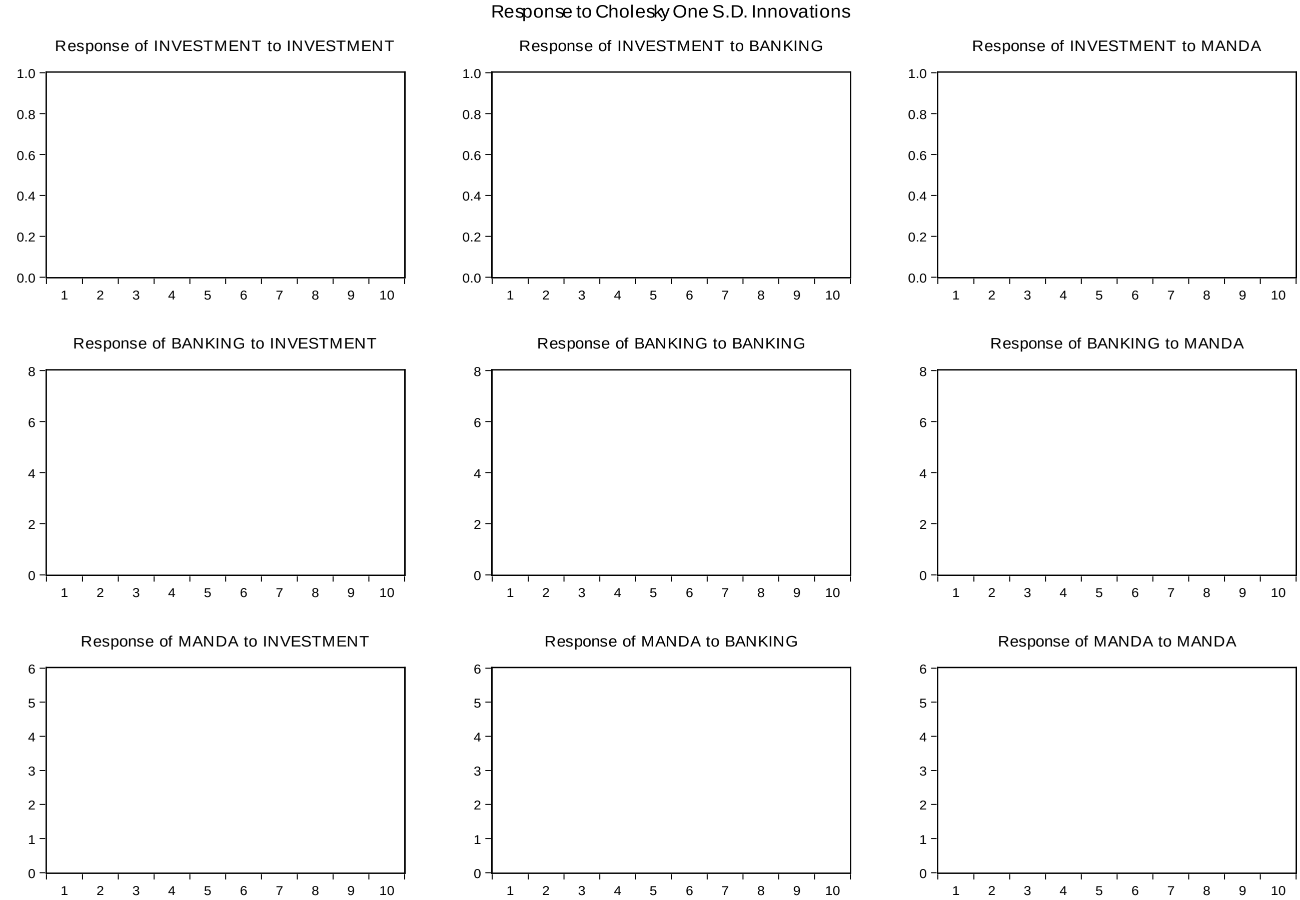

Figure 2. Response of Sectoral Indexes to one Standard Deviation Innovations

Table 7. Decomposition of Sectoral Indexes' Forecast Error Variances

Index	Horizon (days)	Percentage of Forecast Error Variance explained by Shocks to:		
		ΔINV	ΔMAA	ΔBNK
ΔINV				
	1	100.0000	0.000000	0.000000
	2	99.60269	0.042645	0.354665
	4	98.59926	0.272549	1.128189
	6	98.13180	0.463097	1.405100
	8	97.83640	0.623447	1.540152
	10	97.58991	0.774639	1.635455
ΔMAA				
	1	0.056268	99.94373	0.000000
	2	0.278967	99.43775	0.283288
	4	0.878928	97.92741	1.193660
	6	1.413311	96.93068	1.656013
	8	1.773777	96.31538	1.910843
	10	2.055788	95.87777	2.066441
ΔBNK				
	1	2.738926	1.322222	95.93885
	2	5.109879	2.507492	92.38263
	4	8.430392	4.564875	87.00473
	6	9.540744	5.872542	84.58671
	8	9.833218	6.729462	83.43732
	10	9.894880	7.364741	82.74038

For all sectors, own shocks have a larger explanatory power of Forecast Variance than cross shocks at each time horizon. By the end of the 20th day, 97.59% of the investment sector's variance is attributed to own shocks. Similarly, own shocks account for 95.88% and 82.74% of variance in the Manufacturing and Allied and Banking sectors respectively. It is apparent that shocks to the banking sector are most influential in terms of their explanatory power of other sectors' forecast variances. This is inferred from the fact that they account for 1.64% of the Investment sector's variance and 2.07% of the Manufacturing and Allied sector's variance as at the 20-day horizon. The Banking sector plays a role in that it provides the capital to finance the assets and operations of other sectors, and hence its shocks are likely to have systemic effects on all other market sectors.

5. Conclusion

This study endeavors to unearth the dynamic linkages of the NSE's most liquid sectors - the Investment, Manufacturing and Allied and Banking Sectors. Data analysis shows that each sectoral index has a unit root at levels. However, stationary is attained at first difference. Cointegration testing reveals the presence of one cointegrating relation, ostensibly between the investment and banking sectors. Granger causality analysis, which was based on the output of a VECM, shows that the presence of bidirectional granger causality between the Manufacturing and Allied & Banking sectors as well as the Banking & Investment sectors. This implies that the Banking sector's index can be partly predicted, in the short run, on the basis of lagged information from the Investment and Allied and Investment Sectors. Conversely, the value of the banking sector's index, as at any given time, can be partly used to forecast the future values of these Investment and Allied and Investment Sectors. However, there is no granger causality between the Investment and Manufacturing and Allied sectors. The results further imply that the Investment sector has a higher speed of adjustment towards the long run equilibrium relationship than the Banking sector. Results of impulse response analysis and forecast variance error decomposition show that sectoral volatility, and hence returns, of each sector are influenced by both own and cross shocks. The banking sector has the highest tendency to influence other sectors' volatility, while the Manufacturing and Allied Sector is least significant in terms of its ability to influence other sectors' volatility

Similarly to Al Fayami et al., [2] and Wang et al., [10], the study notes that intra-market diversification that involves inclusion of the investment and banking sectors in the same portfolio is likely to be an exercise in futility due to these sectors' existential dynamic linkages. Therefore, the study recommends that stocks that are listed under the Manufacturing and Allied Sector should be considered for diversification purposes due to the low scale of linkages that this sector has with other sectors. But, better still; investors should seek inter-market diversification opportunities in order to tap fully into the benefits of portfolio diversification.

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