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A study on interplay of commodity price movements and equity returns in the Indian market

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Abstract
This comprehensive study delves into the intricate correlation between fluctuations in commodity prices and equity returns within the Indian market. It highlights the crucial understanding of these dynamics in the context of India's expanding economy and diverse sectors. Aiming to address gaps in existing literature, the research meticulously investigates the performance of specific commodities in the Indian market and their consequential impact on related stocks. Drawing from a diverse range of academic and industry literature, the study references influential works by renowned experts, including Black, Markowitz, Sharpe, Erb, Harvey, and Hamilton. The empirical analysis centres on key financial variables, offering insights into data stationarity, risk-return characteristics, correlation analysis, and Granger causality tests. Key findings emphasize the importance of achieving stationarity through differencing, reveal positive correlations, and present limited evidence of Granger causality. The study concludes by advocating for continuous monitoring and refinement of models for adaptive financial analysis and modelling, emphasizing the necessity for caution when making assumptions about predictive relationships. In summary, this research contributes valuable insights to informed decision-making in financial analysis and modelling, providing practical guidance for the development of adaptive financial models.

Keywords: Commodity prices, equity returns, risk-return, correlation, granger causality

Introduction

Within the dynamic arena of financial markets, investors continually seek avenues to optimize returns and manage risks effectively. An intriguing prospect for achieving diversification and value within investment portfolios lies in commodities and related stocks. The Indian market, characterized by a burgeoning economy and diverse sectors, provides a compelling backdrop for an exploration of the performance dynamics of selected commodities and their associated stocks. This research endeavours to conduct a thorough comparative analysis, unravelling the intricate relationship between commodity price movements and the returns generated by companies operating within these sectors.

As globalization and economic interconnectivity reshape the investment landscape, understanding the performance dynamics of commodities and related stocks becomes imperative for both individual and institutional investors. This study aims to address existing gaps in the literature by offering an in-depth exploration of the Indian market. It takes into account nuanced factors influencing the performance of select commodities and their corresponding impact on associated equity securities.

To facilitate a comprehensive analysis, we draw upon a diverse range of academic and industry literature. Pioneering studies such as those by Black (1972) [5], Markowitz (1952), and Sharpe (1964) [17] establish the foundations for portfolio theory and the principles of diversification, emphasizing the significance of asset allocation in maximizing returns for a given level of risk. Further insights into the behaviour of commodity prices and their relationship with equity returns are derived from seminal works like Erb and Harvey (2006) [7], while the impact of macroeconomic variables on commodity markets is explored through the lens of Hamilton (2009) [10] and Gorton and Rouwenhorst (2006) [9].

In the Indian context, researchers have started delving into the intricacies of commodity markets and related stocks. Kumar and Singh (2018) [27] analyse the performance of commodity futures markets, shedding light on implications for investors and policymakers. Additionally, the study by Anand *et al*. (2019) [28] examines the impact of commodity price movements on stock returns, providing valuable insights into the dynamics of these intertwined markets. Against this backdrop, our research contributes to the existing body of knowledge by offering a meticulous examination of the performance of select commodities in the Indian market and their corresponding impact on associated stocks. By incorporating insights from portfolio construction and risk management literature, we aim to provide investors with a robust framework for optimizing their portfolios in the Indian context.

The subsequent sections of this paper will delve into the methodology employed, data sources, and empirical findings, presenting a comprehensive overview of the performance dynamics of select commodities and their associated stocks in the Indian market.

The ever-evolving landscape of financial markets compels investors to continually explore avenues for optimizing returns and mitigating risks. Among the myriad investment options, commodities and related stocks stand out, offering a unique opportunity for diversification and value creation within portfolios. Against the backdrop of India's burgeoning economy and diverse sectors, the performance dynamics of select commodities and their associated stocks present an intriguing subject of study. This research embarks on a comprehensive comparative analysis, aiming to unveil the intricate relationship between commodity price movements and the returns generated by companies operating within these sectors in the Indian market.

Globalization and economic interconnectivity are reshaping the investment landscape, making it imperative for both individual and institutional investors to understand the performance dynamics of commodities and related stocks. This study addresses existing gaps in the literature by conducting an in-depth exploration of the Indian market, taking into account the nuanced factors influencing the performance of select commodities and their corresponding impact on associated equity securities.

The foundation of this research rests on a diverse set of academic and industry literature. Influential studies by Black (1972) [5], Markowitz (1952) [12], and Sharpe (1964) [17] have laid the groundwork for portfolio theory and the principles of diversification. These studies emphasize the significance of asset allocation in maximizing returns for a given level of risk. Additional insights into the behaviour of commodity prices and their relationship with equity returns are derived from seminal works such as Erb and Harvey (2006). The impact of macroeconomic variables on commodity markets is further explored through the lens of Hamilton (2009) [10] and Gorton and Rouwenhorst (2006) [9].

In the context of the Indian market, researchers have begun to delve into the intricacies of commodity markets and related stocks. Kumar and Singh (2018) [27] contribute to this exploration by analysing the performance of commodity futures markets, shedding light on implications for investors and policymakers. Furthermore, the study by Anand *et al.* (2019) [28] examines the impact of commodity price movements on stock returns, providing valuable insights into the dynamics of these intertwined markets.

This research endeavours to contribute substantially to the existing body of knowledge by offering a meticulous examination of the performance of select commodities in the Indian market and their corresponding impact on associated stocks. By incorporating insights from portfolio construction and risk management literature, we aim to provide investors with a robust framework for optimizing their portfolios in the unique context of the Indian market.

The subsequent sections of this paper will delve into the methodology employed, data sources, and empirical findings, presenting a comprehensive overview of the performance dynamics of select commodities and their associated stocks in the Indian market.

Research Questions

1. Do the trends and patterns of specific commodities and their associated stocks show similarities in the Indian market?
2. Do the risk and return profiles of commodities and related stocks in India yield positive outcomes?
3. Is there a connection between the movements of commodity prices and the returns of equities in India?
4. Is there concrete evidence supporting the inclusion of commodities and related stocks in the esteemed portfolio for investors in India?

Review of literature

The intersection of commodity price movements with equity returns is rooted in foundational portfolio theory. Pioneering works by Black (1972) [5], Markowitz (1952) [12], and Sharpe (1964) [17] highlight diversification's pivotal role in risk mitigation, forming the basis for understanding the intricate dynamics between commodities and equities within a diversified investment portfolio. Erb and Harvey's exploration of commodity futures sheds light on commodities' unique characteristics as investment instruments. This theoretical foundation offers insights into commodity markets' functioning and their potential impact on equity returns (Erb & Harvey, n.d.)

Examining the evolving dynamics among commodity prices, equity markets, and exchange rates, "The Changing Relationship Between Commodity Prices and Prices of Other Assets with Global Market Integration" scrutinizes spillover effects of equity market shocks onto commodity markets. The study evaluates predictive capacities of equity markets and exchange rates for commodity prices, underscoring exchange rates' significant predictive power, particularly for economies heavily reliant on primary commodities, known as "commodity currencies" (Rossi, 2012) [15].

Lombardi and Ravazzolo's study on the correlation between commodity and equity returns reveals an increased connection since the 2008 global financial crisis. Their use of Bayesian Dynamic Conditional Correlation (DCC) models emphasizes improved forecasting benefits for portfolio allocation. Contrary to the belief that commodities act as a hedge, the study notes higher volatility when included in a portfolio. While economic gains are observed in an asset allocation exercise, the authors acknowledge the accompanying rise in portfolio volatility. This challenges the traditional view of commodities as a hedge, emphasizing the need for a nuanced understanding of financial stability amid the growing correlation between commodity and equity returns (Lombardi & Ravazzolo, 2013) [11].

Exploring the relationship between stock and commodity prices, a study delves into the predictive capacity of the log stock price-commodity price ratio for stock returns. Emphasizing the importance of incorporating market interactions and employing a dynamic forecasting model, the research reveals the log stock price-commodity price ratio as a potent predictor for stock returns. The study underscores the superiority of rolling forecasts over recursive forecasts in incorporating new data effectively (Black *et al*., 2014) [4].

An article investigating the relationship between stock and agricultural commodity markets focuses on volatility spillover. Analysing the dot.com bubble and the 2008 financial crisis, the study, using the Volatility Impulse Response Function (VIRF), finds a significant increase in volatility spillovers from stock to commodity markets after the 2008 financial crisis. This heightened connection carries implications for practitioners and policymakers, offering insights for portfolio strategies and risk management. The study's innovative volatility-focused methodology contributes to existing literature (Baldi *et al*., 2016) [1].

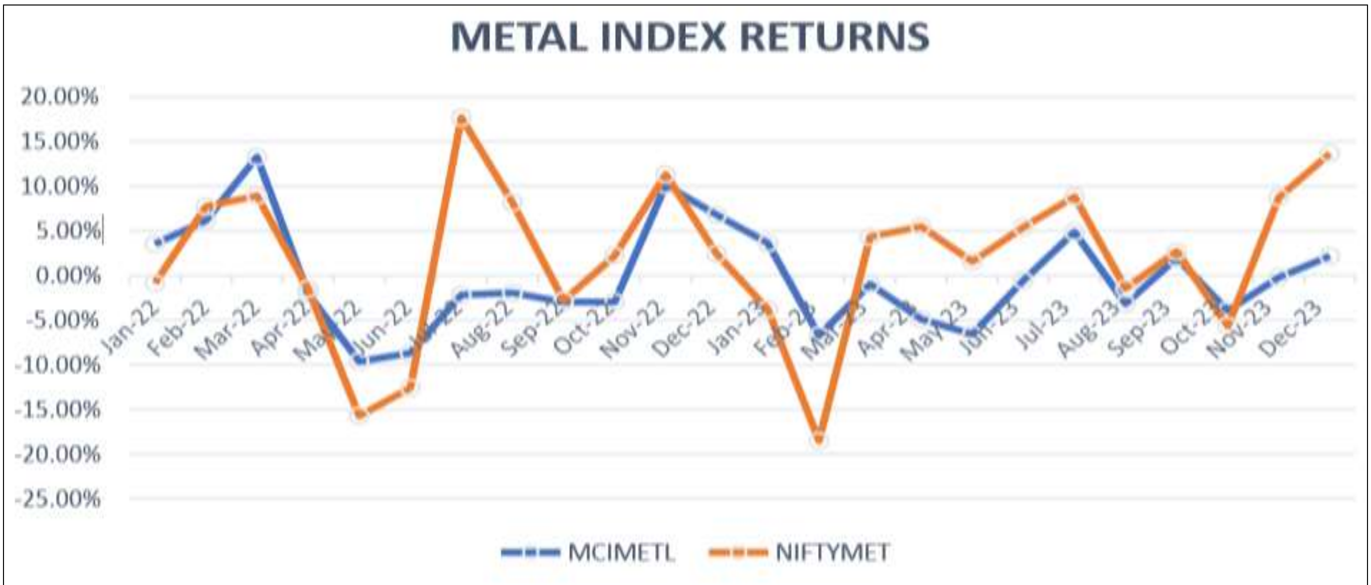
An accepted manuscript delves into financial ratios predicting returns in the Indian stock market. Highlighting sector-specific hypotheses tests, the study reveals varying predictability among financial ratios, stronger at the sector-level. The economic significance of return predictability is assessed, revealing certain financial ratios' impact on portfolio returns and utility. The study examines determinants of time-varying profits, finding that expected and unexpected financial ratio risks explain profitability in different sectors (Bannigidadmath & Narayan, 2016) [2].

Highlighted studies include "Analysing time–frequency co-movements across gold and oil prices with BRICS stock markets: A VaR based on wavelet approach," exploring the relationship between energy prices and stock returns, and investigating the cyclical phenomenon among stock and commodity markets. Each study provides unique insights into the complex interplay of financial markets, enriching our understanding for informed decision-making and market analysis.(Mensi *et al*., 2018) [13].

In "A Cyclical Phenomenon among Stock & Commodity Markets," the analysis of the cyclical relationship between commodity and stock markets, using the U.S. S&P 500 index and the U.S. producer price index (PPI), reveals a robust 31-year cyclical pattern in commodity markets, particularly reflected in the S&P 500. The study also contrasts the impacts of the 2008 financial crisis and the COVID-19 pandemic on both markets, emphasizing variations in recovery speed and effects on unemployment and Gross Domestic Product. With significant implications for investors and researchers, the findings illuminate the alternating pricing-performance leadership over extended periods, offering valuable insights for informed decision-making based on index relationships between stock and commodity markets. Overall, the study enriches our comprehension of the cyclical nature of these markets, contributing valuable perspectives for investment strategies and market analysis.(Zapata *et al*., 2023) [20].

Data and Research Method

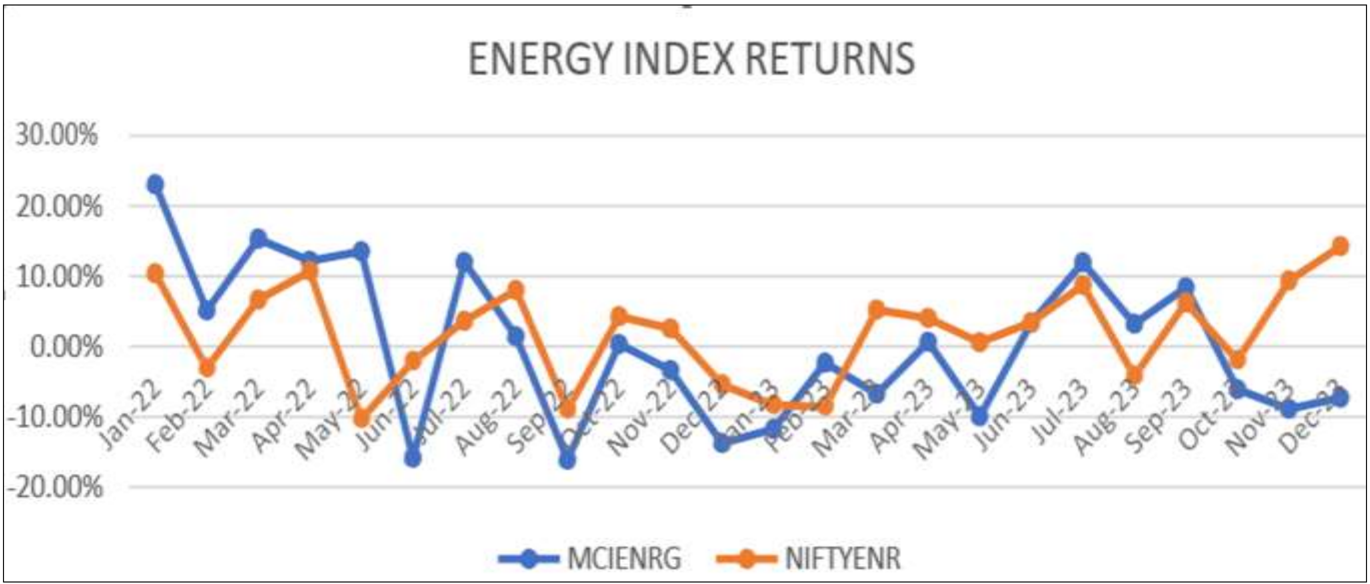
This study utilizes monthly closing price data from Investing.com's MCX iCOMDEX BASE METAL (MCIMETL), MCX iCOMDEX Energy (MCIENRG), MCX ICOMDEX Crude Oil (MCICRD), and Nifty Metal (NIFTYMET), Nifty Energy (NIFTYENR), Nifty Oil & Gas (NIFOILGAS) to represent India's stock market and commodity market portfolios, tracking their price movements. The data covers the period from January 2022 to December 2023, sourced from Investing.com. This timeframe was selected to ensure a comprehensive data window for the study, starting from the earliest available data for MCX and NSE.



Source: (MCX iCOMDEX BASE METAL Historical Rates (MCIMETL), 2024) .; (Nifty Metal Historical Rates (NIFTYMET) - Investing.Com, n.d.)

Fig 1: MCX iCOMDEX Base Metal and Nifty Metal monthly returns movement

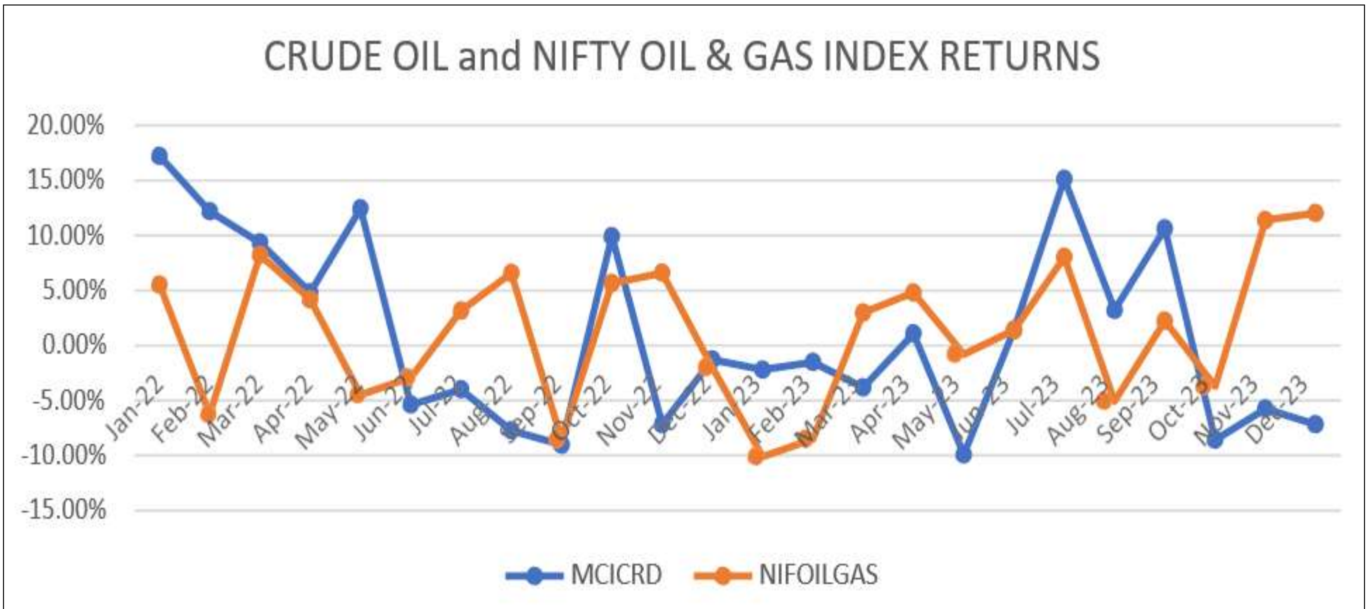
The data compares monthly percentage changes for MCIMETL and NIFTYMET over two years. Notable positive trends occur in March, November, and December 2022 for both, while significant negative changes are seen in May and June 2022. NIFTYMET has high increases in July and November 2022, but faces a substantial drop in February 2023. Both experience a tough February 2023. Overall, these fluctuations show the dynamic nature of financial markets. Investors may consider these trends for decision-making, understanding when positive or negative trends might influence their investment strategies. Further analysis, like checking correlations or external factors, can deepen our understanding of these observed trends.



Source: (MCX iCOMDEX Energy Historical Rates (MCIENRG) - Investing.Com, n.d.; Nifty Energy Historical Rates (NIFTYENR) - Investing.Com, n.d.)

Fig 2: MCX iCOMDEX ENERGY and NIFTY ENERGY monthly returns movement

The data compares monthly percentage changes for four variables—MCIMETL, NIFTYMET, MCIENRG, and NIFTYENR—over two years. Notable positive changes are seen in March, November, and December 2022 for MCIMETL and NIFTYMET, suggesting potential upward trends. July, November, and December 2022 show positive trends for NIFTYMET, while significant drops are observed in February 2023. MCIENRG demonstrates varied changes, with both positive and negative trends. NIFTYENR has positive trends in several months, while facing notable negative changes in others. Comparative analysis reveals common positive trends in November and December 2022 across all variables. Extreme negative changes are notable in February 2023 for MCIMETL, NIFTYMET, and NIFTYENR. The dynamic nature of these financial variables emphasizes the need for investors to consider these trends for effective decision-making, possibly adjusting strategies based on both positive and negative performance periods. Further analysis, considering correlations or external factors, could enhance understanding.



Source: (MCX ICOMDEX Crude Oil Historical Rates (MCICRD) - Investing.Com, n.d.; Nifty Oil & Gas Historical Rates (NIFOILGAS) - Investing.Com, n.d.)

Fig 3: MCX iCOMDEX Crude Oil and NIFTY Oil & Gas monthly returns movement

The data reveals monthly percentage changes for six variables—MCIMETL, NIFTYMET, MCIENRG, NIFTYENR, MCICRD, and NIFOILGAS—over a two-year period. Positive shifts are seen in certain months, like March, November, and December 2022, suggesting potential upward trends, while negative changes occur notably in May and June 2022. NIFTYMET shows positive trends in July, November, and December 2022, but faces a significant drop in February 2023. MCIENRG exhibits varied changes, both positive and negative. NIFTYENR experiences positive and negative trends, and MCICRD and NIFOILGAS show a mix of positive and negative changes in different months. Common positive trends are observed in November and December 2022. Extreme negative changes in February 2023 affect MCIMETL, NIFTYMET, and NIFOILGAS. Understanding these dynamic trends is crucial for effective decision-making in investment strategies, and consideration of both positive and negative performance periods is essential. Further analysis, such as examining correlations or external factors, can enhance our understanding of these observed trends.

Note: Figue-1, 2 and 3 shows the Index returns of selected Commodities index and related stocks index, indicating a trend which means non-stationary data.

Data stationarity

The significance of unit root tests and their crucial role in analysing economic and financial time series data. By covering various aspects such as types of time series, autoregressive unit root tests, and stationarity tests, the document provides valuable insights into making informed decisions about the trend in the data. This understanding is essential for identifying long-term equilibrium relationships among nonstationary time series variables, a key aspect in econometric and financial analysis. The document also addresses challenges associated with traditional tests and introduces efficient unit root tests, contributing to a more accurate and robust analysis. Overall, the importance of unit root tests extends to its role as a valuable resource for researchers, practitioners, and students, enhancing their comprehension and application of unit root tests in the realm of econometrics and financial analysis.(*Unitroot*, n.d.) [19]
Stationarity stands as a vital concept in the analysis of time series data, ensuring precision in econometric modelling and regression outcomes. Non-stationarity in such data can lead to misleading regressions and inaccurate conclusions. Methods for testing time series data for stationarity encompass both informal techniques like scatter plots and formal approaches like Dickey-Fuller and Augmented Dickey-Fuller tests. While these tests wield power, their limitations highlight the importance of careful result interpretation and consideration of alternative methods. The PDF illustrates this with a practical example, examining the stationarity of household final consumption expenditure per capita and GDP per capita in India from 1980-2009. The findings indicate non-stationarity at the level and first difference, but stationarity is achieved at the second difference. (Mushtaq, n.d.) [14].

Description: This statistical test rigorously examines the presence of a unit root within a univariate time series dataset, offering valuable insights into the stationary nature of the data.

Descriptive statistics

There is a significance of statistical analysis, particularly in the context of survey research. It underscores the challenges associated with obtaining high response rates in surveys and the potential impact on study reliability. The reference to the American Statistical Association as a source of guidelines indicates the importance of following established practices in statistical research. The practical examples using SAS software demonstrate the application of statistical tools such as histograms and box plots for effective data summarization and outlier detection. The emphasis on summary statistics like mean and median reinforces their role in statistical analysis. The introduction of the run test and discussion on sampling errors further contribute to a comprehensive understanding of statistical methodologies. Overall, the document aims to provide insights and practical guidance for researchers and practitioners engaging in statistical analysis.(Fisher, 2009) [8].

Correlation

In social science research, correlation analysis is like a detective tool that helps researchers understand how two things are connected. It gives them a number, called a correlation coefficient, which shows how strong and in what direction the link between two factors is. For example, if they're studying income and education, the correlation coefficient can tell if higher education tends to go hand in hand with higher income. Besides, this tool helps researchers predict outcomes based on certain factors and identify any problems like multicollinearity, which is when factors are too similar. It also lets them explore how one factor might affect the relationship between two others. But, remember, just because things are correlated doesn't mean one causes the other – it's more like noticing patterns that can be super useful in understanding social stuff.(Senthilnathan, 2019) [16].

Granger Causality Test

The Granger-causality test is a vital tool in econometrics, used to determine causal relationships in time series data. Its primary role is to unveil the direction and strength of causality among variables, offering valuable insights for decision-making in fields like economics, finance, and social sciences. This test's ability to identify causal connections assists in predicting future outcomes, developing effective policies, and understanding complex system dynamics. It contributes to a deeper comprehension of variable interdependencies, aiding researchers and policymakers in deciphering the underlying mechanisms behind economic and social phenomena. In essence, the Granger-causality test significantly contributes to empirical research and decision-making by providing a systematic approach to analysing causal relationships in time series data.

Empirical Results
Data Stationarity

Table 1: Data Stationarity

Unit Root Test Results Table (ADF)							
Null Hypothesis: the variable has a unit root							
At Level							
		MCI METL	**NIFTY MET**	**MCI ENRG**	**NIFTY ENR**	**MCI CRD**	**NIF OILGAS**
With Constant	t-Statistic	-3.1711	-4.7789	-4.1615	-4.5879	-3.7894	-4.3784
	Prob.	0.0351	0.001	0.004	0.0015	0.0092	0.0024
		**	***	***	***	***	***
With Constant & Trend	t- Statistic	-3.0709	-4.7724	-4.2434	-4.6574	-3.8357	-4.4269
	Prob.	0.1362	0.005	0.0144	0.006	0.0329	0.0098
		n0	***	**	***	**	***
Without Constant & Trend	t- Statistic	-3.2345	-4.611	-4.2784	-4.4646	-3.9353	-4.3506
	Prob.	0.0025	0.0001	0.0002	0.0001	0.0004	0.0001
		***	***	***	***	***	***
At First Difference							
		d(MCI METL)	d(NIFTY MET)	d(MCI ENRG)	d(NIFTY ENR)	d(MCI CRD)	d(NIF OILGAS)
With Constant	t- Statistic	-5.2828	-4.9876	-6.0266	-4.4096	-8.071	-4.8465
	Prob.	0.0003	0.0008	0.0001	0.0028	0	0.0011
		***	***	***	***	***	***
With Constant & Trend	t- Statistic	-5.2094	-4.9192	-5.9263	-5.0037	-7.9059	-5.0488
	Prob.	0.002	0.0044	0.0005	0.0037	0	0.0034
		***	***	***	***	***	***
Without Constant & Trend	t- Statistic	-5.4084	-5.1423	-5.9722	-4.5426	-8.1175	-4.9765
	Prob.	0	0	0	0.0001	0	0
		***	***	***	***	***	***
Notes: a: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1% and (no) Not Significant							
b: Lag Length based on SIC							
c: Probability based on MacKinnon (1996) one-sided p-values.							

Source: Author Calculation

Note: The table presents the stationarity properties of the selected variable based on the outcomes of the ADF Test.

The table summarizes tests conducted on financial variables like MCIMETL, NIFTYMET, MCIENRG, NIFTYENR, MCICRD, and NIFOILGAS to check if they exhibit a unit root, which indicates non-stationarity. These tests are done both at the original level and after taking the first difference of the data. Generally, at the original level, whether including or excluding a constant and trend, the unit root hypothesis is rejected for most variables, implying stationarity. However, consistently, the first difference shows significant results, suggesting that focusing on how the values change over time makes the series stationary. This is vital for accurate financial modelling and analysis, and the probabilities provide insights into the strength of these findings. In simpler terms, examining the changes in values over time enhances our understanding and modelling of these financial variables.

Descriptive Statistics- Risk Return Characteristics

Table 2: Descriptive Statistics on select commodity and stock index's

	MCICRD	**MCIENRG**	**MCIMETL**	**NIFOILGAS**	**NIFTYENR**	**NIFTYMET**
Mean	0.009950	0.003500	-0.002046	0.012692	0.018792	0.019325
Median	-0.014000	0.004800	-0.014550	0.026150	0.035300	0.025650
Maximum	0.172200	0.230500	0.133000	0.120300	0.142500	0.177000
Minimum	-0.099100	-0.161200	-0.096400	-0.101000	-0.103300	-0.185400
Std. Dev.	0.084917	0.107790	0.057459	0.064022	0.070453	0.088679
Skewness	0.468874	0.230533	0.515837	-0.166445	-0.219566	-0.641696
Kurtosis	1.873196	2.141896	2.807186	1.969555	1.969023	3.089793
Jarque-Bera	2.149059	0.948923	1.101526	1.172632	1.255751	1.655157
Probability	0.341458	0.622220	0.576510	0.556373	0.533725	0.437106
Sum	0.238800	0.084000	-0.049100	0.304600	0.451000	0.463800
Sum Sq. Dev.	0.165852	0.267231	0.075934	0.094273	0.114164	0.180870
Observations	24	24	24	24	24	24

Source: Author Calculation

The data reveals key statistical characteristics of six financial variables—MCICRD, MCIENRG, MCIMETL, NIFOILGAS, NIFTYENR, and NIFTYMET. Notably, MCICRD and NIFTYMET exhibit positive means, reflecting an overall positive trend, while MCIMETL has a slightly negative mean. The variability within the data is evident, with MCICRD displaying a wide range from -0.0991 to 0.1722. NIFTYMET stands out with a higher standard deviation, indicating increased variability. Skewness and kurtosis values provide insights into the shape of the data distribution, suggesting a rightward skew for MCICRD and MCIMETL, a leftward skew for NIFTYMET, and relatively peaked distributions for MCIMETL, NIFTYENR, and NIFTYMET. Jarque-Bera tests hint at plausible normality assumptions, with probabilities above 0.05. These statistical insights contribute to a better understanding of the nature and variation of these financial variables, crucial for informed financial analysis and modelling.

Correlation

Table 3: Correlation between commodities and related stocks index

Correlation						
t-Statistic						
Probability	**MCIMETL**	**NIFTYMET**	**MCIENRG**	**NIFTYENR**	**MCICRD**	**NIFOILGAS**
MCIMETL	1.0000					

NIFTYMET	0.4714	1.0000				
	2.0704	-----				
	0.0561	-----				
MCIENRG	0.2537	0.2331	1.0000			
	1.0156	0.9283	-----			
	0.3259	0.3679	-----			
NIFTYENR	0.2362	0.8089	0.4502	1.0000		
	0.9414	5.3278	1.9528	-----		
	0.3614	0.0001	0.0698	-----		
MCICRD	0.3936	-0.0753	0.7993	0.0898	1.0000	
	1.6585	-0.2926	5.1517	0.3494	-----	
	0.1180	0.7739	0.0001	0.7317	-----	
NIFOILGAS	0.2350	0.8036	0.2559	0.9302	-0.0526	1.0000
	0.9363	5.2294	1.0251	9.8140	-0.2039	-----
	0.3640	0.0001	0.3216	0.0000	0.8412	-----

Source: Author Calculation

The correlation table presents associations among financial variables, namely MCIMETL, NIFTYMET, MCIENRG, NIFTYENR, MCICRD, and NIFOILGAS. The values in the table represent correlation coefficients, indicating the strength and direction of relationships. The t-statistic and probability values offer insights into the statistical significance of these correlations. Notable positive associations include MCIMETL-NIFTYMET and MCIENRG-NIFTYENR. However, some correlations, like MCICRD-NIFOILGAS, show complexities with mixed directions and varying levels of significance. A comprehensive interpretation should consider both correlation and statistical measures to understand the financial relationships presented in the table thoroughly.

Granger Causality Test

Table 4: Granger Causality between MCIMETL and NIFTYMET

Pairwise Granger Causality Tests			
Lags: 2			
Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
D(NIFTYMET) does not Granger Cause D(MCIMETL)	21	0.16457	0.8497
D(MCIMETL) does not Granger Cause D(NIFTYMET)		0.24255	0.7875

Source: Author Calculation

The table summarizes Granger causality tests between the changes in two variables, D(NIFTYMET) and D(MCIMETL). The tests aim to see if the past values of one variable can help predict the changes in the other. For D(NIFTYMET) influencing D(MCIMETL), the results show a low F-Statistic and a high p-value (0.8497), suggesting that past values of D(NIFTYMET) don't significantly predict changes in D(MCIMETL). Similarly, for the reverse case, where D(MCIMETL) influences D(NIFTYMET), the F-Statistic is low, and the p-value is high (0.7875), indicating a lack of substantial evidence that past values of D(MCIMETL) contribute to predicting changes in D(NIFTYMET). In simpler terms, based on these results, it appears that the past values of one variable don't strongly influence or predict the changes in the other variable.

Table 4: Granger Causality between MCIENRG and NIFTYENR

Lags: 2			
Null Hypothesis:	Obs	F-Statistic	Prob.
D(NIFTYENR) does not Granger Cause D(MCIENRG)	21	1.2552	0.3116
D(MCIENRG) does not Granger Cause D(NIFTYENR)		2.4078	0.1219

Source: Author Calculation

The table summarizes Granger causality tests between the changes in two variables, D(NIFTYENR) and D(MCIENRG). The tests aim to investigate if past values of one variable can predict changes in the other. For D(NIFTYENR) affecting D(MCIENRG), the results show a moderately low F-Statistic and a relatively high p- value (0.3116), suggesting that past values of D(NIFTYENR) may not strongly predict changes in D(MCIENRG). Similarly, for the reverse case, where D(MCIENRG) influences D(NIFTYENR), the F-Statistic is higher but the p-value is still above the conventional significance level (0.1219), indicating a lack of robust evidence that past values of D(MCIENRG) significantly contribute to predicting changes in D(NIFTYENR). In simpler terms, based on these results, it seems that the past values of one variable do not strongly influence or predict the changes in the other variable.

Table 5: Granger Causality between MCICRD and NIFOILGAS

Lags: 2			
Null Hypothesis:	Obs	F-Statistic	Prob.
D(NIFOILGAS) does not Granger Cause D(MCICRD)	21	1.4086	0.2732
D(MCICRD) does not Granger Cause D(NIFOILGAS)		1.4246	0.2695

Source: Author Calculation

The table summarizes Granger causality tests with a lag of 2, examining the relationship between the changes in two variables: D(NIFOILGAS) and D(MCICRD). The tests explore whether past values of one variable can predict changes in the other. For D(NIFOILGAS) influencing D(MCICRD), the results show a moderately low F-Statistic and a relatively high p-value (0.2732), suggesting that past values of D(NIFOILGAS) may not strongly predict changes in D(MCICRD). Similarly, for the reverse case where D(MCICRD) influences D(NIFOILGAS), the F-Statistic is moderately low, and the p-value is relatively high (0.2695), indicating a lack of robust statistical evidence that past values of D(MCICRD) significantly contribute to predicting changes in D(NIFOILGAS). In simpler terms, based on these results with a lag of 2, it seems that past values of one variable may not strongly influence or predict the changes in the other variable.

Outcomes

The empirical analysis focused on key financial variables, namely MCIMETL, NIFTYMET, MCIENRG, NIFTYENR, MCICRD, and NIFOILGAS. The primary findings are as follows:

- **i) Data Stationarity:** At the original level, the ADF tests consistently rejected the unit root hypothesis for most variables, indicating stationarity. However, emphasizing the significance of analysing changes over time, the first difference of the data revealed significant results, highlighting the importance of achieving stationarity through differencing.
- **ii) Descriptive Statistics:** Risk-Return Characteristics: Descriptive statistics provided valuable insights into the risk-return characteristics of the financial variables. MCICRD and NIFTYMET displayed positive means, suggesting an overall positive trend, with NIFTYMET showing higher variability. Skewness and kurtosis values offered insights into the distribution shape of the data.
- **iii) Correlation:** Positive correlations were notable, particularly between MCIMETL-NIFTYMET and MCIENRG-NIFTYENR. Some correlations, such as MCICRD-NIFOILGAS, displayed complexities with mixed directions and varying levels of significance.
- **iv) Granger Causality Test:** Limited evidence of Granger causality was found between the variables. Past values of one variable did not strongly predict changes in the other, underscoring caution in assuming predictive relationships.

Suggestions

a) Acknowledge the pivotal role of first differences in achieving stationarity for effective modelling.
b) Consider both correlation coefficients and statistical significance to comprehensively understand financial relationships.
c) Exercise caution when assuming predictive relationships, given the limited evidence of Granger causality.
d) Advocate for continuous monitoring and refinement of models to adapt to dynamic market conditions.

These findings contribute valuable insights for informed decision-making in financial analysis and modelling. Ongoing analysis and model adjustments are recommended for the development of robust and adaptive financial models.

Conclusion

The empirical study examined key financial variables in India's stock and commodity markets over a two-year period from January 2022 to December 2023. The analysis included data stationarity tests, descriptive statistics on risk-return characteristics, correlation assessments, and Granger causality tests. The findings highlighted the importance of first differences for achieving stationarity, provided insights into the risk-return profiles of financial variables, identified positive correlations, and indicated limited evidence of Granger causality. The study emphasized caution in assuming predictive relationships and recommended continuous monitoring and model refinement for adaptive financial analysis.

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