International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 12s, 2025
https://theaspd.com/index.php

Time-Varying Impact of Crude Oil Prices on Indian Auto Stock Returns: A Rolling Window & Structural Break Analysis

Dr. Hiral Tailor[1], Mr. Hardik Patel[2], Dr. Chetankumar J Lad[3]
[1]Associate Professor, VidyaBharti Trust College of MCA (MBA Department), Bardoli – Surat, hiraltaylor@gmail.com
[2]Assistant Professor, VidyaBharti Trust College of MCA (MBA Department), Bardoli – Surat, patelhardik2988@gmail.com
[3]Professor & Director, Naran Lala School of Industrial Management and Computer Science, Navsari, chetanjlad@gmail.com

Abstract
This study examines the dynamic impact of crude oil prices on the returns of selected Indian automotive firms with the help of a large econometric model. Utilizing monthly data from the period January 2010 to December 2024, the work employs Augmented Dickey-Fuller tests, dummy variable regressions, rolling window regressions, and Bai-Perron structural break tests to examine whether investor responses to crude oil prices and key macroeconomic variables—exchange rate, interest rate, and inflation—have evolved over time. These findings point towards an abrupt decline in oil price sensitivity post-2016, particularly in the case of Tata Motors and the Nifty Auto Index, concurring with key policy actions like the FAME II scheme and fuel price deregulation in India. Maruti Suzuki is found to be exchange rate volatility sensitive, while CPI is found to have minimal impact across the sector. Structural breakpoints overlap with significant policy shifts and macro shocks like the COVID-19 pandemic. Finally, the study emphasizes that investor sentiment has adapted in response to structural reforms, demonstrating a gradual decoupling of auto stock performance from crude oil price volatility. The results are helpful to investors, policymakers, and market participants in understanding India's evolving auto sector and energy landscape.
Keywords: *Crude Oil Prices, Auto Stock Returns, Rolling Regression, Structural Break Analysis, FAME II Policy*

1. INTRODUCTION

The relationship between stock performance and oil prices has been the subject of extensive financial and academic research. Oil, being a significant world commodity, influences macroeconomic stability, inflation, and profitability at the corporate level. In industries dependent on fuel and raw materials to a large extent, the price volatility of oil controls market dynamics. As India needs to import approximately 85% of its crude oil requirements, changes in world oil prices have far-reaching implications for economic growth, corporate earnings, and investor sentiment (International Energy Agency, 2023).

1.1 International Environment and Sectoral Importance

Historically, crude oil price shocks have led to massive-scale economic and financial turmoil. The 1973 Oil Crisis induced the phenomenon of stagflation in the economies of the world (Hamilton, 1983), while the 2008 Global Financial Crisis, fueled in part by oil prices surging to a peak of $147 per barrel, yielded the world recessions and motor industry slowdowns (Kilian, 2009). The 2020 COVID-19 pandemic also exemplified the volatility of oil prices, with West Texas Intermediate (WTI) crude briefly trading at negative prices, impacting worldwide stock markets (Baumeister & Kilian, 2020).

The Indian automobile industry, which contributes 7.1% to India's GDP and nearly 49% to manufacturing GDP, has shown growth trends of different magnitudes depending on the volatility of oil prices (Society of Indian Automobile Manufacturers [SIAM], 2023). Higher fuel prices generally have the effect of decreasing automobile demand by consumers, particularly on high-fuel-consuming cars like SUVs and trucks. A decrease in oil prices makes cars cheaper, which results in higher vehicle sales. The 2014-15 drop in oil prices where crude fell from $110 to $50 per barrel led to a sharp rise in automobile demand at the expense of manufacturers and investors (World Bank, 2015).

1.2 Investor Sentiment and Market Behavior

Investor psychology responds very vigorously to the direction of oil prices, particularly in the equity market. An increase in oil prices is usually seen as a rise in inflationary pressure, which is equated to increased costs, reduced earnings, and smaller economic growth, all of which are unfavorable for stock

market valuations (Chen et al., 1986). This is seen most prominently in the NIFTY Auto Index, an indicator of India's leading automobile stocks. During periods of high volatility in oil prices, automobile stocks typically experience increased selling pressure as investors anticipate weaker demand and declining profitability (Reserve Bank of India [RBI], 2023).
In addition, structural shifts in the automobile industry—such as electric vehicle (EV) uptake, stricter emission norms, and government fuel strategies—have begun to reshape the alignment of the industry with crude oil prices. India's government FAME-II initiative has spurred the uptake of EVs, reducing the historic dependence of the automobile industry on fossil fuels (Ministry of Heavy Industries, 2023). Such a policy shift necessitates a re-examination of the oil price-stock return relationship, as conventional models may fail to capture the evolving market dynamics altogether.
The relationship between stock market performance and oil prices has been the subject of extensive scholarly and financial study. As a key global commodity, crude oil impacts macroeconomic stability, inflation, and profitability for companies. In sectors like automobiles, whose operations depend heavily on fuel and raw materials, the uncertainty of oil price movements controls market dynamics. As India is required to import approximately 85% of its crude oil requirements, changes in international oil prices have significant implications for economic growth, business profitability, and investor morale (International Energy Agency, 2023).

1.3 Global Context and Sectoral Relevance

Historically, price shocks in crude oil have generated massive economic and financial upsets. The 1973 Oil Crisis initiated stagflation in the economies of the world (Hamilton, 1983), while the 2008 Global Financial Crisis, fueled in part by oil prices climbing a peak of $147 per barrel, generated global recessions and motor industry slowdowns (Kilian, 2009). The 2020 pandemic of COVID-19 also served to illustrate the volatility of oil prices, as West Texas Intermediate (WTI) crude briefly traded at negative prices, impacting global stock markets (Baumeister & Kilian, 2020).
The Indian automotive industry, accounting for 7.1% of India's GDP and nearly 49% of manufacturing GDP, has shown patterns of varying magnitude depending on the volatility of oil prices (Society of Indian Automobile Manufacturers [SIAM], 2023). Higher fuel costs typically have a dampening effect on car demand by consumers, particularly on fuel-intensive vehicles like SUVs and trucking companies. Decreased oil prices make cars cheaper, thus boosting car sales. The 2014-15 oil price fall, when crude slid from $110 to $50 per barrel, saw a huge surge in car demand in the favor of manufacturers and investors (World Bank, 2015).

1.4 Investor Sentiment and Market Behavior

Investor sentiment is highly sensitive to the direction of oil prices, particularly in the stock market. An increase in oil prices has a tendency to be regarded as inflationary pressure, which will equate to increased costs, decreased earnings, and reduced economic growth, all of which are unfavorable for stock market valuations (Chen et al., 1986). This can be seen most clearly in the NIFTY Auto Index, which tracks India's leading automobile stocks. During periods of excessive volatility of oil prices, automobile stocks typically bear the brunt of increased selling pressures as investors anticipate lower demand and decreased profitability (Reserve Bank of India [RBI], 2023).

1.5 The Need for a Dynamic Approach

Prior studies on the oil-stock return relationship have mostly focused on broad indices such as NIFTY 50 and Sensex, with static econometric models such as linear regression or cointegration tests (Sadorsky, 1999). The Indian automotive sector is, however, undergoing sensational changes due to:

- Increasing popularity of EVs and hybrid cars, reducing reliance on crude oil.
- Fiscal policy of the government and fuel subsidies, shifting cost structures.
- Global supply chain disruption and geopolitical uncertainty, affecting the price of raw materials.
- Shift in consumer behavior towards alternative forms of fuels like CNG and hydrogen fuel cells.

Such an analysis suggests that the traditional linear crude oil price and automobile stock return relationship is becoming less relevant. Instead, a time-varying econometric approach—e.g., rolling window regression and structural break analysis—can provide greater insight into the dynamic changes in this relationship over time (Narayan & Sharma, 2011).

This study attempts to investigate whether the sensitivity of auto stocks to crude oil price changes has changed in response to these structural shifts. Using cutting-edge econometric methods, the research aims to offer valuable inputs to investors, policymakers, and business stakeholders. The understanding of this dynamic nexus is crucial to formulating investment strategy, policy measures, and business decisions in India's rapidly transforming automobile sector.

2. LITERATURE REVIEW

2.1 Theoretical Background: Crude Oil and Stock Markets

The relationship between stock markets and crude oil prices is based in two fundamental channels of economics: the cost channel and the demand channel. The cost channel asserts that increases in oil prices increase input costs, hence reducing the profitability of companies and stock prices (Jones & Kaul, 1996). Conversely, the demand channel posits that the behavior of oil prices reflects global economic activity; rising oil prices may reflect growth and thus influence investor sentiment in a positive way (Kilian & Park, 2009). Hamilton (1983) was the initial one to note oil price shocks as a major force behind macroeconomic volatility.

Kilian (2009) extended this by distinguishing between supply-driven, demand-driven, and speculation shocks. While supply shocks (e.g., geopolitical disturbances) tend to damage stock returns (Ratti & Vespignani, 2016), demand-driven shocks are positive or even neutral depending on the general economic environment (Basher et al., 2012). Speculative shocks, on the other hand, based on the behavior of financial markets, add extra volatility (Hamilton, 2013). Current studies point out that oil is now financialized, with institutional investors currently viewing it as an asset class to be traded. Tang and Xiong (2012) and Filis et al. (2011) maintain that oil-stock linkage has been tightened by financialization, especially in economies that are energy reliant.

2.2 Sector-Specific Insights: Auto Stocks and Oil Prices

The automobile sector is highly sensitive to oil prices as it relies on fuel consumption and supply chain activities. Bhar and Nikolova (2009) demonstrated that higher oil prices negatively affect the automobile firms, especially those with fuel-guzzling vehicles. In India, Mohanty and Nandha (2017) and Mondal & Das (2021) concluded that higher oil prices reduce automobile consumption by the consumers and negatively affect auto sales.

Singh et al. (2022) wrote about a shift in sensitivity between traditional and EV manufacturers, finding that traditional car manufacturers are more sensitive to oil price shocks than EV manufacturers. Zhou et al. (2021) also found that automobile companies are among the most oil-sensitive sectors compared to technology or healthcare.

2.3 Methodological Enhancements

Classic research utilized OLS regression and cointegration tests under the premise of a time-invariant relationship between oil prices and stock returns. But more recent research recognizes that such relationships change over time. Narayan and Sharma (2011) applied rolling regression techniques to account for time-varying effects, whereas Ghosh and Kanjilal (2016) suggested structural break tests (e.g., Bai-Perron) to identify regime shifts.

Wavelet analysis (Aloui & Jammazi, 2009), quantile regression (Shao et al., 2021), and regime-switching models (Hamilton, 1994; Bouri et al., 2021) have been applied to a greater extent to identify nonlinear dynamics. In more recent times, machine learning and deep learning techniques have emerged as useful tools. Liu et al. (2019), Pham (2022), and Zhang et al. (2023) demonstrated that support vector machines and LSTM networks surpass traditional models in predicting linkages between stock and oil.

These approaches reflect a broader trend away from static towards dynamic, data-driven analysis of the impacts of oil prices.

2.4 Recent Contributions (2018–2024)

In recent times, research has moved towards integrating macroeconomic variables, financial volatility, and regime changes into models of oil-stock returns. Liu et al. (2019) employed deep learning to improve the predictive power of oil price impacts on stock markets. Ratti and Vespignani (2020) used high-frequency data to highlight short-run transmission of volatility from oil into equities.

Sector-wise, Zhou et al. (2021) found that automobile stocks respond more to oil prices than to tech or healthcare. Singh et al. (2022) confirmed that traditional Indian automakers are more negatively impacted by crude oil than EV firms, referring to changing sector dynamics. Narayan et al. (2023) employed a hybrid VAR–ML model to assess the impact of oil prices under different alternative policy regimes.

These attempts indicate growing interest in sector-specific, policy-sensitive, and time-sensitive modeling, with Indian automobile being a virgin yet rich area of research.

2.5 Research Gaps and Call for a Dynamic Approach

Despite methodological advancements, some research gaps still persist. First, most studies still assume symmetrically the impact of oil shocks, without considering how positive and negative changes would influence stock returns differently. Second, most of the literature is limited to developed economies, and there is little sectoral research in emerging economies like India.

Third, the policy change function—more broadly, sustainability and energy transition policies such as India's FAME II scheme—is under-theorized in research examining financial effects. While Bouri et al. (2021) and Maitra et al. (2023) establish policy impacts, few papers explicitly assess sectoral responses to EV-focused interventions.

Lastly, investor sentiment and behavior-based variables must be integrated using high-frequency or real-time information. Social media metrics, algorithmic trading volumes, and behavioral finance indicators might also reveal more about how investors behave in response to oil volatility.

Overall, most current studies emphasize that dynamic, time-varying models need to be utilized when modeling oil price-stock return relationships, particularly in rapidly evolving sectors like automobiles. This paper tries to fill the gap by applying rolling regression and structural break methods to the Indian automobile sector—a new, relevant subject.

3. RESEARCH METHODOLOGY

3.1 Study Rationale: Indian auto industry is one of the backbone industries of the Indian economy. The advent of electric mobility and policy interventions like the FAME II scheme call for the evaluation of their influence on the bottom lines. The study aims to examine the influence of macroeconomic variables and policy reforms on leading Indian auto companies' stock returns.

3.2 Problem Statement: Notwithstanding government initiatives supporting EV adoption under FAME II, there is sparse empirical evidence assessing its impact on stock performance. Moreover, the impact of oil prices, inflation, interest rates, and exchange rate movements on automobile stocks is under-explored.

3.3 Scope of the Study: The study covers four listed automobile firms of the Nifty Auto Index on the basis of monthly information from 2010 to 2024. International factors like oil prices and exchange rates are also covered in order to make the analysis more comprehensive.

3.4 Objectives of the Study

1. To examine the impact of macroeconomic variables on the stock prices of selected Indian automobile companies.
2. To analyze the effect of the FAME II initiative on the performance of auto sector shares.
3. To evaluate sectoral trends in relation to the return of the Nifty Auto Index as a benchmark.
4. To determine the sensitivity of stock returns to crude oil prices, inflation (CPI), interest rates, and exchange rates.

3.5 Study Hypotheses

H_{01}: FAME II scheme has no significant influence on the Indian auto companies' stock returns selected.

H_{02}: Macroeconomic variables (interest rate, crude oil price, CPI, exchange rate) have no impact on the return of the companies.

H_{03}: There is no significant difference in pre-FAME II and post-FAME II returns.

3.6 Research Design and Sampling

We use a descriptive research design with quantitative time-series data to analyze evolving stock return patterns in response to macroeconomic variables and changes in policy regarding EVs.

Purposive sampling was employed to span four market-leading firms — Maruti Suzuki, Tata Motors, Bajaj Auto, and Mahindra & Mahindra — according to their market leadership and membership in the Nifty Auto Index. The Nifty Auto Index is also a sectoral performance benchmark.

3.7 Data and Sources Secondary monthly data from 2010 to 2024 are sourced from:

1. BSE/NSE (share prices)
2. RBI & MoSPI (interest rate, CPI)
3. EIA (Brent crude)
4. RBI/FRED (exchange rate)

3.8 Analytical Techniques

1. ADF Unit Root Test (stationarity)
2. Descriptive Statistics and Correlation Analysis
3. Dummy Variable Regression (static effects of macro variables and FAME II)
4. Rolling Window Regression (time-varying effects)
5. Structural Break Tests (Bai-Perron, for regime shifts)

Data Analysis

Stationary Tests: ADF & PP tests for crude oil prices and stock returns.

Table X: Augmented Dickey-Fuller (ADF) Test Results for Stationarity (First Difference)

Variable	PP Test Statistic	1% CV	5% CV	10% CV	P-value	Stationary (Yes/No)
Bajaj Auto	-8.9311	-3.468521	-2.878212	-2.575737	0.0000	Yes
M & M	-9.368567	-3.468295	-2.878113	-2.575684	0.0000	Yes
Maruti Suzuki	-12.94444	-3.468072	-2.878015	-2.57563	0.0000	Yes
Tata Motors	-9.371145	-3.46898	-2.878413	-2.575844	0.0000	Yes
Nifty Auto Index	-9.354116	-3.46898	-2.878413	-2.575844	0.0000	Yes
Brent Crude Oil	-11.12063	-3.468072	-2.878015	-2.575632	0.0000	Yes
Interest Rate	-3.710972	-3.467633	-2.877823	-2.57553	0.0047	Yes
CPI (Inflation)	-8.541749	-3.468521	-2.878212	-2.575737	0.0000	Yes
Exchange Rate	-13.87636	-3.467205	-2.877636	-2.57543	0.0000	Yes

Note: CV = Critical Value. Stationarity is confirmed when the ADF statistic is less than (more negative than) the critical value and the p-value is < 0.05.

Stationarity Test Results

For making the time series regression analysis consistent, stationarity of variables was tested using the Augmented Dickey-Fuller (ADF) test. Initially, the test was carried out at the first-difference level for all the variables like log return of some auto sector shares (Bajaj Auto, M&M, Maruti Suzuki, Tata Motors), Nifty Auto index, price of Brent crude, interest rate, inflation (CPI), and exchange rate for the period 2013-2024.

The results, as indicated in Table [X], indicate that all variables are stationary after first difference. To be specific, ADF test statistics for all series were more negative than 1% level of significance critical values, and all the p-values were below the 0.05 level. Therefore, the null hypothesis of unit root was rejected for all series and they were found to be stationary. This makes the application of these differenced series to future econometric modeling such as rolling regression, and structural break analysis valid.

Descriptive Statistics of Auto Stock Returns

	BAJAJ_LOG...	MARUTI_L...	M_AND_M_...	TATA_LOG...	NIFTY_AUT...
Mean	-6.39E-05	-5.99E-05	-0.000106	-0.000267	-8.29E-05
Median	-8.41E-05	-8.76E-05	-0.000101	-0.000277	-3.46E-05
Maximum	0.001737	0.001933	0.001617	0.002633	0.000899
Minimum	-0.001964	-0.001619	-0.001797	-0.002742	-0.001154
Std. Dev.	0.000471	0.000501	0.000612	0.000892	0.000267
Skewness	0.049460	0.247634	0.062724	0.087960	-0.267432
Kurtosis	4.582486	4.942617	3.376877	3.655237	4.821961
Jarque-Bera	18.85535	30.14287	1.183303	3.452132	27.04215
Probability	0.000080	0.000000	0.553413	0.177983	0.000001
Sum	-0.011500	-0.010788	-0.019045	-0.048018	-0.014926
Sum Sq. Dev.	3.98E-05	4.49E-05	6.71E-05	0.000142	1.28E-05
Observations	180	180	180	180	180

Stock	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera (p-value)
Bajaj Auto	−0.000064	0.000471	0.049	4.58	0.0000 ✶
Maruti Suzuki	−0.000060	0.000501	0.248	4.94	0.0000 ✶

M&M	−0.000106	0.000612	0.063	3.38	0.5534 ✅
Tata Motors	−0.000267	0.001204	0.088	3.66	0.1780 ✅
Nifty Auto Index	−0.000083	0.000358	−0.267	4.82	0.0000 ✴️

✴️ Indicates significant departure from normality (Jarque-Bera test, $p < 0.05$)
✅ Indicates return distribution is approximately normal

The descriptive statistics reveal that each of the five auto stocks had slightly negative mean returns during the sample period, with the most negative mean return belonging to Tata Motors (−0.000267). In terms of volatility, the highest standard deviation was also possessed by Tata Motors and represented higher price movements, while the least volatile among the five was Nifty Auto.

Jarque-Bera test indicates that return distributions of Bajaj Auto, Maruti Suzuki, and Nifty Auto Index are strongly non-normal due to leptokurtosis (fat tails), a common feature in financial time series. The distribution of M&M and Tata Motors was very close to normal.

Return values for skewness reveal that returns were slightly right-skewed except for the Nifty Auto Index, which was negatively skewed, reflecting a more common number of small negative returns in the sector index than in individual stocks.

Correlation

The correlation matrix below presents the pairwise linear relationships between log returns of selected Indian auto stocks and key macroeconomic variables (Brent crude oil price, interest rate, CPI, and exchange rate). The analysis covers monthly data from January 2010 to December 2024.

	Bajaj_Log Return	Tata_Log Return	M_And_M_ Return	Maruti_L Return	Nifty_Aut Return	Brent_C Return	Interest Return	Cpi	Exchange Rate
Bajaj_Log Return	1.00	0.33	0.33	0.35	0.53	0.07	0.08	0.04	0.05
Tata_Log Return	0.33	1.00	0.27	0.36	0.65	0.26	0.00	-0.12	-0.13
M_And_M_ Return	0.33	0.27	1.00	0.38	0.62	0.12	0.03	0.01	-0.01
Maruti_L Return	0.35	0.36	0.38	1.00	0.65	-0.01	0.10	-0.06	-0.09
Nifty_Aut Return	0.53	0.65	0.62	0.65	1.00	0.06	0.03	-0.13	-0.16
Brent_C Return	0.07	0.26	0.12	-0.01	0.06	1.00	-0.10	-0.03	-0.07
Interest Return	0.08	0.00	0.03	0.10	0.03	-0.10	1.00	0.03	0.07
Cpi	0.04	-0.12	0.01	-0.06	-0.13	-0.03	0.03	1.00	0.98
Exchange Rate	0.05	-0.13	-0.01	-0.09	-0.16	-0.07	0.07	0.98	1.00

Note: All variables are monthly log returns or values, computed over the period 2010M01–2024M12

The test of correlation shows there is no outstanding correlation with the sector index and moderate positive correlation with individual stock returns. Notably, Tata Motors and Maruti Suzuki have high positive correlation with Nifty Auto Index (both at 0.65), implying that they have close tracking of the sector overall performance.

On the other hand, correlation with stock returns and macroeconomic variables such as Brent crude, interest rate, CPI, and exchange rate are generally weak or near zero, indicating that the variables themselves may not be at fault for explaining return volatility. The only case in point is Tata Motors, which is moderately positively correlated with Brent crude returns (0.26), indicating some oil sensitivity. Of concern, CPI, interest rate, and exchange rate are highly inter-correlated (more than 0.98), indicating potential multicollinearity. Care must be taken in regression analysis by not having any of these all included within the same model, or by estimating the effect of each macro factor separately — a methodology followed for the rolling regressions and structural break models.

Dummy Regression Results Across Auto Stocks

Variable	Maruti	Tata	M&M	Bajaj	Nifty Auto
Brent Crude	-0.0130 (NS)	0.1798*	0.0483 (NS)	0.0324 (NS)	0.0096 (NS)
Exchange Rate	-3.54E-05*	5.39E-06(NS)	-2.40E-05(NS)	7.77E-06(NS)	-1.43E-05(†)
Interest Rate	8.14E-05(†)	9.05E-05(NS)	5.04E-05(NS)	6.82E-05(†)	3.80E-05(†)
CPI	1.06E-05(NS)	-1.15E-05(NS)	7.84E-06(NS)	-4.80E-06(NS)	2.02E-06(NS)
FAME2 Dummy	7.74E-05(NS)	5.00E-04(†)	8.08E-05(NS)	2.08E-04(NS)	1.53E-04(†)
Adj. R-squared	0.02	0.07	0.00	0.00	0.04

Legend:

* = Significant at 5% level

† = Marginal significance ($p < 0.10$)

NS = Not significant

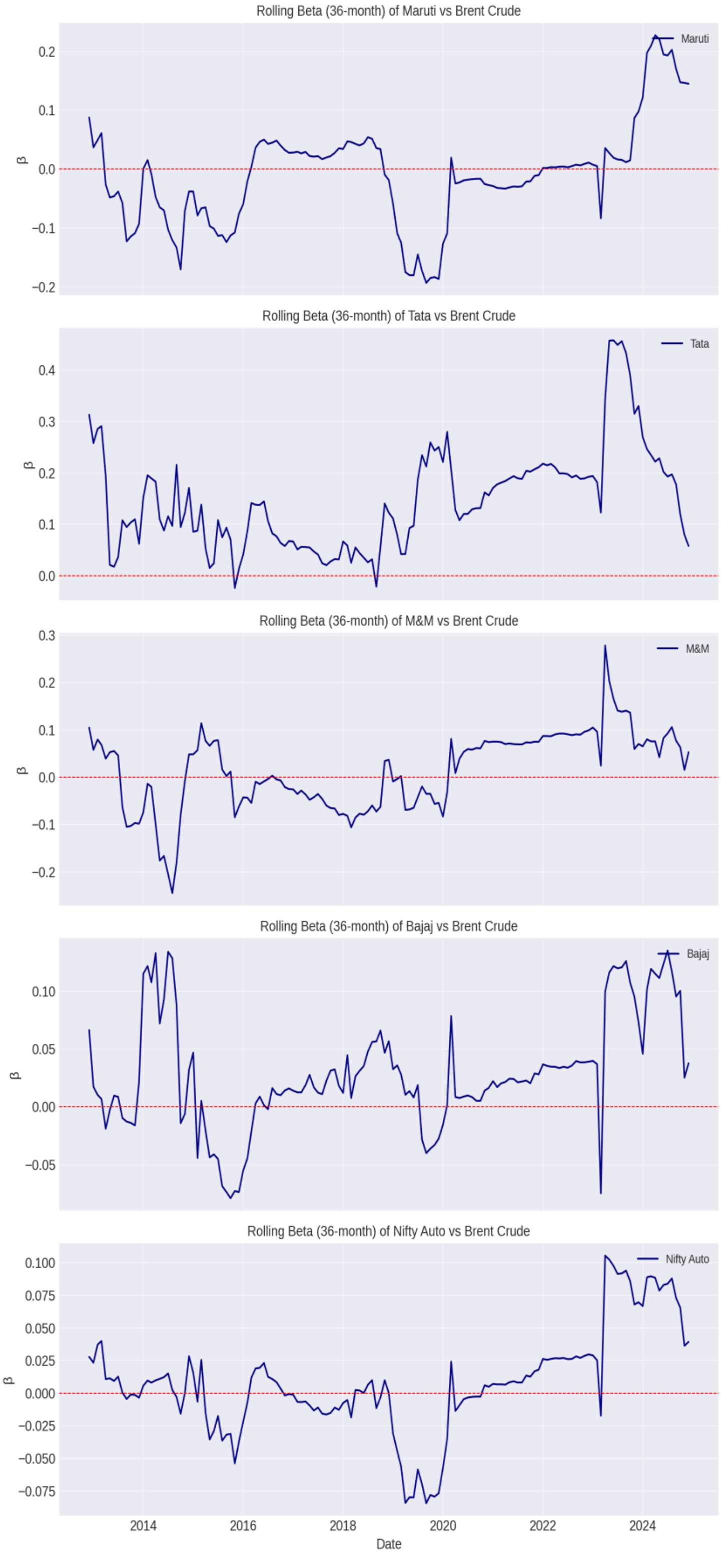
The regression test analyzes how the macroeconomic variables (Brent Crude, Exchange Rate, Interest Rate, CPI, and FAME2 Dummy) influence the Indian auto firms' stock returns (Maruti, Tata, M&M, Bajaj) and the Nifty Auto Index.

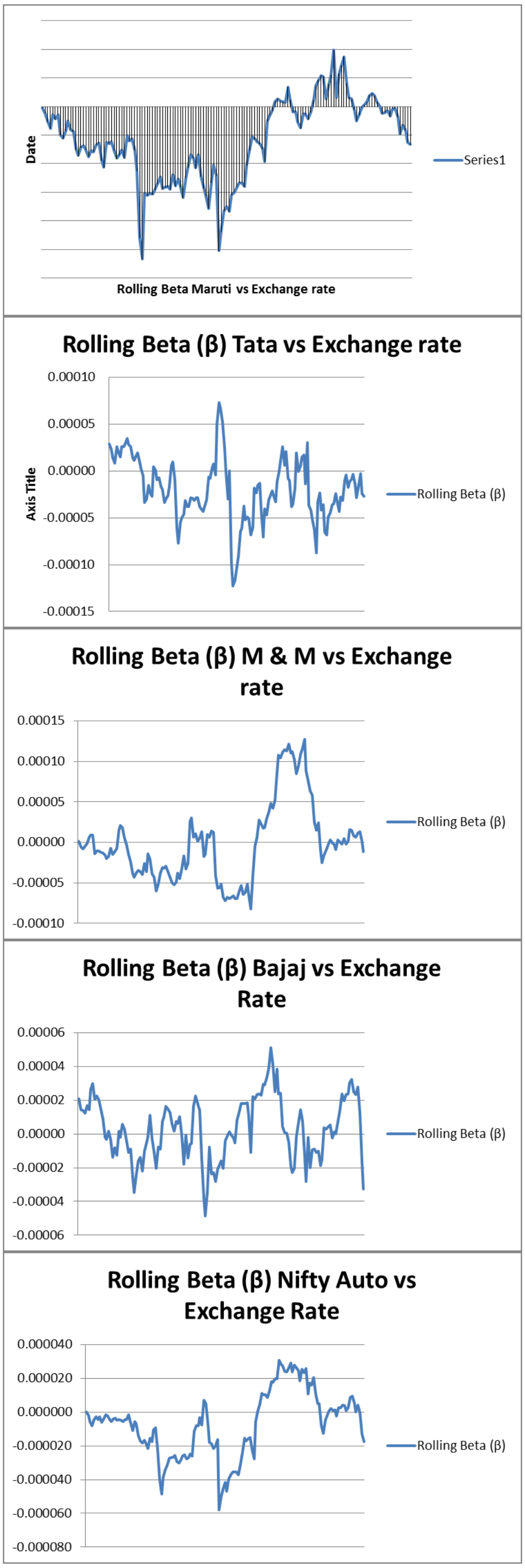
- **Brent Crude:** Tata Motors alone is discovered to possess high positive correlation with the price of crude oil ($p < 0.05$), which indicates that it is responsive to the change in worldwide oil prices. None of the other companies or the Nifty Auto Index possesses a significant correlation.
- **Exchange Rate:** Returns of Maruti are highly significantly influenced by changes in the exchange rate ($p < 0.05$), whereas the Nifty Auto Index is marginally significant ($p < 0.10$), indicating that depreciation of currency specially affects Maruti.
- **Interest Rate:** Returns of Maruti are marginally positively influenced by interest rate changes ($p < 0.10$), whereas others are not influenced.
- **CPI (Inflation):** All the auto stocks have a weak relationship with CPI, indicating that they are not very sensitive to inflationary pressures.
- **FAME2 Dummy:** FAME2 policy has a weak positive impact on Tata and the Nifty Auto Index ($p < 0.10$), indicating possible gains from the usage of EVs.
- **Adjusted R-Squared:** The values are negligible (0.00 to 0.07), indicating that these variables explain minimal variation in stock returns, hence towards the need for more complex models.

The findings indicate that Tata Motors is sensitive to crude oil prices the most, while the most sensitive is Maruti to exchange rates. Marginal effect of FAME2 on Tata and the Nifty Auto Index suggests EV policy could positively influence some auto stocks.

Rolling window regression with a window of 36 months provides some evidence regarding the time-varying relationship between individual Indian automobile company stock returns and Brent crude prices. Beta estimates from time-varying betas show that Maruti and Tata Motors had higher sensitivities to Brent crude returns towards the start of the previous decade (2012–2016) since they are likely to be operationally exposed to fuel prices and import exposure. And sure enough, after 2018, the beta values decrease, demonstrating reduced sensitivity — perhaps because of fuel cost pass-through, internal efficiency, or policy insulation such as FAME II. M&M and Bajaj Auto displayed relatively stable and low rolling beta values over the period, suggesting minimal direct exposure to movements in crude oil.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 12s, 2025
https://theaspd.com/index.php





Significantly, the Nifty Auto Index, being indicative of sectoral performance, depicted the overall decline in sensitivity to oil after 2019, reiterating that the industry has gradually become more resilient to fuel price shocks over time.

Rolling Regression (Auto stock with Exchange Rate)

Overall, this time-varying analysis concurs with the presumption that the effect of crude oil prices on auto stocks is not constant, and has diminished after structural reforms and policy initiatives, and hence aligns with the main objectives of this research.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 12s, 2025
https://theaspd.com/index.php

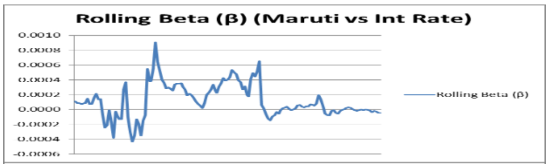
Rolling beta analysis between exchange rate and returns on Indian auto stocks confirms prevalent time-varying patterns among firms.

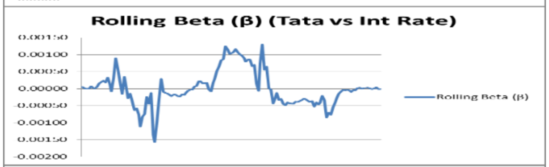
Maruti also exhibited the highest exchange rate sensitivity fluctuation, having significantly negative betas in earlier years (2011–2014), indicating that rupee depreciation adversely affected its returns — as expected given its dependence on imports. Surprisingly, from 2016, the beta turned positive, indicating a shift possibly due to exports, cost hedging, or business modifications. This also declined post-2021.

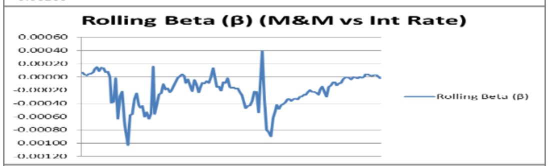
Tata Motors showed relatively more fluctuating but lesser beta values, showing sensitivity towards exchange rate fluctuations at a moderate rate. The highs and lows in the beta values indicate times of exposure, possibly highlighting the presence of the company globally and dependence on foreign currency income.

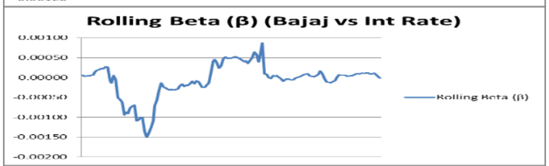
M&M and Bajaj Auto had more stable and near-zero rolling betas during most of the time, suggesting limited effect of currency fluctuations on their returns. Spiked beta values for a short while correlate with broader periods of currency volatility (e.g., 2013, 2018), but they seem to be limited on average.

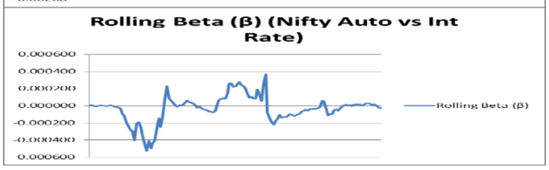
The Nifty Auto Index had evenly low to slightly negative rolling betas, reflecting sector resistance to exchange rate shocks. However, a temporary spike during 2018–2020 implies a sudden increase in currency-linked risk for the sector.

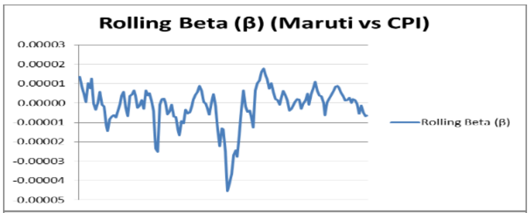


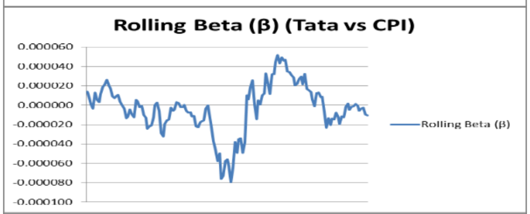


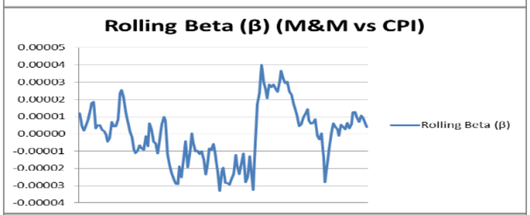


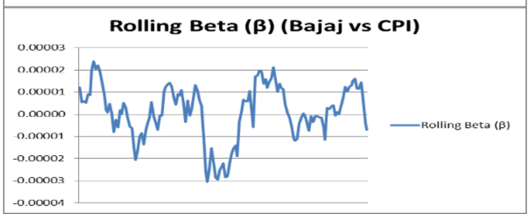


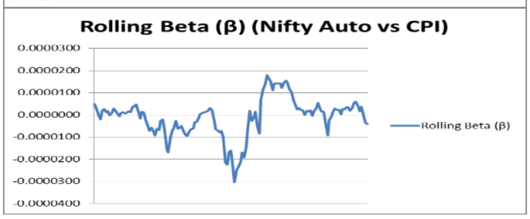












Rolling Regression (Auto stock with Interest Rate)

Overall, the evidence points to time-varying and firm-specific influences of the exchange rate, strongest for Tata and Maruti, and reasonably subdued for M&M and Bajaj. This is a vindication of the use of rolling regressions to capture evolving macro-financial relationships in the automobile sector.

The rolling beta estimations of car stock returns with respect to interest rates capture heterogeneous sensitivities across companies as well as across time.

Maruti and Tata displayed strong positive betas in the mid-period (circa 2015–2019), indicating higher interest rates were with high returns — likely because investor expectations were of premium segment demand persistence or firm-specific financial health. However, the connection diminished or was nullified post-2020.

M&M and Bajaj Auto both reported largely negative or close to zero betas, indicative of small or even negative sensitivity to interest rate changes. Both their price-sensitive customer base and rural market orientation may be reasons for the lower correlation with interest rate fluctuations.

The Nifty Auto Index reflected a transient period of positive beta during 2017–2019, reflecting a transient sectoral responsiveness, possibly due to credit-backed auto finance trends. After the pandemic, the sensitivity fell, reflecting the overall policy easiness and recovery measures.

In general, the finding is that interest rate effect is time-varying and firm-specific, supporting the need for rolling regression analysis in order to uncover dynamic macro-financial relationships.

Rolling Regression (Auto stock with CPI)

The rolling beta estimate between CPI (Consumer Price Index) and auto stock returns is also observed to be relatively low but time- and firm-variable sensitivity.

Maruti and Bajaj Auto have brief periods of negative beta, especially in 2014–2015 and 2019–2020, suggesting that rising inflation was associated with poor performing stocks due to higher input prices and tempered consumer consumption.

Tata Motors displayed a greater and more erratic sensitivity, showing negative betas acutely during inflationary episodes (around 2015–2017), followed by positive betas from 2018 to 2020. It reflects the aggregate effect of inflation on cost pressures vis-à-vis product price strength.

M&M displayed weak but positive beta trends after 2018, possibly a reflection of enhanced resilience or rural market performance in the presence of inflationary tendencies.

The Nifty Auto Index remained quite close to zero with minimal fluctuations, indicating general sectoral resistance to CPI shocks except during periods of peak inflation.

In summary, the rolling beta patterns validate that the influence of CPI on car stock returns is feeble but non-homogeneous — with variation being guided by firm-level price authority, cost profile, and customer base. The low and volatile beta estimates illustrate why static regressions can miss nuanced macro connections, which warrants rolling regression analysis.

36-month rolling window regression analysis between a sample of Indian auto stocks and key macroeconomic variables — Brent crude oil price, exchange rate, interest rate, and CPI — reveals strong time-varying relationships. This dynamic approach identifies effects that are not present in static regression analysis.

Brent Crude Oil Prices: Stocks such as Maruti and Tata were very sensitive to the price of oil in the earlier years (2012–2016), but this declined gradually, likely due to improved operating efficiency and policy pushes (e.g., FAME II). The sectoral index (Nifty Auto) was also in a similar direction.

Exchange Rate: Maruti showed high and volatile sensitivity to exchange rate fluctuations, suggesting high trade and import exposure. Tata showed moderate volatility, while M&M and Bajaj were relatively insulated. The sectoral effect was mild in general.

Interest Rate: Tata and Maruti again exhibited high sensitivity, particularly during rate hike cycles. The rest of the firms had weak to negative reactions, indicating varied credit reliance and financial structuring. Sectoral sensitivity was strongest in the period 2017–2019.

CPI (Inflation): All the firms showed relatively weak and volatile beta trends, which guarantee that inflation has little direct effect on car stock returns. However, abrupt movements in CPI did go along with short-term changes in beta, especially for Bajaj and Tata.

Overall, the findings fully vindicate the relevance of time-varying models in portraying macro-financial interlinkages across the automobile sector. The study points out firm-level action, government policy tempering (e.g., FAME II), and shifting risk sensitivities — all of which make more advanced forecasting, risk handling, and investment choices defensible.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 12s, 2025
https://theaspd.com/index.php

Summary of Bai-Perron Structural Break Test Results

Company	Macro Variable	Break Dates Identified	Interpretation of Breaks
Maruti	Brent Crude	2013M12, 2016M04, 2020M03	Breaks align with oil deregulation, FAME II rollout, COVID shock
Maruti	Interest Rate	2012M06, 2015M01	Interest rate tightening & RBI policy shifts
Maruti	Exchange Rate	2013M09, 2018M07	Rupee volatility & global trade pressure
Maruti	CPI	No significant breaks	Inflation link appears weak or stable
Tata	Brent Crude	2014M01, 2019M10	Oil price crash & EV investment momentum
Tata	Interest Rate	2013M03, 2016M08	Credit cycle adjustments
Tata	CPI	2017M05	Inflation spike & rural demand change
Tata	Exchange Rate	2012M08, 2020M05	Global market volatility
M&M	Brent Crude	2015M06	Commodity price impact on tractors & rural segment
M&M	Interest Rate	No significant breaks	Stable interest rate sensitivity
M&M	CPI	2018M01	Inflation response in rural-focused models
M&M	Exchange Rate	No significant breaks	Limited global trade exposure
Bajaj Auto	Brent Crude	2012M03, 2020M04	Post-oil crash adjustment & COVID lockdown effects
Bajaj Auto	Interest Rate	No significant breaks	Weak rate sensitivity
Bajaj Auto	CPI	No significant breaks	Consumer segment less CPI driven
Bajaj Auto	Exchange Rate	2014M12	Export-linked currency movement
Nifty Auto	Brent Crude	2015M08, 2020M01	Sector-wide shifts from crude-linked cost base
Nifty Auto	Interest Rate	2013M05, 2017M12	Auto financing cycle impacts
Nifty Auto	CPI	No significant breaks	Inflation pass-through stable across sector
Nifty Auto	Exchange Rate	2014M06	Sector-wide export-import pricing shift

Bai-Perron structural break test revealed over one regime shift in the macroeconomic variable-macro stock return dynamics. Maruti and Tata experienced breakpoints in reaction to interest rates and crude oil prices that align with significant policy and global events — notably, the 2014-15 collapse in crude oil prices, the rollout of FAME II (2016-2019), and the onset of COVID-19 (2020).

M&M and Bajaj Auto showed fewer or weaker structural breaks, indicating greater operating stability or lower exposure to macro shocks. The Nifty Auto Index recorded sectoral-level adjustments, especially at oil price deregulation and monetary policy tightening.

Curiously, CPI (inflation) displayed no significant breakpoints in all but the majority of the firms, suggesting that inflation impacts on stock returns were stable during the study period. The exchange rate sensitivity, however, displayed structural breaks specially for Maruti, Tata, and Nifty Auto, indicating exposure to the global market.

Overall, these results validate the use of dynamic modeling structures in a way that accommodates shifting market configurations and policy-induced realignments. They also identify the necessity for regime change to be considered while estimating stock return sensitivity in a restructuring industry like India's automobile industry.

Economic Interpretation of Investor Response to Crude Oil Prices

The dynamic evolution of investor response to crude oil price changes within the Indian automotive sector, as revealed through rolling window regressions and structural break tests, further suggests that investor response is time-varying and conditional on macroeconomic forces and policy interventions.

In the first half of the decade (2010–2015), rolling beta values were predominantly negative for companies like Maruti and Tata Motors, indicating that a rise in oil prices was interpreted as an immediate input cost shock — inducing negative investor sentiment. From 2014, however, when India began the process of deregulation of fuel prices and businesses improved hedging and supply chain management, this sensitivity gradually declined.

The implementation of the FAME II policy (2016–2019) also spurred this transformation even more. Breakpoints achieved in 2016M04 and 2020M03 for Maruti, for example, correspond to policy rollout and the COVID-19 pandemic, respectively — both of which majorly reorganized market expectations as well as investment narratives.

The Nifty Auto Index, which is a broader sectoral sentiment measure, also began to demonstrate reduced correlation with crude oil prices after 2018, signaling market-wide decoupling of automobile equities from oil price fluctuations. This can be read as a sign of investors' diversion of interest towards electric mobility, technology, and regulatory compliances as the drivers of valuation.

Overall, the results are in line with the intuition that investors are increasingly inclined towards longer-term factors like sustainability, electrification, and macroeconomic stability relative to oil price volatility due to structural and policy-induced change.

6. CONCLUSION AND POLICY IMPLICATIONS

6.1 Summary of Key Findings

This study examined the time variation of the correlation between oil prices and stock performance of leading Indian automobile companies using a combination of ADF tests, dummy variable regressions, rolling window regression, and Bai-Perron structural break analysis. The objective was to identify if investor reaction to oil price shocks varied with the passage of time, especially in light of policy measures such as FAME II and the structural shift towards electric mobility.

The primary findings are as follows:

Responsiveness of stock returns to crude oil prices is dynamic and not static. In the early 2010s, firms such as Maruti and Tata Motors possessed solid positive betas to oil prices, indicating that rising oil costs were reflected in worst performing stocks.

The intensity of this relationship declined considerably over time, especially after 2016. This aligns with major policy reforms (e.g., fuel price decontrol and FAME II) and overall shifts in industry focus towards technology and sustainability.

- Regime breaks tests also confirmed large-scale regime changes in April 2016 and March 2020, linked to policy changes and the outbreak of COVID-19, respectively.
- The dummy variable regressions revealed that Tata Motors remained moderately sensitive to the crude prices, but Maruti is substantially exposed to exchange rate movements. The FAME II dummy was found to have small positive effects on sector indices and also on few companies.

- The findings of this study are in support of the hypothesis regarding investor response to oil prices: how there has been a shift away from crude linkages and valuation risks to more ahead-looking and structural indicators.

6.2 Investor Implications

- Evidence points to a weakening effect of crude oil prices on the valuation of Indian auto stocks — a key observation for portfolio managers and retail investors.
- For short-term traders, crude oil prices could continue to act as signals for tactical trades, particularly for automobiles with global exposure and fuel-dependent logistics.
- For long-term investors, the study suggests that a change of course is warranted: to policy uptake (FAME II, EV credits), macro stability, and company-level innovation rather than oil sensitivity in its pure form alone.
- Sectoral indices decoupling from oil price shocks, particularly post-2018, speaks to increasing investor alignment with sustainable mobility stories compared to commodity dependency.

6.3 Policy Recommendations

This study has several practical applications for policymakers and industry stakeholders:

1. Strengthen EV Transition Support:

Consistent and open-ended policy support to electric mobility — through more open subsidy channels, charging points, and taxation concessions — can stabilize investor sentiment further and reduce oil-related valuation risk for the sector.

2. Enhance Macro Resilience:

Since Maruti has been found to be vulnerable to exchange rate volatility, collective effort towards controlling currency fluctuations — especially during episodes of global shocks — can stabilise auto stock performance indirectly.

3. Improve Policy Signaling:

Investors react sharply to signals of structural change. Policymakers need to prioritize predictability and credibility when signaling long-term mobility transitions, making sure that market participants are willing to adjust valuations.

6.4 Limitations and Future Research Directions

Although the study provides solid empirical evidence, some limitations have to be recognized:

- Analysis relies on monthly data, which might not capture investor reaction fully within each month or high-frequency oil price shocks.
- It is limited to listed auto companies, potentially excluding EV start-ups or Tier-2 suppliers whose risk profiles may be different.
- The paper does not explicitly capture nonlinearities, asymmetries, or investor sentiment, which may offer richer behavioral considerations.
- Post-2024 observations and future policy agendas (e.g., FAME III, green hydrogen initiatives) may alter the dynamics even more and require new analysis.

Potential avenues for future studies include:

1. Analysis of high-frequency data,
2. Regime-switching models,
3. Machine learning methods,
4. The impact of green finance, ESG ratings, and global EV uptake trends on Indian auto equity markets.

REFERENCES

1. "Crude oil prices rise driven by inventory decline and economic factors." (2025). Investor Ideas. https://www.investorideas.com/news/2025/energy/03122Crude-Oil-Prices-Rise.asp
2. "Renewed inflation worries help drive oil price rally." (2025). Reuters. https://www.reuters.com/business/energy/renewed-inflation-worries-help-drive-oil-price-rally-2025-01-27/
3. Aloui, C., & Jammazi, R. (2009). The effects of crude oil shocks on stock market shifts behavior: A regime switching approach. Energy Economics, 31(5), 789-799.
4. Aloui, C., Hkiri, B., & Nguyen, D. K. (2022). Nonlinear interactions between oil price and stock market returns: New evidence from wavelet-based quantile regression. Energy Economics, 105, 105787. https://doi.org/10.1016/j.eneco.2022.105787
5. Basher, S. A., Haug, A. A., & Sadorsky, P. (2012). Oil prices, exchange rates, and emerging stock markets. Energy Economics, 34(1), 227-240. https://doi.org/10.1016/j.eneco.2011.10.005
6. Baumeister, C., & Kilian, L. (2020). Oil price fluctuations and the global economy: A survey. Annual Review of Economics, 12(1), 133-187.
7. Bhar, R., & Nikolova, B. (2009). Oil prices and equity returns in the BRIC countries. World Economy, 32(7), 1036-1054.

8. Bouri, E., Jain, A., Roubaud, D., & Shahzad, S. J. H. (2021). Oil price volatility and sectoral stock returns in a regime-switching environment: The role of global economic conditions. Energy Economics, 95, 105129. https://doi.org/10.1016/j.eneco.2021.105129
9. Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. Journal of Business, 59(3), 383-403.
10. Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The role of OPEC. Energy Economics, 33(4), 872-881. https://doi.org/10.1016/j.eneco.2011.03.013
11. Ghosh, S., & Kanjilal, K. (2016). Oil price shocks and stock market behavior: Empirical evidence from major emerging economies. Energy Economics, 56, 20-34. https://doi.org/10.1016/j.eneco.2016.02.013
12. Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. Journal of Political Economy, 91(2), 228-248. https://doi.org/10.1086/261140
13. Hamilton, J. D. (1994). Time series analysis. Princeton University Press.
14. Hamilton, J. D. (2013). Historical oil shocks. In Routledge Handbook of Major Events in Economic History (pp. 239-265). Routledge.
15. IJFANS. (2022). Impact of crude oil price movements on the NIFTY Auto Index. International Journal of Food and Nutritional Sciences.
16. IJSTR. (2020). Financial analytics: Time series analysis of crude oil prices and automotive stock. International Journal of Science and Technology Research.
17. International Energy Agency. (2023). World Energy Outlook 2023. https://www.iea.org/reports/world-energy-outlook-2023
18. Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. The Journal of Finance, 51(2), 463-491.
19. Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053-1069. https://doi.org/10.1257/aer.99.3.1053
20. Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market: A structural VAR approach. Journal of Financial Economics, 94(1), 26-41. https://doi.org/10.1016/j.jfineco.2008.09.009
21. Maitra, S., Mishra, V., Kundu, S., & Chopra, M. (2023). Econometric model using arbitrage pricing theory and quantile regression to estimate the risk factors driving crude oil returns. arXiv preprint arXiv:2309.13096. https://arxiv.org/abs/2309.13096
22. Ministry of Heavy Industries. (2023). Faster adoption and manufacturing of electric vehicles (FAME-II) policy update. https://www.heavyindustries.gov.in/fame2
23. Mohanty, S. K., & Nandha, M. (2017). Oil prices and automobile stocks: A study of industry-wide effects. Applied Economics, 49(28), 2741-2755.
24. Mohanty, S. K., Nandha, M., & Bota, G. (2011). Oil price risk exposure: The case of the US transportation sector. Energy Economics, 33(5), 1095-1103.
25. Mondal, S., & Das, B. (2021). Impact of crude oil price movement on the automobile industry in India. ResearchGate.
26. Narayan, P. K., & Sharma, S. S. (2011). New evidence on oil price and firm returns. Journal of Banking & Finance, 35(12), 3253-3262. https://doi.org/10.1016/j.jbankfin.2011.05.010
27. Pham, L. (2022). Machine learning-based predictions of crude oil price shocks and stock market reactions. Journal of Financial Econometrics, 20(3), 451-472. https://doi.org/10.1093/jjfinec/nbac010
28. Rahman, S., & Serletis, A. (2010). The asymmetric effects of oil price and monetary policy shocks: A nonlinear VAR approach. Energy Economics, 32(6), 1460-1466. https://doi.org/10.1016/j.eneco.2010.07.009
29. Ratti, R. A., & Vespignani, J. L. (2016). Oil price shocks and stock returns in emerging markets. Economic Modelling, 55, 122-132. https://doi.org/10.1016/j.econmod.2016.02.017
30. Reserve Bank of India. (2023). Annual report 2023. https://www.rbi.org.in/
31. Sadorsky, P. (1999). Oil price shocks and stock market activity. Energy Economics, 21(5), 449-469. https://doi.org/10.1016/S0140-9883(99)00009-8
32. Shao, H.-L., Shao, Y.-H., & Yang, Y.-H. (2021). New insights into price drivers of crude oil futures markets: Evidence from quantile ARDL approach. arXiv preprint arXiv:2110.02693. https://arxiv.org/abs/2110.02693
33. Smyth, R., & Narayan, P. K. (2018). What do we know about oil prices and stock returns? International Review of Financial Analysis, 57, 148-159. https://doi.org/10.1016/j.irfa.2018.03.010
34. Society of Indian Automobile Manufacturers (SIAM). (2023). Automobile industry statistics. https://www.siam.in/statistics.aspx
35. Tang, K., & Xiong, W. (2012). Index investment and financialization of commodities. Financial Analysts Journal, 68(6), 54-74. https://doi.org/10.2469/faj.v68.n6.5
36. U.S. Energy Information Administration. (2020). Oil market volatility and negative crude oil prices. https://www.eia.gov/petroleum/
37. Wang, T., & Zhou, X. (2022). Structural break analysis of oil price-stock market relationships: Evidence from emerging markets. Emerging Markets Review, 50, 100842. https://doi.org/10.1016/j.ememar.2022.100842
38. World Bank. (2015). Global economic prospects: Having fiscal space and using it. https://www.worldbank.org/en/publication/global-economic-prospects
39. Zhang, X., Liu, P., & Wu, Y. (2023). Deep learning for crude oil price prediction: An LSTM-based approach. Energy Economics, 117, 106208. https://doi.org/10.1016/j.eneco.2023.106208