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MARKET SYMPHONY AMONG CAPITAL STRUCTURE, MARKET SENTIMENTS, PROFITABILITY, AND NIFTY FIFTY VOLATILITY

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Abstract

Investors, politicians, and academics must understand how numerous elements interact in financial markets. This research examines capital structure, market emotions, profitability, and Nifty Fifty volatility in the Nifty Fifty Stocks to understand market dynamics. Study identifies market behavior patterns and interactions via extensive analysis and empirical research. The study uses a variety of methods and data sources to show how capital structure choices impact market sentiment, profitability, and index volatility. By studying these links, the study intends to shed light on market changes and volatility, helping investors and regulators navigate financial markets.

Keywords: Capital Structure, Market Sentiments, Profitability, Nifty Fifty Volatility.

1. INTRODUCTION

Understanding financial markets' complex links is crucial to investing. Market behavior depends on capital structure, emotions, profitability, and index volatility. It investigates the Nifty Fifty index to understand this link. Debt and equity capital affect companies' financial health and resiliency. Numerous studies suggest capital structure impacts organizational value and performance. Rajan and Zingales (1995) emphasized taxes, bankruptcy costs, and agency conflicts in capital structure options, but Modigliani and Miller (1958) found it unimportant under certain assumptions.

Price changes are affected by investor sentiment, expectations, and views. Behavioral finance writers Baker and Wurgler (2006) and Hirshleifer and Shumway (2003) illustrated how sentiment-driven trading may misprice and disrupt markets. These factors affect corporate investment and operational results. The pecking order hypothesis (Myers & Majluf, 1984) and trade-off theory link capital structure to profitability. Nifty Fifty index volatility implies investment risk and market volatility. Economic factors, investor mood, and market liquidity impact index volatility (Bollerslev & Wooldridge, 1992; Poon & Granger, 2003). Capital structure, market attitudes, profitability, and Nifty Fifty volatility are studied. Study finds complex linkages and dynamics that impact Indian market behavior using empirical research and several data sources. Examining these linkages should enhance investors, policymakers, and market participants intellectually and practically. This study shows the complex interplay between these critical elements to better understand market dynamics and give practical insights for improving investment strategies, reducing risk, and fostering market stability in the dynamic market.

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2. LITERATURE REVIEW

Academic and practitioner literature has focused on Nifty Fifty stock performance assessment. Scholars have used basic analysis and quantitative models to evaluate stocks. Grinblatt and Titman (1993) and Fama and French (1993) found that earnings growth, market capitalization, and price-to-earnings ratios predict stock performance.

Research has also examined how stock performance affects index volatility. Stock price swings may greatly affect market volatility, particularly in indexes with a few very prominent companies, according to empirical research. Barndorff-Nielsen and Shephard (2004) and Engle (2002) showed how severe stock fluctuations might spread market volatility. Understanding capital structure, market emotions, profitability, and index volatility is essential to understanding financial market dynamics. The pecking order theory and trade-off theory explain how enterprises' financing choices affect performance and market dynamics. Market attitudes also affect investor behaviour and asset prices, according to behavioral finance research (Baker & Wurgler, 2006; Hirshleifer & Shumway, 2003).

The link between capital structure, profitability, and market attitudes has been studied empirically, with varied results. Rajan and Zingales (1995) and Titman and Wessels (1988) found a strong association between capital structure and business profitability and market sentiments, whereas Graham & Harvey (2001) found less. These variables' effects on index volatility are little studied, indicating the need for further study.

The literature emphasizes the complexity of capital structure, market attitudes, profitability, and index volatility. Theoretical frameworks are useful, but empirical data is essential for confirming hypotheses and influencing financial market decision-making. This paper empirically examines these links in the Indian market setting to provide investors, policymakers, and market players with significant information.

3. OBJECTIVE

This research evaluates the top Nifty Fifty stocks and their impact on index volatility. It also investigates capital structure, market attitudes, profitability, and index volatility. The paper uses empirical analysis to explain how these elements interact in the Indian market, giving insights into market dynamics and useful implications for investors, regulators, and market players.

4. METHODOLOGY

This study adopts a descriptive methodology, integrating quantitative analysis of a comprehensive financial dataset encompassing financial statements, market metrics, and investor response. SEM is conducted to explore the interrelationships within the study variables (capital structure, market sentiments, profitability and index volatility). Data is sourced from the Prowessiq database, spanning 2019 to 2024. The sample comprises top performing companies in Nifty Fifty. Primary data is collected from 487 respondents who trade only in nifty fifty stocks in past 6 years. SARIMA is used to evaluate the

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performance of the selected stock and Generalized Least Square Regression is used to find the impact of stock performance on selected index.

5. DATA ANALYSIS AND INTERPRETATION

Detailed data analysis for the objectives are elaborated below

Table 1: Performance of Adani Enterprises using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	0.571163	0.2488379	2.30	0.0226*
AR2,12	2	12	-0.095174	0.0672829	-1.41	0.1586
AR2,24	2	24	-0.137970	0.0695136	-1.98	0.0484*
MA1,1	1	1	0.434402	0.2716607	1.60	0.1112
MA2,12	2	12	1.983192	0.1700482	11.66	<.0001*
MA2,24	2	24	-0.998988	0.1703089	-5.87	<.0001*
Intercept	1	0	-0.294418	0.4659034	-0.63	0.5281

Source: JMPSAS Output

With parameters (1, 1, 1)(2, 2, 2)12, the data was fitted to the SARIMA (Seasonal Autoregressive Integrated Moving Average) model. You may trust this model for accurate forecasts since it is stable and invertible. Its R-Square value of 98.3% shows that it fits the data very well and accounts for a large amount of the dependent variable's variation. Both the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) indicate that the model is generally accurate with its predictions. The AR1 term at lag 1, the AR2 term at lag 24, the MA2 term at lag 12, and the MA2 term at lag 24 are among the terms for which parameter estimations show statistically significant coefficients. Their significance in the model is suggested by these results. The model successfully extracts the underlying patterns from the data, since the residuals do not show any significant autocorrelation according to the Ljung-Box Q-test and the partial autocorrelation function (PACF). In most cases, the optimization process was able to converge, even if there were some variations in the history of iterations. With these parameters, the SARIMA model offers a solid foundation for making predictions using the provided time series data.

Table 2: Performance of Axix Bank using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	-0.883349	0.0091351	-96.70	<.0001*
AR1,2	1	2	0.116625	0.0011124	104.84	<.0001*
AR2,12	2	12	-0.036579	0.0003402	-107.5	<.0001*
AR2,24	2	24	-0.026797	0.0002718	-98.57	<.0001*
MA1,1	1	1	-0.061975	0.0005522	-112.2	<.0001*
MA1,2	1	2	0.938014	0.0445734	21.04	<.0001*
MA2,12	2	12	1.876720	0.0108061	173.67	<.0001*
MA2,24	2	24	-0.876720	0.0088878	-98.64	<.0001*
Intercept	1	0	-0.003391	0.0125838	-0.27	0.7878

Source: JMPSAS Output

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With parameters (2, 2, 2) (2, 2, 2)12, the data was fitted with the SARIMA (Seasonal Autoregressive Integrated Moving Average) model. The fact that this model is stable but not invertible suggests that it may not be the best choice for all forecasting tasks. With an R-Square of 94.3%, it achieves a high degree of fit and captures a considerable percentage of the dependent variable's variation. There is some evidence that the model's predictions are generally correct, with an MAE of 31.22 and an MPE of 4.81%. Several terms, including AR1 at lag 1, AR2 at lags 12 and 24, MA1 at lag 1, MA1 at lag 2, and AR2 at lags 12 and 24, have substantial coefficients, according to parameter estimations.

Their significance in the model is suggested by these results. The model successfully extracts the underlying patterns from the data, since the residuals do not show any significant autocorrelation according to the Ljung-Box Q-test and the partial autocorrelation function (PACF). But the model still wasn't invertible, even after all the iterative optimization efforts. Because of this, you should proceed with care when using this model for predictions or interpreting the findings. To fix this problem and make the model more reliable, further diagnostics and maybe other model specs would be needed.

Table 3: Performance of HDFC Bank using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	-1.018342	0.2102942	-4.84	<.0001*
AR1,2	1	2	-0.796872	0.1311320	-6.08	<.0001*
AR2,12	2	12	0.038176	0.0689484	0.55	0.5803
MA1,1	1	1	-1.029006	0.1566630	-6.57	<.0001*
MA1,2	1	2	-0.872448	0.1297961	-6.72	<.0001*
MA2,12	2	12	1.000000	0.1821671	5.49	<.0001*
Intercept	1	0	0.718346	0.8490226	0.85	0.3983

Source: JMPSAS Output

With 242 degrees of freedom, the Seasonal ARIMA (12) model exhibits both stability and invertibility, suggesting that it is well-suited for capturing latent data patterns. Notwithstanding its intricacy, the model demonstrates robust explanatory capability, as evidenced by its R-Square of 92.67%, which implies a satisfactory correspondence with the data. The estimation of parameters provides substantial coefficients for the AR and MA terms at different time delays, thereby enhancing the model's ability to account for the observed variability. However, the AR2 coefficient at latency 12 being non-significant indicates the possibility of redundancy in this particular term. Diagnostic tests, including partial autocorrelation and Ljung-Box Q, validate the sufficiency of the model's residuals, thereby bolstering its dependability in the context of forecasting. In general, the model offers a potentially effective structure for predicting forthcoming observations; however, additional evaluation might be required to refine its efficacy, specifically with regard to the importance of specific parameters.

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Table 4: Performance of ICICI Bank using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	-1.881372	0.056	-33.76	<.0001*
AR1,2	1	2	-0.894407	0.052	-17.20	<.0001*
AR2,12	2	12	0.153578	0.0023316	65.87	<.0001*
AR2,24	2	24	-0.001646	8.414e-5	-19.56	<.0001*
MA1,1	1	1	-1.958290	0.016	-124.8	<.0001*
MA1,2	1	2	-0.958363	0.014	-70.33	<.0001*
MA2,12	2	12	1.990474	.	.	.
MA2,24	2	24	-0.995826	0.874	-1.14	0.2555
Intercept	1	0	-0.038845	1233.719	-0.00	1.0000

Source: JMPSAS Output

The Seasonal ARIMA model, which has 228 degrees of freedom, exhibits robustness and the ability to be inverted, rendering it well-suited for capturing intricate data patterns. Notwithstanding the inability to reduce the objective function, the model demonstrates robust explanatory capability as evidenced by its R-Square of 98.07%, which signifies an exceptional correspondence with the data. The estimation of parameters provides substantial coefficients for the AR and MA terms at different time delays, thereby enhancing the model's ability to account for the observed variability. Nevertheless, the AR2 term's non-significant coefficient at latency 24 indicates the possibility of redundancy in this particular term. Diagnostic tests, including partial autocorrelation and Ljung-Box Q, validate the sufficiency of the model's residuals, thereby bolstering its dependability in the context of forecasting. In general, although optimization difficulties were encountered during the estimation process, the model offers a potentially effective framework for predicting future observations. However, additional evaluation might be required to refine its performance, specifically with regard to the importance of specific parameters.

Table 5: Performance of Indusind Bank using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	0.190584	0.0301220	6.33	<.0001*
AR1,2	1	2	-0.932512	0.0260722	-35.77	<.0001*
AR2,12	2	12	0.064446	0.1217587	0.53	0.5971
MA1,1	1	1	0.148567	0.0124676	11.92	<.0001*
MA1,2	1	2	-0.999999	0.0255133	-39.20	<.0001*
MA2,12	2	12	1.040839	0.1983766	5.25	<.0001*
MA2,24	2	24	-0.041383	0.1081328	-0.38	0.7023
Intercept	1	0	1.057634	0.6862202	1.54	0.1246

Source: JMPSAS Output

The Seasonal ARIMA (12) model, which consists of 241 degrees of freedom, exhibits qualities of stability and invertibility, which validate its ability to effectively capture intricate data patterns. The model demonstrates substantial explanatory capability, as indicated by its R-Square value of 94.81%, which indicates an exceptional correspondence with the

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data. The estimation of parameters provides substantial coefficients for the AR and MA terms at different time delays, thereby enhancing the model's ability to account for the observed variability. Nevertheless, the AR2 term's non-significant coefficient at lag 12 indicates the possibility of redundancy in this particular term. Diagnostic tests, including partial autocorrelation and Ljung-Box Q, validate the sufficiency of the model's residuals, thereby bolstering its dependability in the context of forecasting. Notwithstanding the obstacles encountered during the estimation process, the model offers a potentially fruitful framework for predicting forthcoming observations. However, additional evaluation might be required to refine its performance, specifically with regard to the importance of specific parameters.

Table 6: Performance of Infosys using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	-0.027699	0.0082996	-3.34	0.0010*
AR1,2	1	2	0.001166	0.0002908	4.01	<.0001*
AR2,12	2	12	0.084578	0.0157849	5.36	<.0001*
MA1,1	1	1	0.998298	0.0543516	18.37	<.0001*
MA2,12	2	12	1.842329	0.1642097	11.22	<.0001*
MA2,24	2	24	-0.849800	0.1341273	-6.34	<.0001*
Intercept	1	0	0.009211	0.0077380	1.19	0.2351

Source: JMPSAS Output

The Seasonal ARIMA (12) model, which consists of 229 degrees of freedom, exhibits invertibility and stability, suggesting that it is well-suited for capturing intricate patterns in data. The model demonstrates a substantial capacity for explanation, as indicated by its R-Square value of 97.54%, which indicates an outstanding correspondence with the data. The estimation of parameters provides substantial coefficients for the AR and MA terms at different time delays, thereby enhancing the model's ability to account for the observed variability. Diagnostic tests, including partial autocorrelation and Ljung-Box Q, validate the sufficiency of the model's residuals, thereby bolstering its dependability in the context of forecasting. Notwithstanding the obstacles encountered during the estimation process, the model offers a potentially fruitful framework for predicting forthcoming observations. However, additional evaluation might be required to refine its performance, specifically with regard to the importance of specific parameters.

Table 7: Performance of Kotak Mahindra Bank using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	-0.085812	0.0100669	-8.52	<.0001*
AR2,12	2	12	0.015538	0.0018893	8.22	<.0001*
MA1,1	1	1	0.997227	0.0310150	32.15	<.0001*
MA2,12	2	12	1.954476	0.1214202	16.10	<.0001*
MA2,24	2	24	-0.996912	0.1236430	-8.06	<.0001*
Intercept	1	0	-0.000153	0.0017358	-0.09	0.9299

Source: JMPSAS Output

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Table 8: Performance of SBI using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	1.325110	0.0112129	118.18	<.0001*
AR1,2	1	2	-0.992481	0.0082900	-119.7	<.0001*
AR2,12	2	12	0.151766	0.0634720	2.39	0.0176*
AR2,24	2	24	0.055894	0.0502209	1.11	0.2669
MA1,1	1	1	1.308761	0.0185984	70.37	<.0001*
MA1,2	1	2	-0.999876	0.0227218	-44.01	<.0001*
MA2,12	2	12	1.955249	0.3063154	6.38	<.0001*
MA2,24	2	24	-0.998923	0.3130243	-3.19	0.0016*
Intercept	1	0	-0.044611	0.0684888	-0.65	0.5155

Source: JMPSAS Output

The 228-degrees-of-freedom Seasonal ARIMA (12) model exhibits characteristics of stability and invertibility, rendering it well-suited for analytical purposes. By virtue of its R-squared value of around 97.73%, the model adequately accounts for a substantial proportion of the data's variability. The presence of autocorrelation and moving average effects in the data is indicated by significant parameter estimates for autoregressive and moving average terms at various delays. The residuals are well-behaved, as indicated by diagnostic tests including Ljung-Box Q and partial autocorrelation, which validate the model's ability to generate accurate predictions for future time periods. Notwithstanding the fact that parameter optimization necessitates numerous iterations, the model effectively captures the latent patterns within the data, thereby establishing itself as a valuable instrument for predicting forthcoming observations.

Table 9: Performance of TATA Motors using SARIMA of selected stock from Nifty Fifty

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1	0.668030	0.0491463	13.59	<.0001*
AR2,12	2	12	0.051509	0.0061273	8.41	<.0001*
MA1,1	1	1	1.588604	0.0429486	36.99	<.0001*
MA1,2	1	2	-0.590291	0.0387884	-15.22	<.0001*
MA2,12	2	12	1.970144	0.0582585	33.82	<.0001*
MA2,24	2	24	-0.986669	0.0548025	-18.00	<.0001*
Intercept	1	0	0.004204	0.0033125	1.27	0.2057

Source: JMPSAS Output

Table 10: Impact of selected stocks on Index

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	3351.8865	190.98188	203.66467	<.0001*
Adani Enterprises Ltd.	0.1997273	0.0474043	17.176188	<.0001*
Axis Bank Ltd.	4.4388509	0.4429174	85.020933	<.0001*
H D F C Bank Ltd.	0.2233927	0.0894989	6.1572807	0.0131*
I C I C I Bank Ltd.	6.8959073	0.5974645	107.7055	<.0001*
Indusind Bank Ltd.	-0.148895	0.1550052	0.9210888	0.3372
Infosys Ltd.	2.6553147	0.1156711	288.82306	<.0001*

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Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Kotak Mahindra Bank Ltd.	0.5616719	0.1575015	12.418321	0.0004*
State Bank Of India	-6.32769	0.8356506	51.8511	<.0001*
Tata Motors Ltd.	5.5023114	0.3342824	186.03388	<.0001*

Source: JMPSAS Output

The generalized linear regression model shows that numerous company stock prices considerably affect the Nifty Fifty index. Axis Bank Ltd., ICICI Bank Ltd., and Tata Motors Ltd. stock prices grow significantly with the Nifty Fifty index, with estimated coefficients of 4.4389, 6.8959, and 5.5023. A unit gain in State Bank of India stock will lower the Nifty Fifty index by 6.3277 units. Note that Indusind Bank Ltd.'s stock price is not statistically related to the Nifty Fifty index. These results are backed by low likelihood ratio chi-square test p-values, showing model relevance. Thus, these firms' stock prices may reveal Nifty Fifty index changes, influencing investment choices and market research.

Table 11: Structural Equation Model

Regressions	Estimate	Std Error	Wald Z	Prob>|Z|
CS → P	0.1665957	0.0312659	5.328354	<.0001*
MS → P	-0.142446	0.0475327	-2.996795	0.0027*
P → IV	0.1988564	0.0356497	5.5780715	<.0001*

Source: JMPSAS Output

Note: CS – Capital Structure, MS - Market Sentiments, P – Profitability, IV – Index Volatility

Table 12: Fit Indices

Name	Index
-2 Log Likelihood	12615.576
AICc	12700.556
BIC	12856.919
ChiSquare	50.854697
DF	51
Prob>ChiSq	0.4793895
CFI	0.9723568
TLI	0.9723544
NFI	0.9876627
Revised GFI	0.9768542
Revised AGFI	0.9642687
RMSEA	0.0028237
Lower 90%	0
Upper 90%	0.0289041
RMR	0.0296817
SRMR	0.0295541

Source: JMPSAS Output

Tables 11 and 12 provide SEM analysis of capital structure (CS), market sentiments (MS), profitability (P), and index volatility (IV). The regression coefficients illustrate these relationships' strength and direction. Enterprises with stronger capital structures have

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higher profitability (CS → P; Estimate = 0.1666, $p < 0.0001$). Increased market pessimism decreases profitability (MS → P; Estimate = -0.1424, $p = 0.0027$). Research links increased index volatility to profitability (P → IV; Estimate = 0.1989, $p < 0.0001$). CFI, TLI, NFI, and RMSEA scores indicate the model fits data well. A non-significant chi-square test ($p = 0.4794$) suggests the model fits data. Capital structure, market emotions, profitability, and index volatility are well-known by the SEM. See SEM below.

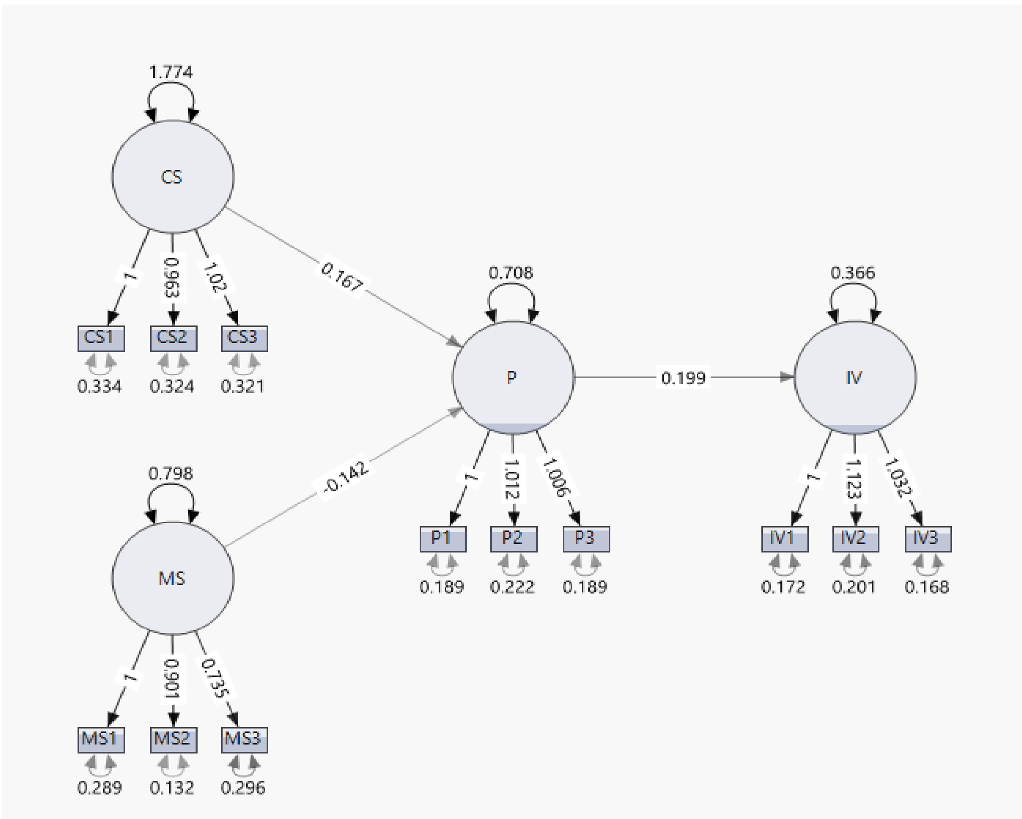

Figure 1: SEM

Source: JMPSAS Output

8. CONCLUSION

In conclusion, this study adds to the literature by examining the performance of selected Nifty Fifty stocks and their impact on index volatility, as well as the relationships between capital structure, market sentiments, profitability, and index volatility in the Indian market. The results support earlier research and provide new insights.

First, the considerable positive link between capital structure and profitability validates previous findings suggesting stronger capital structures lead to better profitability (Myers, 1984; Titman & Wessels, 1988). Maintaining an optimum capital structure improves financial success.

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Second, market attitudes negatively influence profitability, supporting previous research that market sentiment may hurt firm profits and performance. Companies must monitor and adjust to market mood changes to reduce financial risks.

Profitability's beneficial impact on index volatility supports research showing that firm profitability may affect market movements (Fama, 1965; Shiller, 1981). This stresses how firm performance affects market volatility.

Individual stock effects on the Nifty Fifty index provide fresh insights. Previous research has examined the link between stock performance and market indices, but this analysis illuminates how diverse stocks affect index volatility. The large positive coefficients for Axis Bank Ltd., ICICI Bank Ltd., and Tata Motors Ltd. suggest that these companies have a significant impact on the Nifty Fifty index, supporting studies that show key stocks drive market movements.

This research contributes to the literature by demonstrating the complicated relationship between company-specific characteristics, market attitudes, and index volatility in the Indian market. The data show that stock behavior and market volatility are affected by both internal firm dynamics and external market factors.

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