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Does Lead-Lag Relationship Exist Among Large Cap, Mid Cap and Small Cap Segments of Indian Capital Market?

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Abstract

The study investigates the lead-lag relationship among the large-cap, mid-cap, and small-cap segments of the Indian capital market. The daily total return index values data represent three segments i.e., Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250 are collected. The Granger causality test is employed to capture the lead-lag relationship among the indices. The dynamic interaction and decomposition among the indices have been explained using the Impulse Response Function (IRF) and Variance decomposition (VDC). The empirical analysis reveals that Nifty Smallcap 250 is caused by both Nifty 100 and Nifty Midcap 150. The study concluded that Nifty 100 is the market leader, and Nifty Smallcap 250 is the market's follower. The study results are relevant for investors and portfolio managers as they may

keep track of Nifty 100 index, which might bring considerable additional benefits and help the investor in portfolio risk management.

Keywords: Granger causality test, Largecap index, lead-lag relationship, Midcap Index, Smallcap Index

1. Introduction

"Who leads, who lags?" has always been a question among different communities of investors. To answer this question, the prior research emphasised the importance of understanding the lead-lag relationship of the global capital market. As the world is becoming more economically and financially integrated, it is crucial for all stakeholders, especially international stock market investors, to recognise the relationships between certain economies (Singh, Kishor, 2017). Transfer and translation of information to markets are among the most pressing issues confronting the financial system. According to traditional asset-pricing theories, in an efficient market, information is instantly disseminated (Hou, 2007). However, there is enough empirical evidence that investors are faced with significant friction, and the transmission of information is slow in the market. A small proportion of stocks in the stock market are leading market indicators because fluctuations in these stocks have ripple effects and thus influence more stocks. The follow-up stocks tend to replicate the price movement of leading stocks later. This effect is known as lead-lag (Fan et al., 2021).

Substantial evidence suggests a lead-lag effect on equity markets. The lead-lag effect may be described as when a company's stock prices reflect a delayed response to price movement of another stock. This is also an asymmetric effect. With an example, let's understand that returns of small company are linked to previous returns given by large companies, but not the other way around (Lo, Mackinlay, 1989). As an explanation for these cross-relationships, they exclude nonsynchronous trade. Consequently, several additional explanations were proposed. Transaction costs account for the asymmetry in the cross-relationship between large and small stock returns. This demonstrates that price adjustment in large stocks is more significant than in small stocks. (Mech, 1993). However, numerous market frictions are quoted in the literature, which may identify the lead or lag stocks in one market on the other. The identification of leader stocks in the market has always been a crucial issue. There is always a discussion among the investors about when to buy, and what to buy so they can build their portfolio by considering the companies of different sizes. Company size is also an important factor in investment. Traditional wisdom holds that small business stocks outperform large-cap stocks over a long period of time. If the lead-lag relationship between large-cap, mid-cap, and small-cap stocks persists, an investment manager will find it simple to devise techniques to foresee movements in one group of stocks using the other (Rehman, Shah, 2018). The critical relationship between different portfolios is essential for earning higher stock returns and creating alternative investment strategies. Investors can predict the movements of small-cap stocks and build investment strategies if large-cap stocks lead to small-cap stocks.

On the contrary, Small-cap stocks will instead lag large-cap stocks (Kayali, Akarim, 2011). In comparison to small stocks, large stocks are focused more by institutional investors. So, additional information is collected to analyse the large stocks. Investors who specialise in small stocks only have to rely on large stock price movements because price movements in large-cap stocks indicate the information quality generated by institutional investors (Chan, 1993). The information disseminated by large stocks guides the investors to book short-term benefits and purchase them again for speculative trading. Many investors have thus become confused about when to buy these stocks. However, the market favours different companies at different times, which leads to a rotation of the market capital. Some of the investors also compare their returns with the different index returns from time to time. The index is the number that represents the whole stock market. In order to ensure uniformity in the investment universe, the regulator of the Indian capital market Securities Exchange Board of India (SEBI), segregated the companies according to their size and in order of their market capitalisation. SEBI defined them as large-cap, mid-cap and small-cap. Large-cap are the 1st-100th companies; mid-cap are the 101st-250th companies, and small-cap 251st onwards. National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) are two major stock exchanges in India. Nearly 5400 companies are listed on BSE, and 2000 companies are listed on the NSE. NSE of India stands among the top five stock exchanges of the world and has a market capitalisation of $3.21 trillion. Sensex and Nifty 50 are the major indices of the BSE and NSE, respectively. The top 100 companies, also termed as large-cap companies, represent around 77% of the free-float market capitalisation of companies listed on the NSE and other mid and small-cap companies represent the rest of the market capitalisation. Morgan Stanley Capital International (MSCI), one of the leading index providers, includes 107 stocks in the MSCI India index from large-cap and mid-cap segments representing 11 sectors of the Indian equity market. So, it is necessary to investigate the lead-lag relationship among large-cap, mid-cap and small-cap indices. This investigation helps investors to study these movements together with the market, economy, and stock.

The contribution of current research to the existing literature is performed in different ways. The study used total return index values for the analysis. The total return index has more significance and factuality as it analyses price fluctuations and dividend payout in index participant stocks. The study employed the Vector Autoregressions (VAR) Granger causality test, one of the best techniques to measure the multiple variables' lead-lag relationship. Further, the study also employed Impulse Response Function (IRF) and Variance Decomposition (VDC) to make the findings robust. Thus, the study allows the stakeholders to understand the Indian capital market and design their portfolios.

The rest of the paper is structured as follows: Section two discusses the existing literature on the lead-lag relationship, and section three contains the study's objectives. Sections four and five discuss the empirical research design, analysis, and results. Section six concludes the paper.

2. Literature Review

This section discusses prior studies conducted on the lead-lag relationship. Camilleri et al. (2019) looked at the links between stock prices and major macroeconomic indicators of Belgium, France, Germany, the Netherlands, and Portugal from 1999 to 2017. According to Vector Autoregressions (VAR) models applied in this study, stock prices significantly outpaced inflation in all countries over the data period, and the association was mainly positive. Ratanapakorn and Sharma (2007) looked at the relationship between the six macroeconomic variables and the US stock index. Pan and Mishra (2018) looked into the relationship between the financial market and economic growth. Kaur and Sidhu (2014) discovered a unidirectional causal relationship between India's exports and agricultural GDP based on time series data from 1970 to 2011. Joshi (2016) used IRF and VDC to examine one variable's response to shocks delivered to other variables. Victor et al. (2021) found that the CNY, USD, and JPY have a short-run causal linkage with the NSE Nifty. The index has also appeared to impact the exchange rates of INR/USD. The IRF adds to the findings of the Granger causality test by revealing the time it takes for the Nifty to recover from a shock induced by exchange rate fluctuations. Sajjan and Sahu (2020) used Johansen co-integration, and pairwise Granger Causality tests to analyse the data from the DAX, FTSE, Nikkei, SSE, and S&P stock indices to investigate the nature of the relationship between Nifty and chosen foreign market indices and found that Nifty is influenced by the other stock indices except for the index of China.

Let us now explore the prior literature on the lead-lag relationship between the spot and futures markets. Chang and Lee (2015) and Shao et al. (2019) investigated the lead-lag relationship between the spot and futures market of crude oil. Raju and Shirodkar (2020) used the Vector Error Correction Model (VECM) and found that the futures market contributes more to price discovery than the spot market. The Toda Yamamoto modified Granger causality test results of Singh and Singh (2018) deduced no causality from futures trading volume to macroeconomic variables. Wang et al. (2017) concluded that a lead-lag relationship exists between the spot and futures prices of the CSI 300 index. Using the three-step approach, Kharbanda and Singh (2017) analysed the lead-lag between the spot and futures prices of the foreign exchange market. First, Augmented Dickey-Fuller Test (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) were used to test the stationarity of the data. Second, the residual-based approach of Engle and Granger and Johansen's co-integration test were used to determine the long-run co-integrating relationship between the markets. Last, the VECM is used to estimate error correction to determine the leading market. The study discovered that the futures market is emerging as the leading market and has a long-term relationship with the spot market. Debasish and Mishra (2008) found that futures prices contain vital information about spot prices.

Market capitalisation indicates stock market performance. Therefore, knowing a company's size is necessary when comparing one to another. Using the Granger causality test, Kang and Yoon (2011) discovered unidirectional transmissions from large stocks to medium and small stocks. Switzer (2010) examined the relative performance of small-caps and large-caps. Rehman and Shah (2018) attempted to determine whether there is a consistent lead-lag relationship between the returns of small and large stock portfolios. Bhaumik et al. (2018) discovered that reforms had a considerably more significant impact on mid-cap companies than large-cap and small-cap companies in the Indian stock market. Jagannarayan and TA (2021) looked into whether the movements of large-cap, mid-cap, and small-cap stocks impact the Sensex's overall movement. The study's findings demonstrate that indices show a significant positive association with the Sensex movement. Karmakar (2010) used the VAR model, VDC, and IRF analysis to identify a casual and dynamic association between large and small stocks. Sachdeva (2020) tries to analyse the impact of small-cap and mid-cap returns on the BSE Sensex return, and the study's findings imply that mid-cap equities of the BSE are less risky than small-cap stocks. Arora (2017) indicates that Nifty 50 and the Midcap 50 do not have a long-term co-integrating relationship. The VAR Model, VDC, and IRF show that the current return of Nifty 50 is influenced by its previous return. On the other hand, the Midcap 50 is heavily influenced by the lagging returns of Nifty 50 and its own returns. As a result, Nifty 50 is leading the Midcap 50.

In light of the above-reviewed literature, there is extensive research on the lead-lag relationship among international stock indices, macroeconomic variables, stock indices, and spot and futures markets. However, it could be seen that there is scarcity of research on the lead-lag relationship among the large-cap, mid-cap and small-cap indices of the Indian capital market. The study identifies the leader indices among all indices for taking the strategic investment decision and establish the lead-lag relationship among these indices with the help of an econometric approach.

3. Objectives of the study

This study aims to address the gap found in previous research. The study's main objective is to determine the lead-lag relationship among the large-cap, mid-cap, and small-cap indices of NSE. The study uses the Granger causality test (1969, 1987) to capture these indices' lead-lag relationship. The research also uses IRF to capture one variable's response to the other variables and VDC to capture variation in one variable to the shocks given to other variables. To address the objective, the following null hypothesis has been formed:

H_0 = There is no lead-lag relationship exists among the Largecap, Midcap, and Smallcap segments of the NSE

4. Research design

A research design is a method for addressing a research problem in a structured way. The researcher attempts to describe the several steps they undertake in examining their research problem and the logic that supports them. The layout of the research design is discussed as follows:

4.1 Data

To determine the lead-lag relationship among the large-cap, mid-cap, and small-cap segments, the authors obtained the data from the NSE website (www.niftyindices.com). The daily closing values of the total return index of Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250 are collected. The data spans 11 years, from 1st Jan 2010 to 31st Dec 2020. The log return of each series is calculated using $R_t = log(P_t/P_{t-1})$. For further empirical analysis, the calculated return series are taken into consideration.

4.2 Unit root test

Before considering the econometric test for checking relationships, it is necessary to check the non-stationary properties in the time series data. The distance between two time periods determines the covariance between them, not the moment it is computed; hence, the constant mean and variance indicate the time series is stationary (Gujarati, 2004,)heteroscedasticity, autocorrelation, model specification. If the series is non-stationary, taking the first difference makes the series stationary (Barreto & Ramesh, 2018).

In the present study, the authors selected two popular tests, the ADF test (1979) and the PP test (1988), to check the stationarity of the time-series data. The ADF test is used to overcome the problem of autocorrelation. To estimate the ADF test, the following regression equation is formed:

$$\Delta Y_t = \theta_0 + a_1 Y_{t-1} + \sum_{j=1}^{k} \beta_j \Delta Y_{t-j} + \varepsilon_t \quad (1)$$

The PP test rectifies t-test statistics for handling the considerable autocorrelation in error terms without a lagged differenced component. For the PP test, the regression equation shown below is computed.

$$\Delta Y_t = \theta_0 + \beta Y_t + \varepsilon_t \quad (2)$$

4.3 Sequencing of Variables

The contemporaneous relationships between the variables are sorted out using economic theory in a structural VAR. Structural VARs need the use of “identifying assumptions” in order to interpret correlations causally. These identifying assumptions can involve the complete VAR to spell out all causal relationships in the model or only a single equation highlighting a single causal relationship. When each equation is estimated using Ordinary Least Square (OLS), the residuals are uncorrelated across equations (Stock, Watson, 2001). Changing the order of the variables alters the VAR equations, coefficients, residuals, and recursive VARs to represent all possible orderings. The IRF and VDC findings are heavily influenced by order variables in a VAR model (Patra, Poshakwale, 2008). The exogeneity technique is used to determine the order of variables. The super exogenous variable will be placed first, followed by the weak exogenous variable.

4.4 Lag Length Selection

The choice of lag length is a sensitive issue in carrying out the Granger causality test (-Gujarati, 2004, p.696). Too many lags lead to the loss of a degree of freedom, and choice of negligible lags may lead to model misspecification, so the choice of lag length in the VAR model has always been an empirical issue in prior literature because it explores the relationship between the variables. The paper employs the Akaike information criterion (AIC) for optimal lag selection out of several lag selection methods.

4.5 VAR Granger Causality Test

The lead-lag relationship among the variables has been tested through the Granger causality test. The Granger (1969) method determines whether the past value of other variables can explain the current value of one variable (Kolawole & Eleanya, 2018). Following this, the method attempts to see if adding lagged values to the first variable improves the explanation or not. For example, prices of "X" is said to be Granger caused by prices of "Y" if prices of "Y" help to predict prices of "X" or equivalently if the coefficients on lagged "X" prices are statistically significant and vice-versa (Surya & Natasha, 2018). The causality in both directions may or may not exist. This phenomenon aids current research in determining which index leads and which index lags. In the case of more than two variables, the Granger causality test should be conducted under a multivariate VAR framework (Victor et al., 2021). The Granger causality test estimates the following regression equation:

If Y causes X

$$X_t = \delta_0 + \sum_{j=1}^{k} \beta_j x_{t-j} + \sum_{j=1}^{k} \gamma_j y_{t-j} + \mu_{xt} \tag{3}$$

If X causes Y

$$Y_t = \theta_0 + \sum_{j=1}^{k} \beta_j x_{t-j} + \sum_{j=1}^{k} \gamma_j y_{t-j} + \mu_{yt} \tag{4}$$

In the above equations, k is the positive integer, β_j and γ_j are parameters, δ_0 and θ_0 are constants, and μ_t is the error term with the constant means and variance. The null hypothesis in both equations is that Y does not cause X and vice versa.

4.6 Impulse Response Function (IRF)

Estimating the coefficient of the VAR model is always a tricky task, so researchers often employ IRF (Gujarati, 2004). Since Sim's (1980) significant contribution, the impulse response or "error shock" methodology has been frequently used to explain the dynamic interaction between variables and disturbances in VAR (Alemany et al., 2020). IRF looks into the time trajectories of one variable in response to a one-unit shock on the other variables and vice versa (Kantaphayao & Sukcharoensin, 2021; Karmakar, 2010). The IRF graph plot illustrates the impact of a one-standard-deviation shock given to current and future values of endogenous variables.

4.7 Variance Decomposition

The Granger causality test does not discover exogeneity among the variables outside the sample period (Masih & Masih, 2002). The VDC test addresses this limitation. The VDC calculates the relative relevance of each random innovation in influencing the system's variables. The forecast errors reveal the portion of movements produced by own shocks as opposed to shocks in other variables (Patra & Poshakwale, 2008). The magnitude of shocks in a VAR system is distributed across time in terms of percentages imposed by the variables on each other measured by using the VDC (Retumban, 2016).

5. Empirical Analysis and Results

5.1 Descriptive Statistics

First and foremost, summary statistics are calculated for three return series. Table 1 summarises the mean, median, standard deviation, skewness and kurtosis of the variables for the sample period. The Nifty Midcap 150 can be seen has having the highest mean average returns. It is evident from the statistics that Nifty Smallcap 250 exhibited the highest standard deviation compared to Nifty 100 and Nifty Midcap 150, which means the series is more spread out. The value of skewness for normal distribution is zero. All three indices have a long left tail indicating negative skewness. A kurtosis score of higher than 3 shows that the distributions are higher peaked than normal. All the series exhibit a higher value than three, which means each series is leptokurtic. Skewness and kurtosis indicate the deviation of the return series from the normal distribution. Further, the probability value of Jarque-Bera statistics also rejects the null hypothesis of normality. It means all series under consideration are not normally distributed.

Table 1. Descriptive Statistics of Index

Descriptive Statistics	Return Nifty 100	Return Nifty Midcap 150	Return Nifty Smallcap 250
Mean	0.000420	0.000495	0.000354
Median	0.000754	0.001654	0.001638
Minimum	-0.136270	-0.139146	-0.132000
Maximum	0.080908	0.054851	0.058815
Kurtosis	17.36832	15.83765	12.80675
Skewness	-1.058149	-1.465070	-1.412237
Std. Dev.	0.010899	0.011169	0.012045
Jarque-Bera	23966.63	19701.55	11834.05
Probability	0.000000	0.000000	0.000000

a. Author's own calculation

5.2 Unit Root test Results

The data stationarity must be checked before an econometric analysis can be performed. With the help of the ADF and PP tests, the stationarity of the data is checked. The test is performed at the level. A probability value of less than or equal to 0.05 (p=5%) indicates that the null hypothesis is rejected. According to the ADF test and PP test results presented in table 2, the p-value is zero; this suggests that the null hypothesis of a unit root for all three indices is strongly rejected. Thus, there is no evidence of unit root in the data series.

Table 2. Unit Root Test

Index	ADF		PP	
	T-Stat	P-Value	T-Stat	P-Value
Return Nifty 100	-14.2367	0.0000	-51.3833	0.0001
Return Nifty Midcap 150	-13.0886	0.0000	-46.5264	0.0000
Return Nifty Smallcap 250	-12.8418	0.0000	-43.8137	0.0000

a. Author's own calculation

5.3 Sequence of Variables

One of the drawbacks of VARs is that changing the order of variables in the VAR system alters the results that can be produced. The exogeneity criterion is used to order the variables. The stationarity series of the data are considered for checking the exogeneity of the variables. The most exogenous variable in terms of lower r square is placed first, followed by the second. The order of the three variables is Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250.

5.4 Optimal Lag

The VAR model's results depict the effect of lagged values of the dependent and independent variables on the dependent variable. The lagged nature aids in analysing the dynamic influence of the independent variables on the dependent variable. The authors considered ten lags in the first step to determine the correct lag length. A lower AIC value leads to a better model (Kharbanda & Singh, 2017), so the seven lag is considered for further analysis as per the lower AIC value.

5.5 VAR Granger Causality Test Results

The direction of causality is determined through Granger's causality test, used to see if any of the variables cause each other or not. Table 3 shows the results of the Granger causality test. The study assumed the series does not follow any co-integrating relationship, so the test is conducted under the VAR framework. If the p-value is less than the 5% significance level, the null hypothesis is rejected, indicating a causal relationship between the two variables. The results indicate the direction of causality is from both Nifty 100 and Nifty Midcap 150 to Nifty Smallcap 250 since the p-value is significant at a 5% level. This implies Nifty 100 and Nifty Midcap 150 influenced Nifty Smallcap 250 but not the other way round. Here, an important question arises: Why do Nifty 100 and Nifty Midcap 150 influence Nifty Smallcap 250? These two indices represent the majority of market capitalisation. Companies under the Nifty 100 and Nifty Midcap 150 index are more prominent by size and more established companies, but companies under Nifty Smallcap 250 have smaller ownership, and they are still in the growing and expanding phase. The large number of investments flow to Nifty 100 and Nifty Midcap 150 with the expectation of stability and continuous growth, but the flow of investment to companies under Nifty Smallcap 250 is low due to high-risk involvement. From a market scenario, we know that market participants tend to react quickly to any new information flows to the market, whether positive or negative; the investors of companies under Nifty 100 and Nifty Midcap 150 react first because of the massive amount of investments, and by watching the sentiment and behaviour of the large investors, the investors of Nifty Smallcap 250 react and follow them.

Table 3. VAR Granger Causality Test

Dependent	Independent Wald χ^2 Statistics		
	Return Nifty 100	Return Nifty Midcap 150	Return Nifty Smallcap 250
Return Nifty 100	-	9.3793 (0.2266)	11.5270 (0.1172)
Return Nifty Midcap 150	10.8809 (0.1439)	-	11.6532 (0.1126)
Return Nifty Smallcap 250	14.1055** (0.0493)	16.9979** (0.0174)	-

a. (**) significant at the 5%;

5.6 Impulse Response Function Results

The impulse responses represent a variable's dynamic response route due to one standard deviation shock to another variable. The VAR system's impulse responses could determine how rapidly shocks in one variable are communicated to other variables. Figure 1 presents the results. The impact of one standard deviation shock given to Nifty 100, the response of Nifty Midcap 150, and Nifty Smallcap 250, although started with a gradual fall, remained positive during the first four periods and became negative in the last period. Nifty 100 shocks significantly impact the movement of the other indices. Also, Nifty Smallcap 250 responds positively during the first five periods and becomes negative during the last two periods in response to the shock given to the Nifty Midcap 150. However, this is not true for vice versa, meaning the movement in the Nifty Midcap 150 has an impact on the movement of Nifty Smallcap 250. Apart from this, all the variables respond positively to the shocks given to their own lagged values, implying that past information significantly impacts the current movement. Therefore, it can be said that Nifty Smallcap 250 lags both large- and mid-cap indices because the information transmission is from large- and mid-cap companies to the small-cap companies, and small-cap companies are lagging in reflecting the information.

5.7 Variance Decomposition Analysis results

The VDC results can identify the most exogenous variables in the VAR system. Table 4 shows the findings of the VDC with a breakdown of results for periods ranging from one to seven days. The Nifty 100 of the Indian stock market is the most influential index that, explained by its own variance accounting for 100% on day one, remains higher for all subsequent periods, meaning this index is only influenced by its own lagged values; the previous information of the Nifty 100 does have a significant impact on the current movements. 77% of variations in Nifty Midcap 150 were explained by Nifty 100, which implies Nifty 100 influences the movement of Nifty

Midcap 150. However, Nifty Smallcap 250 is the most affected index, with 68% of variations explained by Nifty 100, 22% of variations explained by Nifty Midcap 150 index, and 9% of variations in Nifty Smallcap 250 explained by its own lagged values. This variation explains that movement in the Nifty Smallcap 250 index is affected by the action in large- and mid-cap indices due to interdependencies because it is believed that investors of the small-cap companies always mimic the investors' behaviour of the large-cap companies. Therefore, the authors argue that Nifty Smallcap 250 index is the most influenced one, and Nifty 100 is the least influenced among all three indices.

Figure 1. Impulse Response Function (IRF)

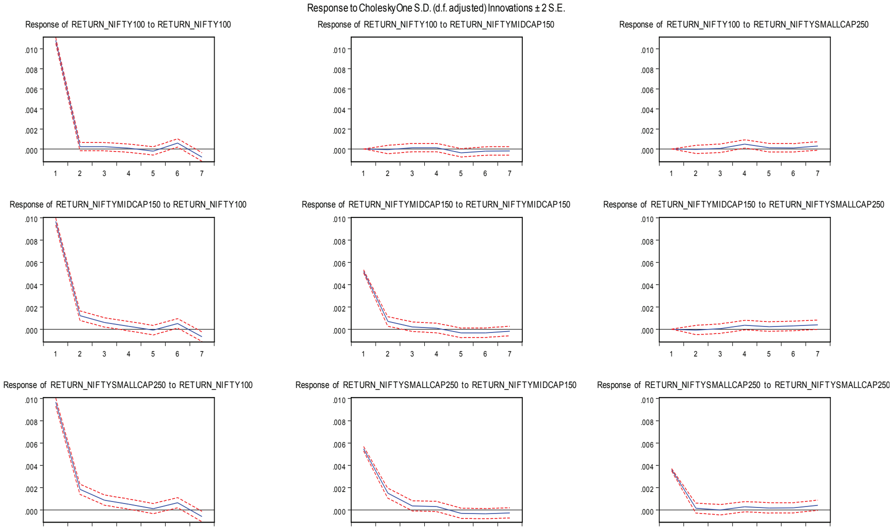

Table 4. Variance Decomposition Analysis

Period	S.E.	Return Nifty 100	Return Nifty Midcap 150	Return Nifty Smallcap 250
Variance Decomposition of Return Nifty 100:				
1	0.010827	100.0000	0.000000	0.000000
2	0.010830	99.99608	0.002472	0.001452
3	0.010834	99.97424	0.019459	0.006297
4	0.010847	99.73996	0.037578	0.222457
5	0.010856	99.60237	0.160107	0.237521
6	0.010876	99.55489	0.195031	0.250074
7	0.010911	99.45030	0.221978	0.327724
Variance Decomposition of Return Nifty Midcap 150:				
Period	S.E.	Return Nifty 100	Return Nifty Midcap 150	Return Nifty Smallcap 250
1	0.010993	77.62573	22.37427	0.000000
2	0.011081	77.58728	22.40681	0.005906
3	0.011099	77.62522	22.36763	0.007154
4	0.011108	77.55238	22.33741	0.110210
5	0.011116	77.44871	22.39937	0.151918
6	0.011137	77.37630	22.40372	0.219980
7	0.011166	77.34489	22.31229	0.342813
Variance Decomposition of Return Nifty Smallcap 250:				
Period	S.E.	Return Nifty 100	Return Nifty Midcap 150	Return Nifty Smallcap 250
1	0.011698	68.45976	22.02195	9.518296
2	0.011939	68.12138	22.72099	9.157629
3	0.011976	68.22637	22.67257	9.101063
4	0.011994	68.20378	22.66709	9.129133
5	0.011999	68.14889	22.70783	9.143276
6	0.012023	68.16910	22.70038	9.130527
7	0.012048	68.13276	22.65565	9.211592
Cholesky Ordering: Return Nifty 100 Return Nifty Midcap 150 Return Nifty Smallcap 250				

a. Author’s own calculation

6. Discussion and Conclusion

Today's Indian capital market provides a wide range of financial products that benefit investors. Investors need to know about particular investment opportunities. The function and achievements of the different market indices can help the investor pick a better fund. Using 11 years of time-series data, the current study seeks to identify the lead-lag relationship among the Indian capital market's large-cap, mid-cap, and small-cap segments. The indices used for the study are Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250. The study used six steps to analyse the data, starting with confirming stationarity using the ADF and PP tests, then organising the variables in order of exogeneity, and finally selecting lag length for more robust findings. The Granger causality model is employed to identify the direction of causality, which is also proved by IRF and VDC. According to the VAR Granger causality, Nifty Smallcap 250 is caused by Nifty 100 and Nifty Midcap 150. A unidirectional causality runs from Nifty 100 and Nifty Midcap 150 to Nifty Smallcap 250. In further analysis, IRF also supports the findings that Nifty Smallcap 250 responded significantly to the shocks given to Nifty 100 and Nifty Midcap 150. From VDC results, it is interpreted that the other two indices highly influence Nifty Smallcap 250. The statistical findings indicate that Nifty 100 is the leader in the market and Nifty Smallcap 250 is the follower in the market; it is also worth mentioning that Nifty Midcap 150 also contributes to the movement of Nifty Smallcap 250 but not much as Nifty 100. The current study finds it more reliable and different from Arora (2017) in the way that our research considered three major indices representing all large-cap, mid-cap, and small-cap segments, whereas Arora (2017) have only considered two indices, i.e., Nifty and Nifty Midcap 50.

The study answers the research's prime question: who leads and who lags. However, subsequently, another question arises among the investors why lead lag exists among these indices to understand the particular investment opportunity. All the market participants start from small to prominent players, including foreign institutional investors, domestic institutional investors, and high net worth investors who usually invest in the growth companies of large-cap indices. These investors try to limit their attention to the small-cap companies because of high risk and low growth opportunities; this may be why the large-cap index leads. Information transmission among the indices may be another reason behind the lead-lag relationship among these indices. In today's globalised and interconnected markets, the large and small companies are involved in the business transactions among themselves; if any disruption happens in the business of large-cap companies, it will automatically impact the business of the small-cap companies, resulting in the lag behaviour. Stocks of large-cap indices are usually well-known companies belonging to different sectors. In some cases, the large companies also enjoy the monopoly and do the business well in the market. In contrast, in the case of small companies, investors are rarely aware of their business and their products, so they try to avoid investments in these companies, and this behaviour of the investors affects the fundamental performance of the small-cap companies, which ultimately results in lagging the large-cap companies

An individual investor expects optimal risk and returns in shifting market circumstances. Investors always search for answers to four questions of investment strategies. The first question is about which assets to invest in; the second is the amount to invest, followed by the investment period, and the last is strategies to manage the investments. The study's findings address these concerns of the investors. The evidence of causality and shock transmission among the indices suggests that when the large-cap stocks start reacting positively or negatively to the market information, the investors can buy or sell the small-cap stocks accordingly to achieve the optimal benefit of the investments. The market tends to be more volatile when investors focus on short-term profits with changing economic scenarios. After a significant correction, when the market is in an uptrend; investors are advised to evaluate the financial parameters of individual companies and then they can add them to their portfolio basket. If investors want a quick return and have low-risk exposure, they can invest in large-cap stocks. The mid-cap and small-cap stocks also begin acquiring pace and start responding to the large-cap stocks as the mid-cap and small-cap stocks tend to follow the market movement, so an investor should wait for a correction and then only after the rise of large-cap stocks should start investing in mid-cap and small-cap stocks to achieve the desired gain.

The research makes a unique contribution by investigating the lead-lag relationship among the large-cap, mid-cap, and small-cap segments of the Indian capital market. To the best of the authors' knowledge, none of the previous studies included a small-cap index to analyse the lead-lag relationship. This small-cap index also contributes to the movement of the market. The small-cap indices are also an integral part of the capital market, having more companies included in this index than the mid-cap and large-cap indices. For the empirical study, total return index values of three indices were selected, as these indices have a unique nature in that it represents both price and dividend distribution among the index listed companies. To obtain more precise results, the study has ordered the variables in terms of their exogeneity and employed the Granger causality test for the lead-lag relationship, a superior method among all, followed by IRF and VDC for more robust results. Our method identified the leader and lagger indices. Investors can design portfolios using the evidence of the lead-lag relationship because these three indices would use each other's information to determine their future movements.

Maybe large-cap has strong growth potential, but the stocks are quite pricey; small-cap shares are lower in price, so retail investors can invest in small-cap companies with strong fundamentals. One of the important explanations for the study's findings is that investors tend to enter the market quickly when large-cap leader stocks are rising, and as a result, the followers' small-cap stocks also start rising. If different market capitalisation stocks possess a systematic lead-lag relationship, it will be effortless for the portfolio manager to forecast the movement of one stock return based on the movement of another stock. This enables managers to follow a winner-loser strategy and generate abnormal profits. In addition to this, our findings also suggest that investing in small-cap equities can provide significant additional benefits in the long run. The research is confined to indices from the Indian capital market. Investigating the long-run co-integrating relationship among the large-cap, mid-cap, and small-cap indices would be good for further research. Further, future studies can focus on building portfolios considering firms from different capital market segments based on the existence of a lead-lag relationship among the large-cap, mid-cap, and small-cap indices.

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