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Decoding The Intersectoral Dynamics Of The Indian Economy: A Study Through Nifty50 And Sectoral Indices.

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Abstract
The Indian stock market, as of 2025, is the world's 4th largest with a market capitalization exceeding $4.4 trillion. However, the dynamic and volatile nature of the market necessitates for the stakeholders to understand the patterns of movement of the overall market and the individual sectors. One of the ways of decoding the Indian stock market is through its various indices.
The current study aims at an empirical analysis of major Indian stock market indices, through a benchmark index Nifty50 and seven major sectoral indices (Auto, IT, Bank, FMCG, Metal, Finance, and Pharma). The data used in the study is indices' prices for January 1, 2024 – March 31, 2026 (for estimating the response variable); and April 01, 2026 - June 30, 2026. for model predictions.
To estimate weekly returns in Nifty50 as a linear function of returns in sectoral indices, a Multiple Linear Regression (MLR) model was selected based on (adjusted)R2, AIC and BIC values. The selected model had adjusted R2 value 0.9481. Proportionate changes in all the sectoral indices were significant except Nifty Pharma. Bank was dropped from the model as its high correlation with Finance resulted in multicollinearity in the model. Predicted values were consistent with the observed values. An autoregressive model with one-period lag of Nifty50 and Finance as independent predictors had both AIC and BIC values higher than those of the MLR model, thus indicating that current returns of independent predictors were more informative in estimating Nifty50 returns than its own previous returns..
Keywords: Autoregressive models, Indian stock market, Nifty50, Multiple Linear Regression, Stock Indices..

Introduction

The capitalization of stock market has increased at an exponential rate in India for the stock markets. According to reports, the market capitalization in June 2026 stood at 5008.440 bn USD, compared to 4894.507 bn USD in the previous month, marking an increase of 2.3%. As of date, its all-time high value was 5,663.221 bn USD in Sep 2024, more than 100 times that of 55.322 bn USD in Apr 1993 (A. Aali-Bujari (2017)). The growth of stock market has always attracted and challenged researchers and analysts to discover the patterns of growth. There have been some indicators that point in the direction of market movements, such as stock market indices. Various indices cater to different segment categories of the market. There are broader indices such as Sensex, Nifty, Nifty100, Nifty50 etc., which represent a general overall movement of the market and sectoral indices serving sectors such as finance, banking, textile, heavy metals, etc. However, there is no single index that captures the overall movement of the market. The broader indices are a weighted average of sectoral indices, which in turn are based on individual representative stocks. Stocks in a sectoral index and sectoral indices in a broader benchmark index are chosen on the basis of their total market capitalization and the market liquidity. Also, all sectors do not necessarily move in the same direction, and they do not have the same extent of movement. So different sectors contribute in a different manner to the overall market movement. (B. Hari Prasad Rao (2024)). Investors, whether individuals or large institutions, need to understand the behaviour of different market sectors. With unique patterns of growth and risk profiles for different sectors present in the broader market index, it becomes important to understand these movements so that investors can make efficient decisions. We need to assess whether the risk and volatility of one sector impact the complete market or not. Even if it does, is there any evidence to conclude that some sectors drive market trends and the remaining sectors lag?

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The Nifty50, comprising 50 large Indian companies, is one of flagship indices. Based on 6-month average data, these 50 companies collectively represent approximately 45% of the total full market capitalization, 30% of the most liquid traded equity stocks at NSE, and 55% of the total free-float market capitalization. Over the years, the Nifty50 Index has delivered an annual return of 14.04% with a volatility of 21.94% annually. The Nifty50 has delivered a return of 10.51% by December 2025. Financial Services was the highest contributor to the index return in the past 1 year, while Power and Automobile & Auto Components were the sectors with the lowest contributions to the index returns. (NSE Indices Limited (2025, September)).

The trends in the stock market indicate the performance of the economy (A. Aali-Bujari (2017)). However, the short-term movements may be affected by other factors such as political events, business news, and economic news which, due to increased volatility, might make long-term analysis of the market difficult (H¨onig (2019), Audrino (2019), Jiang (2021), Lee (2019)). Macroeconomic-level indicators are difficult to model because of the low explanatory power of granular micro factors in isolation (e.g., correlations often below 0.15). This can lead to the risk of overfitted models and losing interpretability (Pražák, 2020). An alternative to the unattainable micro-level exhaustiveness can be examination of sectoral funds and their relationship to the benchmark index.

The sectoral indices are aggregated single values for the entire sectors in an economy. It has been observed over a period of 10 years that the average return of a sectoral index has performed better than any growth indicator (Shanmurgasundram (2013)). They also identified that the risk factors across indices need not be the same. B. Hari Prasad Rao (2024) observed that different sectors respond differently to economic shocks during a severe economic crisis. During the COVID-19 pandemic, when most of the indices were negative, Nifty FMCG was the least affected index. In a similar study by Guru (2021), the data from the crisis period only showed that there was an overall increase of 6% in the total volatility spillovers. The particular study by them identified oil and gas as the major volatile sector, whereas FMCG still acting as the defensive sector.

Studies have examined the relationship between Nifty50 and sectoral indices. The studies provide enough evidence about the interrelationships, performance dynamics, and diversification potential of the Nifty50 and its sectoral indices. Florence (2020) identified that there is a relationship amongst eight NSE sectoral indices using a variance-based Granger causality framework. Raval (2020) analysed the changing relationship among the Nifty50, Nifty Finance and Nifty Pharmaceuticals sectors over a decade, reporting that there is a strong association amongst them. In a 2017 study by Pandey (2017), the author identified a relationship amongst the indices using correlation and multiple regression. Mohanty (2019) also saw this relationship through correlation analysis. Singh (2020), in their study to analyse the trends within the Nifty50 and its sectoral indices, found out that the financial sector was growing better than other indices. Bidirectional relationships between benchmark and sectoral indices have also been found out in various studies. Nithya (2014) examined the volatility pattern followed by the Indian sectoral indices and suggested that the significant correlations between most sectoral indices showed that the movements in the sectoral indices were mainly due to the overall market movement and not by themselves. A 2017 study by Aravind (2017) showed a strong bidirectional relationship between Nifty50 and private sector banking indices.

Most of the studies about the market indices are either descriptive analysis or high-level time series models that depict the market or sector growth over time. However, there is limited clear evidence about how different sector indices are connected to the broader market indices like the Nifty50. The present study involves proportionate weekly changes in the benchmark index Nifty50 and similar changes in sectoral indices Nifty Bank (Bank Nifty), Nifty Auto, Nifty Metal, Nifty FMCG, Nifty IT, and Nifty Financial Services. While Nifty50 is the flagship index of NSE and adequately captures the stock market movements, the sectoral indices have their own characteristics. Nifty Finance and Nifty Bank are volatile indices; Nifty Auto is a stable and non-cyclical index; Nifty metal is cyclical in nature; Nifty FMCG is defensive in nature and is a general indicator of the direction the economy is moving towards; and Nifty IT is highly volatile and somewhat unstable in nature.

In an attempt to understand co-variabilities between the broader market index and sectoral indices, the present study attempts to:

Identify a relationship between the proportionate weekly changes (returns) in benchmark index and sectoral indices and use this relationship for prediction purposes

Identify a time series relationship between the returns in Nifty50 values using Finance as a covariate due to its high correlation with Nifty50.

Compare the two models in terms of their prediction powers.

Besides introduction, the paper has three more sections: material and methods, results and discussions.

2. MATERIAL AND METHODS

2.1 Material

The secondary data for this study were the weekly (opening and closing) price data collected from an investment and financial data platform, Investing.com (https://www.investing.com) for the period January 1, 2024 to June 24, 2026.

The contribution of the chosen sectoral indices in Nifty50 is summarised in Table 1 below:

Table 1: Decomposition of Nifty 50 in terms of the chosen sectoral indices

Sectors	**Proportion**
Financial Services (including banks)	36%
IT	9% - 11%
Pharma	3% - 4%
FMCG	5% - 6%
Automobiles	7%
Metals and Mining	2% -3%

The data was used to calculate the weekly percentage return for each sector given by:

$$Percentage\ Change = \frac{(Closing\ Price\ \text{-}\ Opening\ Price)}{Opening\ Price} \times 100 \quad (1)$$

2.2 Methods

A general linear regression model for regressing the weekly percentage changes in Nifty50 on a set of independent predictors (the sectoral indices) was obtained as

$$Nifty50 = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon \quad (2)$$

where X_i represent the weekly percentage changes in sectoral indices; $i = 1, 2..., k(\leq 7)$; β_0 is the intercept term, $\beta_1, \beta_2, ..., \beta_k$ are coefficients of regression to be estimated from the data, and ε is the error term.

A sequence of models was obtained starting with a two-variable model with an independent predictor having the highest correlation with the response variable. The model was subsequently modified by inclusion of other independent predictors, one at a time, which had the next highest correlation with the response variable. Final model was based on the highest adjusted R^2 and lowest AIC and BIC values.

Another autoregressive model regressed Nifty50 on its past values and the present values of the highest correlated sectoral index Nifty Finances as

$$(Nifty50)_t = \beta_0 + \beta_1 (Nifty50)_{t-1} + \beta_2 (Finance)_t + \varepsilon; \quad t = 2, 3, , ..., 118 \quad (3)$$

Prior to fitting the models, the assumptions of the models were tested. The predictive efficiencies of the models were obtained as a ratio of correct predications to the total predictions and compared.

3. RESULTS

The data was collected from the data platform Investing.com for Nifty50 and the sectoral indices for a period from January 1, 2024 to June 24, 2026. The percentage weekly changes for all the variables were calculated and were used in the present study.

Table 2 below lists various descriptive statistics related to the benchmark index Nifty50 and the sectoral indices considered in the study.

Table 2: ***Descriptive statistics displaying essential features of Nifty50 and sectoral indices***

Statistic	**Index**							
	Nifty50	Finance	Banking	Auto	Metal	IT	Pharma	FMCG
Mean	0.0675	0.1643	0.1509	0.2396	0.2789	-0.1420	0.2602	-0.1168
Median	0.1082	0.0970	0.1227	0.4981	0.2032	-0.1198	0.4162	-0.2268
SD	1.6674	1.9897	2.0006	2.7372	3.0897	3.0483	2.1278	1.9569
Range	10.2864	13.8152	13.1764	18.9288	15.9645	17.2318	12.5291	13.2277
Skewness	0.1827	0.4481	0.2718	-0.0351	0.0920	-0.5342	0.0864	0.8342
Kurtosis	3.8635	5.3459	4.6611	4.3255	3.2194	3.6810	3.6013	5.6103

Nifty Metal returns showed the highest mean amongst all the indices studied at 0.27% with a high standard deviation of 3.09% suggesting a “high return, high risk” pattern. Nifty IT return was worst with a negative mean and high standard deviation. Nifty FMCG is a defensive sector. Nifty50, i.e., the benchmark index, shows an average return of 0.06% with a moderate standard deviation of 1.66% which is lower than that of any other index. The most volatile sector during this period were Nifty Metals and Nifty IT.

3.1 Multiple Linear Regression Model

The first aim of the study was to develop a multiple linear regression model to describe the relationship between Nifty50 and the sectoral indices. It should be noted that Nifty50 is a weighted average of various stocks, which may be part of their sectoral indices also. So Nifty50 is a function of various sectoral indices.
Before fitting the model, the assumptions of a general multiple linear model were tested:

Normality of the response variable, i.e. the Nifty50 weekly returns:
A QQ plot was used to examine the normality of Nifty50 returns (Figure 1):

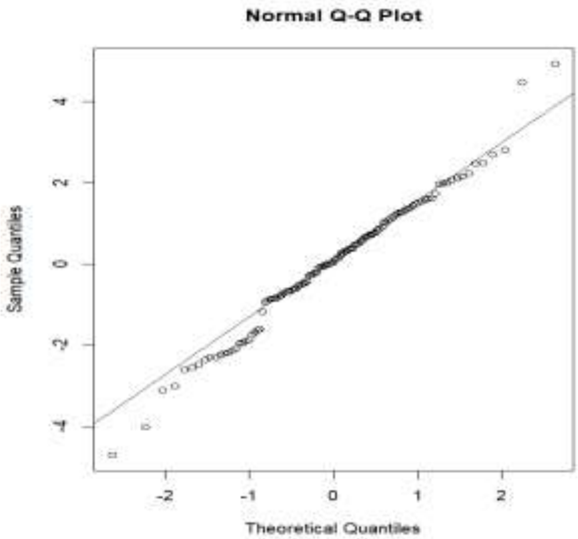

Figure 1: QQ plot to test the normality of the weekly Nifty50 percentage return

The QQ plot visual results were corroborated by the Anderson-Darling test, which yielded the value A = 0.50868, (p-value = 0.195). Both the procedures confirmed the normality of Nifty50 returns.

Linear relationship between the response variable and the predictors
Next was the assumption of a significant linear relationship of the response variable with the independent predictors. The correlation coefficients of all sectoral indices with Nifty50 were high and significant (p-value <0.001), showing a linear association.

Table 3: Linear relationships between the Nifty indices

	Nifty50	Finance	Banking	Auto	Metal	IT	Pharma	FMCG
Nifty50	1.0000							
Finance	0.8623	1.0000						
Banking	0.8482	0.9630	1.0000					
Auto	0.7944	0.6027	0.5957	1.0000				
Metal	0.6856	0.5435	0.5707	0.6289	1.0000			
IT	0.4532	0.1631	0.1812	0.3192	0.2004	1.0000		
Pharma	0.5569	0.3455	0.3235	0.5581	0. 4631	0.2895	1.0000	
FMCG	0.6103	0.4323	0.412	0.4829	0.3187	0.2385	0.4514	1.0000

This assumption was used for model selection also. We started with a two-variable model with independent predictor being the one having the highest correlation with Nifty50 returns. Subsequent models were fitted by adding predictors having next highest correlations and for each model, R^2, adjusted R^2, AIC, BIC and Variance Inflation Factors (VIF) of independent predictors were computed. The first predictor selected was Finance. The inclusion of banking not only did not improve AIC and BIC values but also it led to huge values of VIF. Since data was not scarce and was not a source of multicollinearity so the problem was inherent in the two predictors. The underlying structure of Nifty Finance included a major representation of banking sector (up to 65%), so it was decided to drop Banking from further analysis. For all other models, VIFs of the predictors were much less than 5. The results are presented in Table 4 below:

Index	Finance	Auto	Metal	IT	Pharma	FMCG
VIF	1.781337	2.435299	1.848908	1.145417	1.633519	1.471270

Table 4: Inclusion sequence of independent predictors in the regression model

Regression model with independent predictors	**R^2**	**Adj R^2**	**AIC**	**BIC**	**Predictors with VIF ≥ 5**
Finance	0.7435	0.7415	329.9469	338.5495	
Finance + Banking	0.7479	0.744	329.7074	341.1775	Finance (13.7644), Banking (13.7644)
Finance + Auto	0.8621	0.8599	251.3265	262.7967	
Finance +Auto +Metal	0.8755	0.8726	239.9719	254.3096	
Finance +Auto + Metal + FMCG	0.9041	0.901	208.0657	225.2709	
Finance +Auto + Metal + FMCG +Pharma	0.9089	0.9053	203.3444	223.4171	
Finance +Auto + Metal + FMCG + Pharma +IT	0.9505	0.9481	126.0915	149.0318	

The final model was one with six independent predictors viz, Finance, Auto, Metal, FMCG, Pharma and IT as it had the highest adjusted R^2 and lowest AIC and BIC values. The model summary of the final model is presented in Table 5 below:

Table 5: Multiple Linear Regression model with percentage change in returns of Nifty50 as response variable

Coefficients	Estimates	Standard error	t-value	Pr(>|t|)
Intercept	-0.03315	0.03389	-0.978	0.330
Finance	0.47959	0.02371	20.229	< 0.001
Auto	0.14096	0.01938	7.272	< 0.001
Metal	0.07532	0.01504	5.007	< 0.001
IT	0.12247	0.01236	9.906	< 0.001
Pharma	0.03108	0.02021	1.538	0.127
FMCG	0.12563	0.02103	5.975	< 0.001
Residual standard error (111degrees of freedom)				0.362
Multiple R^2	0.9516		Adjusted R^2	0.949
$F_{(6,111)}$	363.9		p-value	<0.001

The regression was highly significant with R^2 equal to 0.9516 and the p-value of the F-statistic less than 0.001. All the sectoral indices were significant in estimating the percentage change in returns of Nifty50 except for Pharma. However, Pharma has traditionally been a defensive sector with stable descriptive statistics.

In the final fitted model, the problem of multicollineaity was not there as can be seen from the VIFs of predictors in the final model (Table 6):

Table 6: Variance inflation factors of the sectoral indices

Remaining assumptions of a MLR model were found to be met:

Heteroscedasticity

The skewness and kurtosis of the response variable were close to 0 and 3, respectively with no standardized values outside ±3 limits, showing no effect of heteroscedasticity in the response variable.

Autocorrelation

Lag 1 autocorrelation coefficient was -0.0538 with a Durbin-Watson statistic 2.1035 (p-value 0.614). The null hypothesis of no autocorrelation was accepted.

Normality of residuals
Anderson-Darling normality test of residuals yielded a statistic value of 0.68708 (p-value- 0.07097) thus accepting the normality of residuals. The AIC and BIC values of the model were respectively 103.8316 and 125.997.

In all, the model was a good fit.

3.2 Autoregressive model of order 1 (AR(1)) with Finance as a predictor

Before running the AR(1) model, the stationarity of the time series data was tested using the Augmented Dickey-Fuller test on Nifty50. As the stock market is a highly dynamic market, we started with lag size 1. The Dickey-Fuller statistic was -8.795, with p-value 0.01. The null hypothesis was rejected at 5% level of significance and the stationarity of the time series was established. Finance was taken as a predictor as it had the highest correlation with Nifty50, and in a dynamic market, relying solely upon the past values may not produce good estimates or forecasts.
The AR(1) model had the following results (Table 7):

Table 7: AR(1) model with percentage change in returns of Nifty50 as response variable and, lag 1 Nifty 50 and Finance as independent predictors

Coefficients	Estimates	Standard error	t-value	Pr(>|t|)
Intercept	-0.03411	0.07846	-0.435	0.6645
$(Nifty50)_{t-1}$	-0.09648	0.04895	-1.971	0.0511
Finance	0.75063	0.04341	17.293	<0.001
Residual standard error (114degrees of freedom)				0.8479
Multiple R^2	0.7274		Adjusted R^2	0.7225
$F_{(2,114)}$	152.1		p-value	<0.001

Surprisingly, the lag Nifty50 variable not only had a negative sign but was significant only at 10% level of significance. Again, with R^2 equal to 0.7274, the model was a good fit. The AIC and BIC values of the AR(1) model were 298.3888 and 309.4375 respectively.

3.3 Comparison of the two model through prediction.

The two fitted models were:

Model 1: MLR

$$\begin{aligned} Nifty50 = &-0.03315+0.47959Finance+0.14096Auto+0.07532Metal \\ &+0.12247IT+0.03108Pharma+0.12563FMCG \end{aligned} \tag{4}$$

Model 2: AR(1) with Finance as a predictor

$$(Nifty50)_t = -0.03411-0.09648(Nifty50)_{t-1}+0.75063(Finance)_t ;t=1,2,...,118 \tag{5}$$

The models were used for predictions for a period of 01April 2026- June 24, 2026 i.e. 12 values were predicted. The Figure 2 depicts the predictions made by two models:

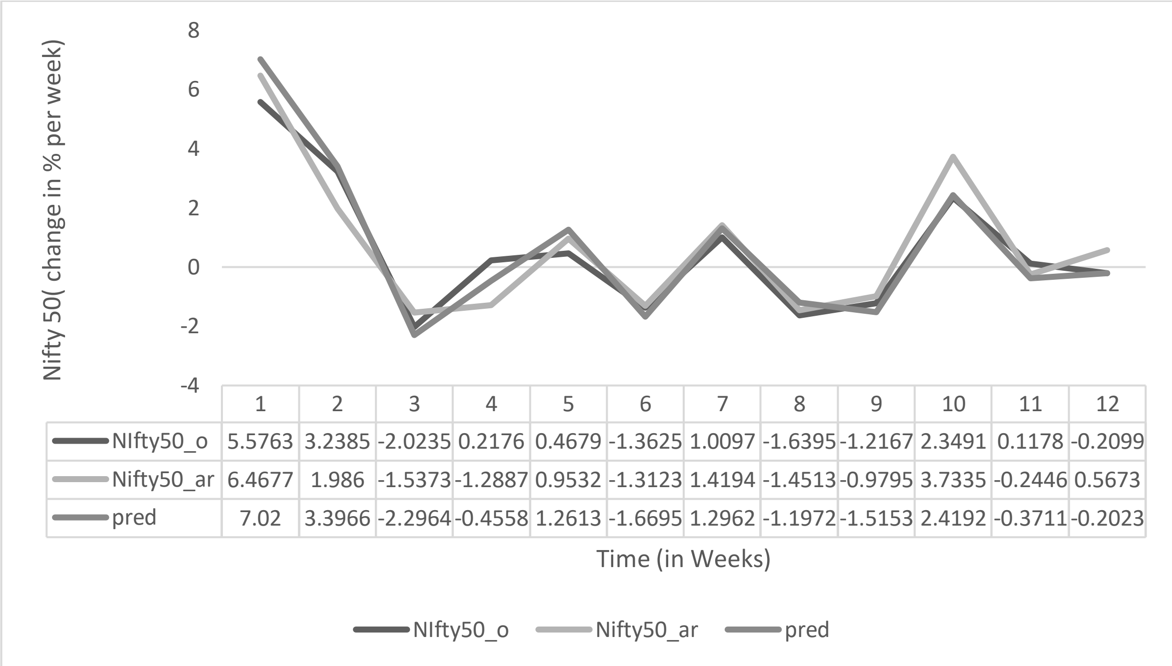

Figure 2: Comparison of predictive accuracy of the two models

Nifty50_o are the observed values of Nifty50 weekly returns, Nifty50-ar are the autoregressive model's predictions and pred are MLR model predictions. The MLR model outdid the AR(1) model on (i) AIC and BIC criteria; and (ii) prediction. Most of the predictions by the MLR model were closer to the observed values than the predictions by AR(1) model.

4. DISCUSSION

According to "Investment Called India" (2025) by NSE, the past 30 years have seen NSE as fundamental in the growth of the capital markets with the introduction of efficient methods of price discovery, changing technology, and efficient risk management with the introduction of institutions like SEBI. It has played an important role in providing investors, whether Indian or global, with access to the Indian capital markets in a better way.

The stock market is a place that provides investors with insights into the ever-changing market, thereby aiding them in making investment decisions; researchers and analysts the insight into numbers manifesting in trend identification, investors' perspectives and expectations; and policymakers in identifying the directions the policies should aim at. The market indicators, i.e., the indices, whether broad or sectoral, play a major role in decoding the numbers and identifying trends. By grouping the information about stocks of similar types, the indices point at the direction of movement of the particular sector or the market as a whole. However, not all the indices move in the same direction or by the same extent. If studied in isolation, an index may present only one dimension of the market, which may be in conflict with another dimension represented by another index. Various indices need to be synchronised and studied coherently in order to have a complete general market picture. A benchmark index is a weighted average of various sectoral indices, with weights chosen in proportion to the market coverage of the sectoral indices. For example, the financial services sector saw a growth of 22% in this time period, whereas the IT sector contained its growth trend in 2025. These market trends are used to adjust the weights of different sectors in the benchmark indices. In particular, in Nifty 50, the financial services sector has marked its increasing dominance, whereas the traditional sectors such as Metals & Mining have steadily diminished. (An investment called India , September, 2025). However, manufacturing sectors such as Auto and Metals have witnessed rapid growth, whereas FMCG and Pharma sectors were stable, and their contribution to the Nifty50 even marked a decline.

This study examines eight major Indian equity indices: the broad-market benchmark (Nifty50) and seven important sectoral indices (Auto, IT, Financial Services, FMCG, Metals, Banking, and Pharma) to understand how they relate to each other and analyses their movements over time for a period of two years i.e. January 1, 2024 – March 31, 2026. The descriptive statistics of weekly percentage change of funds under study reveal four key insights: (i) Sectors delivering higher returns are accompanied by higher volatility, confirming consistent risk-return profiles; (ii) Nifty50 has consistently proved its balancing nature with the lowest standard deviation and narrowest range; (iii) Nifty Finance turns out to be the most attractive risk adjusted index; and (iv) Most sectors show a higher and positive median while certain extremely negative values reduce the mean significantly. The maximum correlation among sectoral indices was between Nifty Bank and Nifty Finance. The reason is that around 65% of the weightage of Nifty Finance is from the banking sector. Also, this was the reason for the presence of multicollinearity in the data, and consequently, it was decided to drop the Banking index from the final selected model.

The highest correlation of indices with Nifty50 can be observed in Financial (0.86), and Nifty Auto (0.79). This can be attributed to the higher weights assigned to these indices in the Nifty50 composition. On the other hand, the Nifty IT has the lowest correlation with the Nifty50 (0.44). This can be attributed to the fact that weekly changes in the information technology sector have more implications for global IT markets and foreign exchange rates rather than domestic markets.

The MLR model for estimating Nifty50 weekly returns on the basis of independent predictor indices' returns was highly significant. Finance returns had the highest regression coefficient, and Pharma and Metal returns the smallest, although both had the highest mean return. The reason is that these are stable indices with smaller weights in Nifty50 which do not show much fluctuation and hence had a smaller contribution towards measuring the change in Nifty50 returns to the extent that Pharma returns turned out to be insignificant, in spite of having significant correlation with Nifty50 returns.

The objective of estimating an autoregressive model was to examine the effect of previous changes in Nifty50 returns on the change in present returns. In order to determine the size of lag, models up to lag size 4 were estimated (lag size 4 was suggested by R software). However, only lag 1 was found to be significant. Naïve model was not a good fit so it was decided to include present returns of one of the sectoral indices as a covariate. With Finance having the highest correlation with Nifty50 returns, it was chosen as the covariate. In this model, Finance was highly significant and lag1was significant at 10% level of significance. The overall model was significant. It clearly indicated that in a dynamic market, present values of changes in returns of independent predictors are more significant than the lag values of the response variable, even if lag size is just of order 1.

Both the models did well in predicting the values of Nifty50. However, it was MLR model which produced better results than the AR(1) model. MLR model was better than AR(1) model with both estimation and predication.

Although the assumption of a linear relationship between the response variable and independent predictors may seem oversimplified in a dynamic market and volatile environment, still it held true for most of the time points. Only a few points on the scatterplot of residuals were elevated- suggesting that some time points observed higher market movements than that can be captured by a linear model.

It must be noted that the study period was a relatively stable period where the sectoral indices generally moved in positive territory. Hence the predictions were generally good. The same may not be true for a volatile period or long- term predications. However, the study gives a useful insight of financial markets in a simplified manner.

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