ECONOMIC ANNALS, Volume LXIX, No. 242 / July – September 2024
UDC: 3.33 ISSN: 0013-3264

https://doi.org/10.2298/EKA2442093M

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IMPACT OF CRUDE OIL PRICE VOLATILITY ON INDIAN STOCK MARKET RETURNS: A QUANTILE REGRESSION APPROACH

ABSTRACT: *This paper examines the heterogenous effect of oil price volatility on Indian sectoral stock returns for the period January 2011 to September 2022 using the quantile regression method, which helps us to analyse the impact in bearish, normal, and bullish periods. The results show that total and sectoral stock returns are negatively affected by oil price fluctuations and the negative effect is stronger during the bearish period. In the normal and bullish periods, oil price volatility does not affect stock returns greatly. The interest rate and exchange rate changes have a stronger effect on sectoral returns in the bearish period in the pharmaceutical, healthcare, banking and finance, IT, fast-moving consumer goods (FMCG), and consumer durables sectors. The study shows that the impact of oil price volatility on sectoral returns is less than the impact of interest rate and exchange rate changes. The study also shows that oil price volatility directly impacts market portfolio returns initially, which subsequently spills over to sectoral returns, which implies that sectoral returns are impacted by oil price volatility through an indirect channel.*

KEY WORDS: *oil price volatility, sectoral returns, quantile regression, bearish, bullish*

JEL CLASSIFICATION: C32, G10, E44

Acknowledgement: The author would like to thank the supervisor, Dr. Anoop S Kumar (Assistant Professor at Gulati Institute of Finance and Taxation), for his valuable feedback.

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1. INTRODUCTION

Crude oil is an important resource for all countries across the world. As countries develop, urbanise and modernise, the demand for this black gold rises. The irregularity of crude oil prices might affect business cash flow as crude oil is a major input used in production and can affect stock exchange growth (Belhassine & Karamti, 2021). Fluctuations in crude oil prices have a significant impact on stock market returns since they adversely affect discount factors and future cash flows of firms (Youssef & Mokni, 2019).

Theoretically, this relationship is justified by the fact that asset prices are evaluated using the current discounted value of future dividends and earnings. The links between stocks and oil prices can be attributed to changes in expected cash flows or discount rates. Expected cash flows can be affected by oil prices, as oil is a crucial input in most firms' production process and leads to changes in costs, affecting earnings and dividends and, hence, stock prices. On the other hand, discount rates comprise an expected inflation and a real interest rate component. Higher oil prices may lead to overestimation of the expected inflation and thus higher nominal interest rates; and since discount rates are negatively related to stock prices, increases in interest rates depress stock prices.

Like oil price changes, the crude oil market's unpredictability also affects economic and financial structures and influences stock returns (Nath et. al, 2014). However, most of the research has used crude oil and stock prices measured by historical price series. Now, instead, there is a fresh perspective to explore the relationships between the oil price volatility and the stock market by using the oil volatility index (OVX). The crucial reason for this is that the OVX derived from market options contains both historical and future volatility information, and is thus regarded as a direct and more accurate measure of uncertainty in the oil market (Xiao et.al, 2018). Oil price volatility quantifies the degree of uncertainty associated with fluctuations in oil prices within the market. High volatility is indicative of significant price fluctuations, which pose challenges for both oil-exporting and oil-importing nations. Increased uncertainty in oil prices escalates the costs involved in managing this critical resource, thereby adversely impacting economic stability and planning (Choi & Hong, 2020). Therefore, it is essential to investigate the oil market and stock returns from the perspective of ambiguity.

Uncertainty in the oil price might reduce investment, production, and aggregate outputs (Bloom, 2009).

There exist a large number of studies that highlight the relationship between oil prices and economic activities. Since the stock market is considered the barometer of an economy, most of the studies have focused on oil prices and the stock market as a whole. The use of aggregate stock returns may not be appropriate to analyse the underlying dynamics of the relationship between oil prices and stock returns across sectors due to cross-correlations (Arouri et al., 2012; Smyth & Narayan, 2018). Aggregate indices may mask the heterogeneity at the sector level. Therefore, using sectoral indices allows us to better understand the transmission channels of oil market shocks to the stock market (Ahmadi et al., 2016).

Oil price volatility may have a differential impact on sectoral stock returns depending on whether they are from oil-intensive or non-oil-intensive sectors.

i) Oil-intensive sectors: Sectors that are highly dependent on oil as a key input, such as energy and transportation companies, might be more directly impacted by oil price volatility. When oil prices rise, the costs of production and transportation increase, which can lead to lower profits and stock prices. On the other hand, when oil prices fall, these companies tend to benefit from lower input costs, which can boost profits and stock prices.
ii) Non-oil-intensive sectors: Sectors that are less dependent on oil as a key input, such as technology and healthcare firms, might be less directly impacted by oil price volatility. However, they can still be affected indirectly through higher transportation costs, increased inflation, and changes in consumer spending. Higher oil prices can lead to increased production and transportation costs, which can lead to reduced profitability and lower stock prices for non-oil-intensive companies.

This paper focuses on the heterogenous impacts of oil price uncertainty measured by the OVX on Indian sectoral stock returns under different market conditions by using the quantile regression method to observe the dependence under bearish, normal, and bullish market conditions. There is a paucity of studies that investigate the relationship between oil price uncertainty and the Indian stock market, especially from the perspective of oil price volatility. As India is a net oil

importing country, the study and the understanding of the effects of oil price volatility (i.e. a measure of ambiguity) on sectoral stock returns is indeed crucial. In this regard, this study contributes to the existing literature.

The main findings of the study are: Oil price volatility negatively affects Indian sectoral returns at all quantiles and is stronger at the lowest quantiles. In normal and bullish periods, the relationship is more or less stable in most of the sectors. Furthermore, interest rate and exchange rate changes also affect sectoral returns at all quantiles. However, the impact of interest and exchange rate changes on sectoral returns is greater than the impact of oil price volatility.

The remainder of the study is organised as follows. The following section provides a review of literature. Section 3 explains the data and methodology. Section 4 deals with a discussion of the results, and the final section provides our conclusion and discussion.

2. LITERATURE REVIEW

2.1. Studies based on the link between oil prices and stock markets

The foundational work of Hamilton (1983) established a critical link between oil prices and economic activity, suggesting that fluctuations in oil prices could precipitate economic recessions. This early research laid the groundwork for subsequent studies exploring the dynamic relationship between oil prices and stock markets. Later studies on the effects of oil prices on stock markets by Brown and Otsuki (1990), Ferson and Harvey (1995), Kaneko and Lee (1995), and Jones and Kaul (1996) reported negative effects. Malik and Ewing (2009), conducting an early study focusing on six US sectoral stock market indices, found that oil price volatility positively affects sectoral stock market volatility, although this effect was not observed in the financial and industrial sectors. Vo (2011) examined the relationship between the S&P 500 index and West Texas Intermediate (WTI) crude oil price volatilities from 1999 to 2008, discovering a mutual interdependence between the two. This was corroborated by Mensi et.al (2013) who found positive bidirectional effects between S&P500 and WTI volatilities, although the same did not hold for Brent crude oil. Numerous studies have been conducted on the potential links between crude oil prices and stock (Filis et al., 2011; Jammazi et al., 2017, Maghyereh et al., 2019). Degiannakis et al.

(2018) gives a comprehensive review of the research papers dealing with the relationship between the oil price and the stock market. The review indicates that the causal effects between oil and stock markets are heavily influenced by whether the research utilises aggregate stock market indices, sectoral indices, or firm-level data, as well as whether the stock markets are situated in net oil-importing or net oil-exporting countries. Furthermore, the conclusions vary based on whether studies examine symmetric or asymmetric changes in oil prices, or whether they focus on unexpected changes in oil prices. Ultimately, the review finds that most studies demonstrate that oil price volatility transmits to stock market volatility and that incorporating measures of stock market performance enhances the forecasts of oil prices and oil price volatility.

Most of the papers examine return spillovers or return volatilities, and the evidence implies that rising crude oil prices could impact the world economy. Sadorsky's (1999) results from a vector autoregression show that oil prices and oil price volatility both affect real stock returns. There is evidence that oil price changes explain a larger portion of the forecast error variance in real stock returns than changes in interest rates, and oil price volatility shocks have asymmetric effects on the economy. Basher and Sadorsky (2006), using a multi-factor model that allows for both unconditional and conditional risk factors, investigated the relationship between oil price risk and emerging stock market returns and found strong evidence that oil price risk impacts stock price returns in emerging markets. Nandha and Faff (2008) analyse 35 DataStream global industry indices to study the extent to which oil price shocks affect stock market returns. Their results show that oil price rises negatively impact equity returns for all sectors except mining and oil and gas industries. These results are consistent with economic theory. Kilian and Park (2009) document that oil price changes have different impacts on equity returns, depending on the source (demand vs. supply) of the structural shock. Kilian (2009) proposes a structural vector autoregression approach to disentangle oil price shocks into demand and supply shocks at monthly frequency. The extent of volatility transmission between the oil and stock markets in Europe and the US at the sector level is examined by Arouri et al. (2012). They found that those industries which make use of oil and oil-related products as their inputs or output are affected more by oil price volatilities. The general notion is that oil price changes matter to some industries but not all. Sreenu (2022) examines the asymmetric effects of ambiguity shockwaves by

applying the positive (+) and negative (-) fluctuations of the crude oil price volatility index and also measures whether the reform of 2012 stimulated the oil price volatility index and stock market relationship. The results indicate that the changes in the oil price volatility index mostly confirm the significant adverse effects on the aggregate and various economic sectoral stock returns and also show that the information content of the crude price oil volatility index improves the volatility forecasts for stock market returns. Joo and Park (2021) investigate the effects of oil price volatility on the stock market returns of ten major oil-importing countries. They make use of both quantile regression and quantile-on-quantile regression approaches and find that oil price uncertainty has an asymmetrical effect on stock returns and this asymmetric behaviour depends on the level of stock returns and also on oil market conditions.

2.2. Studies based on various methodologies

A wide range of literature uses different methodologies to understand the relationship between oil prices and stock market returns. Arouri and Rault (2012) analyse the long-run relationship between oil prices and stock markets in the Gulf Cooperation Council (GCC) using recent bootstrap panel cointegration techniques and seemingly unrelated regression (SUR) methods and find that oil price increases have a positive impact on stock prices, except in Saudi Arabia. Gogineni (2010) investigates the impact of oil price changes on the stock returns of industries by classifying them into oil- intensive and non-oil-intensive groups and concludes that sensitivity of industries' returns to oil price changes depends on oil on both the cost-side and demand-side dependence and that the relative effects of these factors vary across industries. Broadstock et al. (2014) attempt to decompose the impact of oil price shocks on stock returns into two channels of effects: direct and indirect. A rise in oil prices increases the operational costs of the firms belonging to some industries, which results in lower profit and low stock prices. This relates to the effect through the direct channel, whereas the indirect channel arises through the impact on systematic risk. Jammazi et al. (2017) investigate the presence of time-varying causal interdependencies between shocks in oil prices and stock returns for oil-importing countries (including Spain). They combine wavelet analysis and a new version of the dynamic causality test of Lu et al. (2014) and find a significant bidirectional oil and stock market causal relation over various periods for all nations. Zhang (2017) makes use of the methodology of measuring connectedness developed by Diebold and Yilmaz

(2014) to study the association between oil shocks and returns at six major stock markets around the world and come up with the finding that the contribution of oil shocks to the world financial system is limited and only significant shocks matter. Using the spillover index approach developed by Diebold and Yılmaz (2009, 2012, 2014, 2015) and the dynamic correlation coefficient model developed by Engle (2002), Antonakakis et al. (2018) investigate the volatility spillovers and co-movements among oil prices and stock prices of major oil and gas corporations in order to identify the transmission mechanisms of volatility shocks. Wei et al. (2019) study the connectedness between crude oil prices and the China stock market by applying a nonlinear threshold cointegration method within a multivariate framework. The results show that the long-term relationships between them shift significantly across different market regimes and have seen substantial improvement in recent years due to changes in China's refined oil pricing mechanism and exchange rate system.. Umar et al. (2021) examines both the static and dynamic linkages between risk, demand, and supply shocks in oil prices and the performance of equity indices in Spain, covering the period from January 2000 to July 2019.They used Ready's (2018) methodology for disentangling the oil price shocks and Diebold and Yılmaz's (2014) approach for analysing the connectedness between the disentangled oil shocks and the sector equity returns. They document differences over time and between sectors, mainly during the recent global financial crisis and the European sovereign debt crisis. Overall, financials, telecommunications, industrials and utilities are the most influential sectors. Chowdhury & Irfan (2022) examine the connectedness between the sectors in the Indian stock market for the period January 2011 through December 2020 making use of a TVP-VAR-based connectedness approach which shows that nearly 84% of the forecast error variance throughout the entire study period may be attributed to cross-sectional shocks within the network of Indian stock market sectors. Thus, shocks only explain 16% of the total variability, indicating strong overall sectoral reliance. The results suggest that cyclical stocks are the net transmitters of shocks and noncyclical stocks the net receivers.

There are a few studies on oil-importing countries which analyse the influence of oil price uncertainty on stock returns (Maghyereh et al., 2019; Silvapulle et al., 2017).

The aforementioned studies analyse the connection between the oil and stock markets using some linear models and/or conditional mean specifications, such as vector autoregression. Although the conditional mean specification offers some insightful information on the linear relationship, it might fall short in explaining several significant elements of oil and stock price trends. These models contain only the average relationship between oil and stock prices and do not capture the distributional heterogeneity. Such models or specifications do not consider such market conditions as the boom or bust of oil and stock markets. Unfortunately, the underlying relationship at lower and higher quantiles of data cannot be captured by these conditional mean-based time series models. When the distribution of the time series under study is skewed and leptokurtic, it is difficult to find some noteworthy correlations between different quantiles of the time series variables. In order to give a more thorough examination of the connection between oil price volatility and Indian sectoral stock returns, it is imperative to use an appropriate methodology that captures the entire dependence structure of oil and stock market returns. To accommodate this aspect, this study makes use of a quantile regression method which considers the entire conditional distribution of the dependent variable and offers an alternative approach to analyse the potential heterogeneity (and capture the asymmetric nature) in the data.

3. MATERIAL AND METHODS

The study makes use of Chicago Board Options Exchange (CBOE) crude oil price volatility index (OVX) data and Indian sectoral returns data from the automobile, consumer durables, realty, metal, pharmaceutical, IT, healthcare, fast-moving consumer goods (FMCG), and finance and banking sectors and total aggregate index Nifty 50 data from the National Stock Exchange of India database. Daily stock returns data and daily sectoral returns data are used in the study. The period considered is from January 2011 to September 2022. The daily call money interest rate and exchange rate (with respect to the dollar) data are taken from the Reserve Bank of India database.

3.1. Quantile regression approach

The quantile regression model is used to explore the dependence between oil price volatility and sectoral stock returns in India. Quantile regression is an

extension of standard regression, providing a complete picture of a conditional distribution. Only focusing on mean effects may lead to inaccurate estimation of relevant coefficients or omission of important relationships (Binder & Coad, 2011). The quantile regression estimator is less sensitive to the presence of outlier observations, skewness, and heterogeneity of the response variable (Koenker & Hallock, 2001). Quantile regression was first introduced by Koenker and Bassett (1978). This method assumes that the value of ϵ_i conditional on the regressors in the τ-th quantile is zero. Then, the conditional quantile model of y_i given x_i is specified as follows:

$$Q_{y_i}(\tau|x) = \alpha(\tau) + x_i'\beta(\tau), \tag{1}$$

where $0 < \tau < 1$, $Q_{y_i}(\tau|x)$ denotes the τ-th conditional quantile of y_i, $\beta(\tau)$ is the estimated parameter in the equation, and α presents the unobserved effect. x includes variables assumed to affect the dependent variable. The coefficients of the τ-th quantile of the the conditional distribution are estimated as:

$$\hat{\beta}(\tau) = arg \min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau\big(y_i - x`_i\beta(\tau) - \alpha(\tau)\big), \tag{2}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the check function and $I(.)$ is an indicator function (in this case, $u = y_i - x`_i\beta(\tau) - \alpha(\tau)$).

The stock market usually has diverse market conditions. It oscillates between bearish, normal, and bullish periods. Therefore, policymakers and stockholders are interested in understanding in detail how the crude oil price unpredictability impacts stock market returns under diverse market circumstances in order to devise appropriate investment and risk management strategies. In such a scenario, the quantile regression technique proposed by Koenker and Bassett (1978) could be an appropriate estimation procedure to capture the impact of independent variables on the different conditional distributions of the dependent variable. Also, compared to the ordinary least square (OLS) regression, the quantile regression can produce more precise results since it is less susceptible to outlier observations, skewness of the distribution, and heterogeneity of the dependent variable (Koenker & Hallock, 2001).

A functional understanding of the correlation between oil prices and stock returns necessitates an accurate analysis of extreme tail event risk and its time-varying impact on the market. Consider the following regression model to analyse how the impact of oil price uncertainty varies across different quantiles of stock returns:

$$r_t = \alpha + \beta_1 OVX_t + \beta_2 IR_t + \beta_3 ER_t + \varepsilon_t \,, \tag{3}$$

where r_t is the sectoral stock return at time *t*, OVX_t is the oil price volatility at time t, $IR_t$is the call money interest rate at time t, and ER_t is the exchange rate at time t; ε_t denotes the usual error term. To increase the explanatory power of the model, the call money interest rate and exchange rate are added as control variables in addition to the oil price volatility. Oil price changes might affect stock prices by influencing expected earnings. However, it is essential to control for interest rate changes that could also affect stock prices which directly influence the discount rate on expected earnings. Spiro (1990) reported that the interest rate is primarily responsible for the short-term volatility of stock price indices. Similarly, the exchange rate also affects stock prices, which is evident from the flow-oriented model of Dornbusch and Fischer (1980), which posits that changes in the foreign exchange rate can affect trade balances and international competitiveness. The phenomenon can be explained as follows: a depreciation (or appreciation) of the local currency will make domestic firms more (or less) competitive by having cheaper (or expensive) exports in international trade which will ultimately lead to an appreciation (or depreciation) of the stock prices of domestic firms. In this regard, the causality will run from the exchange rate to stock prices. Therefore, it is necessary to control for the effect of the exchange rate on stock returns as well.

We can then write the conditional quantile function of r_t given the covariates as:

$$Q_{r_t}(\tau|x_t) = \alpha(\tau) + \beta_1(\tau) OVX_t + \beta_2(\tau) IR_t + \beta_3(\tau) ER_t \,, \tag{4}$$

where $Q_{r_t}(\tau|x_t)$denotes the τ^{th} conditional quantile of r_t, $0 < \tau < 1$, and $\alpha(\tau)$ and $\beta_i(\tau)$, i = 1,2,3, are the regression quantile coefficients.

We can estimate the regression quantile $\beta_i(\tau)$, i = 1,2,3, by solving the following minimisation problem:

$$\min_{(\alpha,\beta`)`\in\backslash\mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(r_t - \alpha(\tau) - \beta_1(\tau)OVX_t - \beta_2(\tau)IR_t - \beta_3(\tau)ER_t), \quad (5)$$

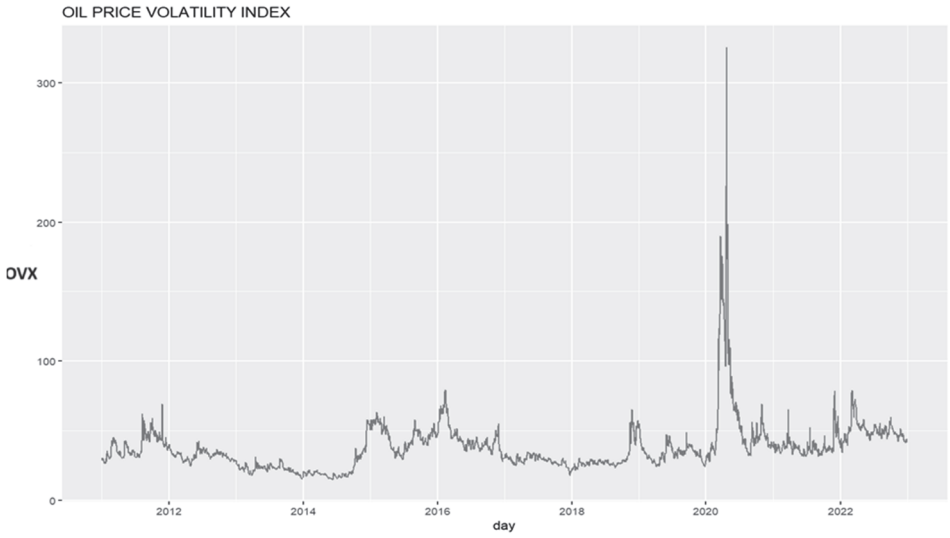
where $\rho_\tau(u) = u\big(\tau - I(u < 0)\big)$ is the check function and $I(\cdot)$ is an indicator function. In Eq.(5) $\beta_1(\tau)$ measures the marginal effects of oil price volatility at the τ quantile levels. In the quantile regression model, we represent stock market conditions by different quantile levels. In the empirical analysis, we choose nine quantiles, τ = (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9), where the low quantile (0.1), middle (0.4, 0.5, 0.6), and high quantiles (0.9) represent bearish, normal, and bullish market conditions, respectively. Therefore, the quantile regression analysis allows us to investigate the impact of oil price volatility under different stock market conditions. The *quantreg* package developed by Roger Koenker was used for the purpose of this analysis.

4. RESULTS AND DISCUSSION

The index returns, which represent the change in value of an index over time, can be computed using the first difference of the natural logarithmic series. $r_t = \ln(p_t - p_{t-1})$, where r_t is the return on the index at time *t*, and p_t and p_{t-1} are the price or index at time *t* and *t*-1, respectively. Log returns are also taken for the exchange rate and oil price volatility index but the interest rate is used at the levels.

As we can see from the diagram, there are substantial spikes in the OVX throughout the sample period. For example, the most substantial spike is during the 2020 COVID crisis. The oil price volatility is extreme during this crisis. In the 2015–16 period, the oil price volatility index also has a minor spike. The oil price volatility index changes indicate high uncertainty in the Indian crude oil market.

Figure 1. Oil price volatility index over the period.



In order to analyse how the changes in the oil price volatility index affect Indian sectoral stock returns under different market conditions, the quantile regression method is applied. Tables 1 and 2 show the OLS and quantile regression estimation outcomes. OLS regression coefficients are included in the table to make a comparison with the quantile regression coefficients. The OLS regression helps to understand the average effect of the independent variable on the dependent variable values. Based on the value of the OLS coefficients in Table 1, the study finds that the oil price volatility index deviations negatively affect the sectoral stock returns. This signifies that higher uncertainty in the crude oil market leads to lower stock market returns. One explanation for this outcome is that crude oil plays a significant role in the production of various goods and services. The increase in crude oil price uncertainty negatively affects investments in the real economy, which in turn leads to lower stock returns (Sreenu , 2022).

Table 2 shows the respective quantile regression coefficients from 0.01 to 0.99. The bearish period is represented by $\tau = 0.01, 0.05, 0.1$, the normal period by τ =0.4,0.5,0.6, and the bullish period by $\tau = 0.9$, 0.95, 0.99. These coefficients capture the heterogeneous dependence of crude oil price uncertainty on sectoral stock returns under diverse market conditions.

Table 1. OLS regression results.

SECTORS	Nifty 50	Automobile	Consumer	Finance	FMCG	Metal	Realty	Health	Pharma	IT	Bank
OVX	0.033***	-0.04***	0.023***	0.023***	-0.021***	-0.05***	0.037***	0.019***	-0.021***	-0.024***	0.041***
Interest rate	0.000	0.000	-0.000015	0.000	0.000	-0.0003.	0.00023	0.000	0.000	0.000	0.00003
Exchange rate	-0.758***	-0.860***	-0.7819***	-1.106***	-0.444***	-0.931***	-1.282***	-0.281***	-0.253***	-0.183***	-1.099***

Note: Significance levels: *** $p< 0.001$, ** $p< 0.01$, * $p< 0.05$, . $p< 0.1$

Table 2. Quantile regression results

QUANTILES													
SECTORS	**0.01**	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**	**0.99**
Nifty50													
Intercept	-0.031***	-0.014***	-0.009	-0.003	0.000	0.001	0.000	0.002	0.004	0.007	0.009	0.013	0.03***
OVX	-0.066*	-0.042***	-0.036***	-0.036***	-0.035***	-0.033***	-0.032***	-0.026***	-0.026***	-0.025***	-0.027***	-0.029***	-0.032
InterestRate	0.0008	-0.0002	-0.0003	-0.0004**	-0.0004***	-0.0004***	0.0001	0.0001	0.0001	0.000	0.0004*	0.001**	-0.001
ExchangeRate	-0.961*	-0.827***	-0.772***	-0.736***	-0.68***	-0.692***	-0.688***	-0.717***	-0.717***	-0.771***	-0.770***	-0.607***	-0.462
Automobile													
Intercept	-0.031***	-0.014***	-0.009	-0.003	0.000	0.001	0.000	0.002	0.004	0.007	0.009	0.012	0.029***
OVX	-0.066	-0.043***	-0.037***	-0.036***	-0.039***	-0.034***	-0.027***	-0.027***	-0.029***	-0.035***	-0.033***	-0.042***	-0.032
InterestRate	0.003**	0.0005	-0.000	-0.0004*	-0.0004*	-0.0004***	0.0001	0.0004**	0.0002	0.0001	0.0001	-0.005	-0.001
ExchangeRate	-1.087***	-0.902***	-0.862***	-0.705***	-0.688***	-0.685***	-0.702***	-0.782***	-0.833***	-0.857***	-0.802***	-0.615***	-0.645***
Consumer													
Intercept	-0.037***	-0.017***	-0.011***	-0.004***	0.0001	0.001	0.000	0.002*	0.004	0.008***	0.013***	0.016***	0.034**
OVX	0.003	-0.024***	-0.027***	-0.029***	-0.021***	-0.024***	-0.022***	-0.021***	-0.022***	-0.022***	-0.018***	-0.014	-0.016
InterestRate	0.001	-0.0001	-0.0003	-0.0005**	-0.0005***	-0.0004***	0.0002.	0.0002	0.0003*	0.0002	0.000	0.001.	-0.0001
ExchangeRate	-1.181*	-0.955***	-0.851***	-0.754***	-0.723***	-0.681***	-0.644***	-0.635 ***	-0.645***	-0.682***	-0.666***	-0.674***	-0.898
Finance													
Intercept	-0.039***	-0.021***	-0.002***	-0.005***	0.000	0.001*	0.000	0.000	0.004***	0.007***	0.012***	0.021***	0.042***
OVX	-0.028	-0.029***	-0.032***	-0.033***	-0.026***	-0.029***	-0.026***	-0.024***	-0.024***	-0.019***	-0.013***	-0.021***	-0.027
InterestRate	0.002	0.001	0.0003	-0.0002**	-0.0002***	-0.0004***	0.0002	0.0008**	0.0007*	0.0010*	0.0012*	0.0008	0.0007
ExchangeRate	-0.853***	-1.051***	-1.033***	-0.900***	-0.910***	-0.824***	-0.818***	-0.834***	-0.859***	-0.835***	-0.984***	-0.803***	-0.706***
FMCG													
Intercept	-0.022*	-0.0103***	-0.008***	-0.005***	-0.002*	0.000	-0.0008**	0.000	0.002**	0.004***	0.011***	0.014***	0.025***
OVX	-0.037	-0.023**	-0.024***	-0.019***	-0.019***	-0.019***	-0.018***	-0.017***	-0.017***	-0.018***	-0.017***	-0.023**	-0.030**

InterestRate	-0.0008	-0.0009**	-0.0005*	-0.0003	-0.0003*	-0.0003*	0.0003***	0.0004***	0.0004***	0.0006***	0.0003	0.0005	0.0003
ExchangeRate	-0.40	-0.436***	-0.503***	-0.438***	-0.42***	-0.374***	-0.39***	-0.357***	-0.3670***	-0.366***	-0.451***	-0.513***	-0.750*
Metal													
Intercept	-0.053***	0.028***	-0.019***	-0.008***	-0.001	0.003***	0.000	0.004**	0.009***	0.015***	0.024***	0.031***	0.05***
OVX	-0.098	-0.071***	-0.052***	-0.058***	-0.049***	-0.041***	-0.038***	-0.042***	-0.044***	-0.052***	-0.051***	-0.067***	-0.047
InterestRate	0.0013	0.0001	-0.0002	-0.0006**	-0.0009***	-0.0010***	-0.0001	0.0000	-0.0002	-0.0002	-0.0005	-0.0006	-0.001
ExchangeRate	-1.246***	-1.024***	-1.032***	-0.99***	-1.022***	-1.031***	-0.976***	-0.998***	-1.019***	-0.939***	-0.865***	-0.766***	-0.12
Realty													
Intercept	-0.044**	-0.021***	-0.010***	-0.006***	-0.002	0.002*	0.000	0.001	0.006***	0.011***	0.018***	0.023***	0.051***
OVX	-0.083	-0.043*	-0.039**	-0.038***	-0.037***	-0.033***	-0.037***	-0.030***	-0.031***	-0.027***	-0.036***	-0.025	0.007
InterestRate	-0.002	-0.002***	-0.002***	-0.0011***	-0.0009**	-0.0008***	0.0002	0.0005*	0.0005*	0.0007*	0.001	0.001**	0.00
ExchangeRate	-1.735***	-1.648***	-1.465***	-1.304***	-1.381***	-1.237***	-1.227***	-1.176***	-1.155***	-1.214***	-1.164***	-1.176***	-1.100**
Health													
Intercept	-0.037***	-0.02***	-0.017***	-0.01***	-0.004***	-0.001	0.000	0.000	0.004***	0.009***	0.015***	0.021***	0.041***
OVX	-0.032	-0.021**	-0.027***	-0.025***	-0.026***	-0.019***	-0.020***	-0.016***	-0.017**	-0.011*	-0.01***	-0.005	-0.003
InterestRate	0.001	0.0006*	0.0007***	0.0003	0.0001	-0.0001	0.0002*	0.0003**	0.0001	-0.0001	-0.0004*	-0.0004	-0.0019*
ExchangeRate	-0.857**	-0.324***	-0.280***	-0.278***	-0.273***	-0.230***	-0.221***	-0.261***	-0.229***	-0.237***	-0.179**	-0.118	0.086
Pharma													
Intercept	0.041***	-0.042***	-0.021***	-0.018***	-0.005***	-0.002	0.000	0.000	0.004***	0.009***	0.017***	0.025***	0.044***
OVX	-0.035	-0.023**	-0.031***	-0.028***	-0.025***	-0.017***	-0.019***	-0.015***	-0.014**	-0.011*	-0.014*	-0.013*	0.005
InterestRate	0.002	0.0005	0.0007***	0.0004	0.0001	0.0000	0.0002*	0.0004**	0.0002	0.0000	-0.0004*	-0.0008**	-0.002*
ExchangeRate	-0.783***	-0.326**	-0.23**	-0.23***	-0.261***	-0.237***	-0.208***	-0.232***	-0.231***	-0.206***	-0.298***	-0.080	0.112
IT													
Intercept	-0.032***	-0.02***	-0.015***	-0.007***	-0.003**	0.001*	0.000	0.002	0.005***	0.009***	0.016***	0.022***	0.041***
OVX	-0.021	-0.041	-0.034***	-0.022***	-0.025***	-0.02***	-0.019***	-0.020***	-0.021***	-0.021***	-0.019*	-0.016*	-0.024
InterestRate	-0.0008	0.0000	0.0002	-0.0002	-0.0002	-0.0004	0.0001***	0.0002	0.0001	0.0000	-0.0001	-0.0002	-0.0012
ExchangeRate	-1.046	-0.371***	-0.195*	-0.12*	-0.055	-0.074	-0.073	-0.115*	-0.094	-0.173*	-0.093	-0.067	-0.013
Bank													
Intercept	-0.039***	-0.024***	-0.012***	-0.005***	0.000	0.001**	0.000	0.000	0.004***	0.008***	0.014***	0.02***	0.041***
OVX	-0.082	-0.049**	-0.041***	-0.037***	-0.043***	-0.041***	-0.033***	-0.036***	-0.032***	-0.027***	-0.027***	-0.032**	-0.054
InterestRate	0.0003	0.0004	-0.0005	-0.0006**	-0.0006***	-0.0006***	0.0001	0.0003	0.0003	0.0004	0.0005	0.0006	-0.0003
ExchangeRate	-0.986*	-1.2422***	-1.171***	-1.065***	-1.014***	-0.934***	-0.93***	-0.931***	-0.983***	-1.166***	-1.029***	-0.895***	-1.121*

Note: Significance levels: *** $p< 0.001$, ** $p< 0.01$, * $p< 0.05$, . $p< 0.1$

Table 2 shows that most of the quantile regression coefficients are significant and show a negative effect at all quantiles. We can observe that the negative effects of oil price volatility vary with the change of the quantiles. This implies that oil price volatility negatively affects the sectoral stock market in the bearish, normal, and bullish periods. However, as we can see from Figures 2 to 9, in most cases, it is evident that the increasing oil price volatility causes decreasing stock returns, and these effects are larger when the stock markets are more bearish. Figures 2 to 9 display the plots of the regression estimate for quantiles from 0.01 to 0.99 for all of the explanatory variables. In each plot, the horizontal axis indicates the quantile scale and the vertical axis indicates the relationship between the stock returns and one explanatory variable (coefficient values; $\beta_1, \beta_2, \beta_3$,), keeping other explanatory variables constant. In the plots, *OVX* represents the relationship between oil price volatility and stock returns (i.e. β_1), *Interest Rate* represents the relationship between interest rate and stock returns (i.e. β_2) and *Exchange Rate* represents the relationship between exchange rate and stock returns (β_3). The regression quantiles of $\beta_1, \beta_2, \beta_3$, are represented with a dashed black line and its bootstrapped 95% confidence band is represented by the grey shaded area. The straight solid red line and dashed lines denote the $\beta_1, \beta_2, \beta_3$ for the OLS model and its 95% confidence band, respectively.

Figure 2. Quantile regression results for NIFTY 50

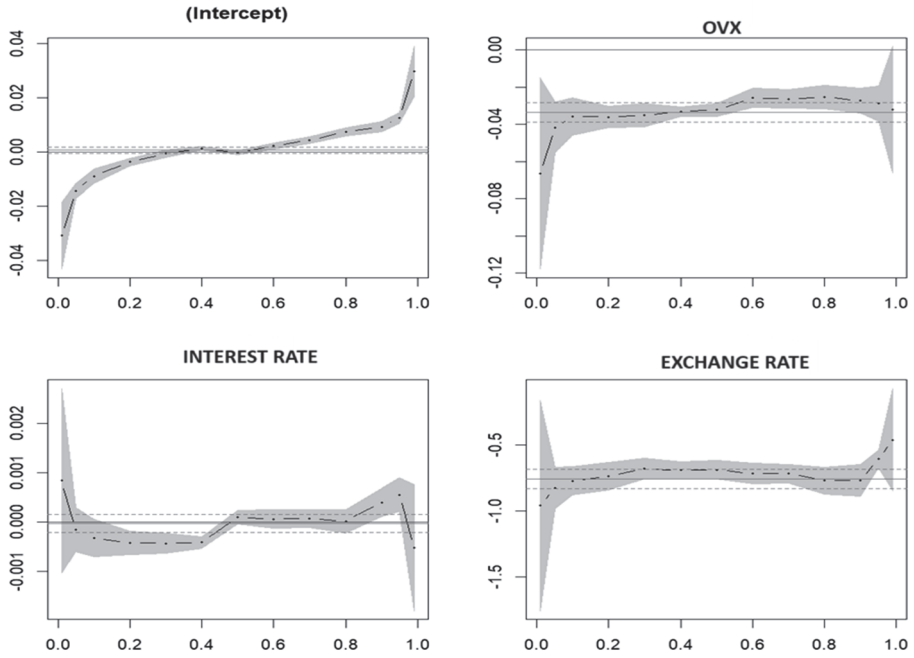
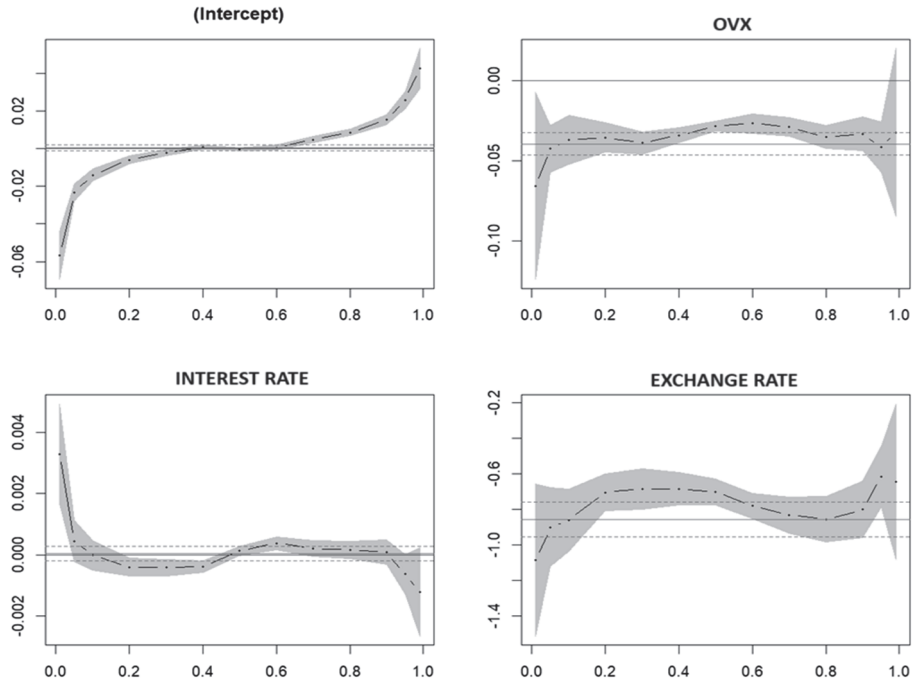


Figure 2 shows that oil price volatility has a significant and negative effect on aggregate stock returns, and the negative effect is much stronger during the bearish period. Interest rate changes also negatively affect stock market returns.

Figure 3. Quantile regression results for the automobile sector.



Oil price volatility has statistically significant negative effects for nearly all quantiles in the automobile sector, as can be seen in Figure 3, with the effect being stronger during the bearish period. The automobile sector being an oil-intensive sector, higher oil prices are associated with lower automobile manufacturer returns. This can be through either an increase in the demand for more energy-efficient vehicles (demand-side effects) or a rise in oil prices through the rise in production cost and profitability (supply-side effects) (Arouri, 2011).

Figure 4. Quantile regression results for consumer durables.

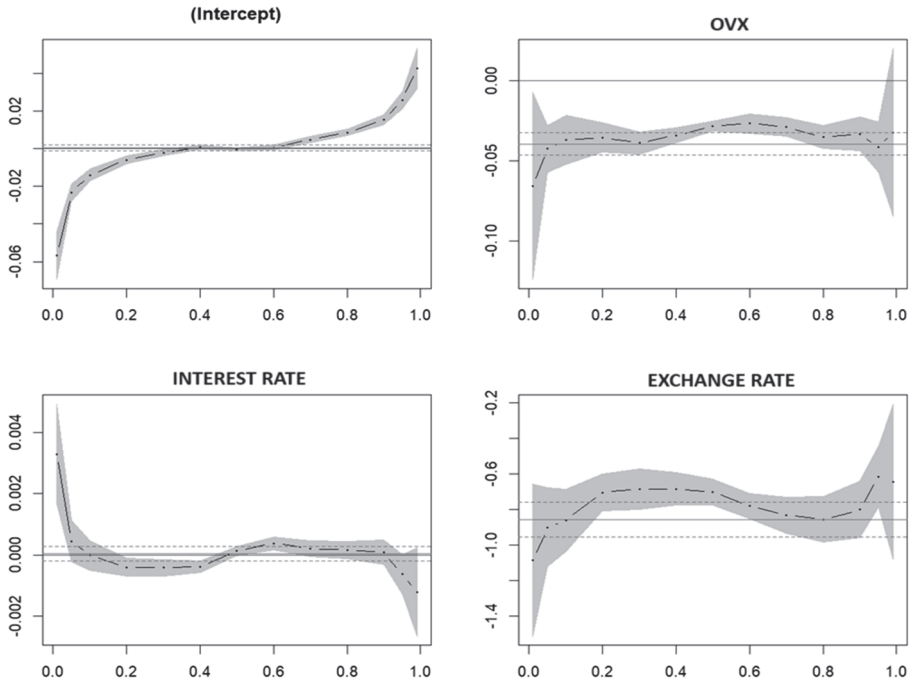


Figure 4 depicts the consumer-durable sector (non-oil-intensive sector). Oil price volatility has statistically significant negative effects for nearly all quantiles, but OVX is more negatively affected at the lower quantiles. It is evident from the figure that interest rate changes have more impact on the stock returns of consumer durables. Higher interest rates can increase the cost of borrowing for consumers, which can reduce their ability to purchase consumer durables, such as cars, appliances, and furniture. This can lead to lower sales and earnings for companies in the consumer durable sector, which can in turn negatively affect their stock returns.

Figure 5. Quantile regression results for finance.

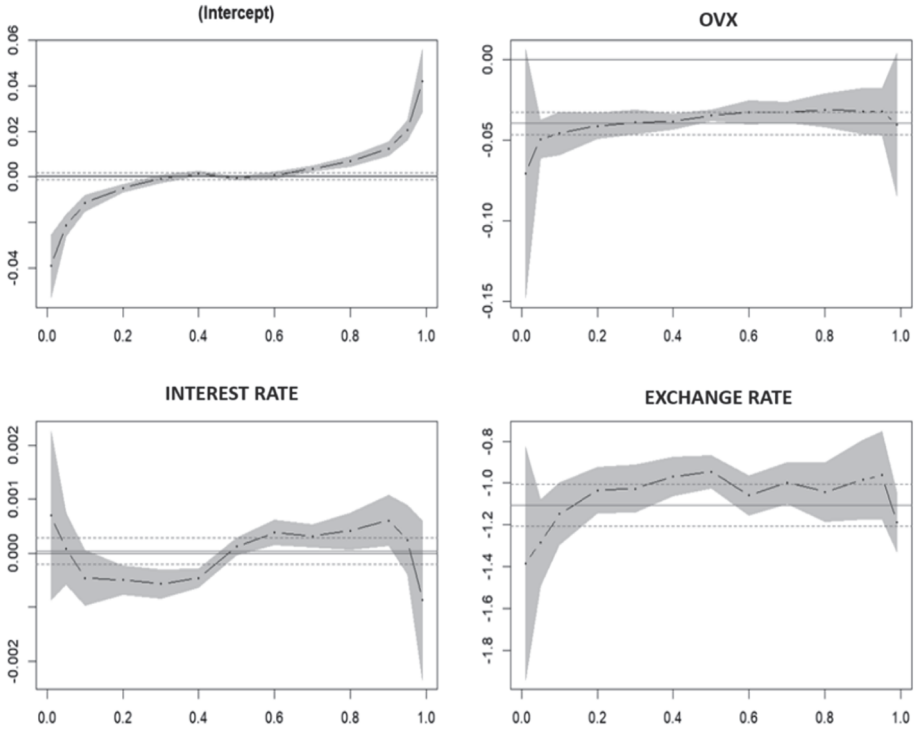
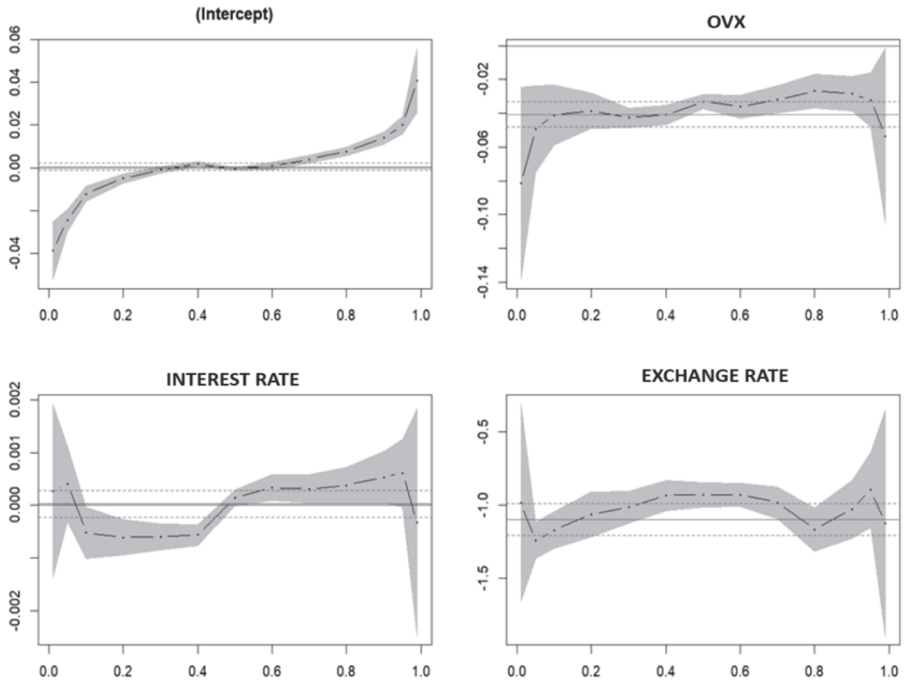


Figure 6. Quantile regression results for banking.



In the case of the financial service and banking sectors (non-oil-intensive sectors) in Figure 5 and Figure 6, oil price volatility has a significant and negative effect on stock returns at all quantiles and it is much stronger during the bearish period. The negative relationship between oil price changes and financial and banking sector stocks are mainly through two distinct channels: the inflation effect channel and the economic growth channel. Oil prices can be an indicator of inflation expectations. Higher oil prices or price volatility can lead to higher inflation expectations (Elder & Serletis, 2010), which can lead to higher interest rates and lower demand for financial and banking sector stocks. Oil prices can also be a proxy for economic growth expectations. Higher oil prices or price volatility can lead to reduced economic growth expectations, negatively affecting the financial and banking sectors, as they rely on strong economic conditions to drive demand and earnings.

Figute 7. Quantile regression results for pharmaceutical.

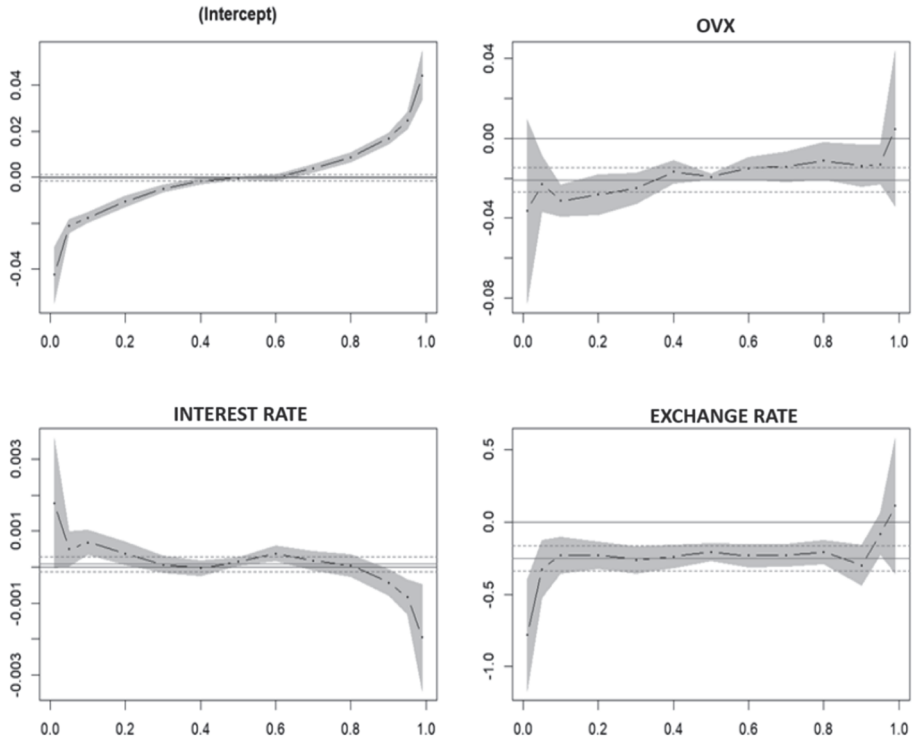


Figure 8. Quantile regression results for healthcare.

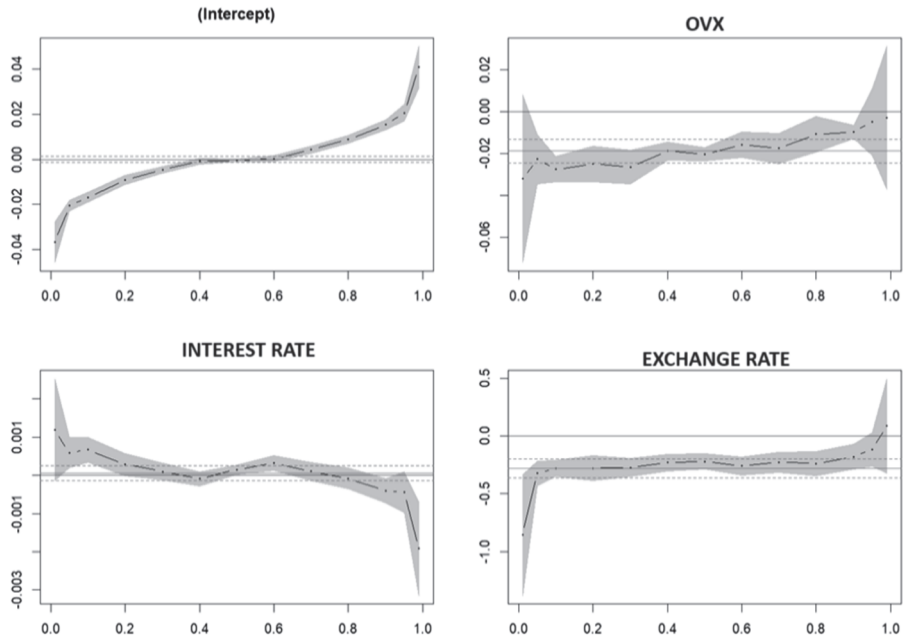
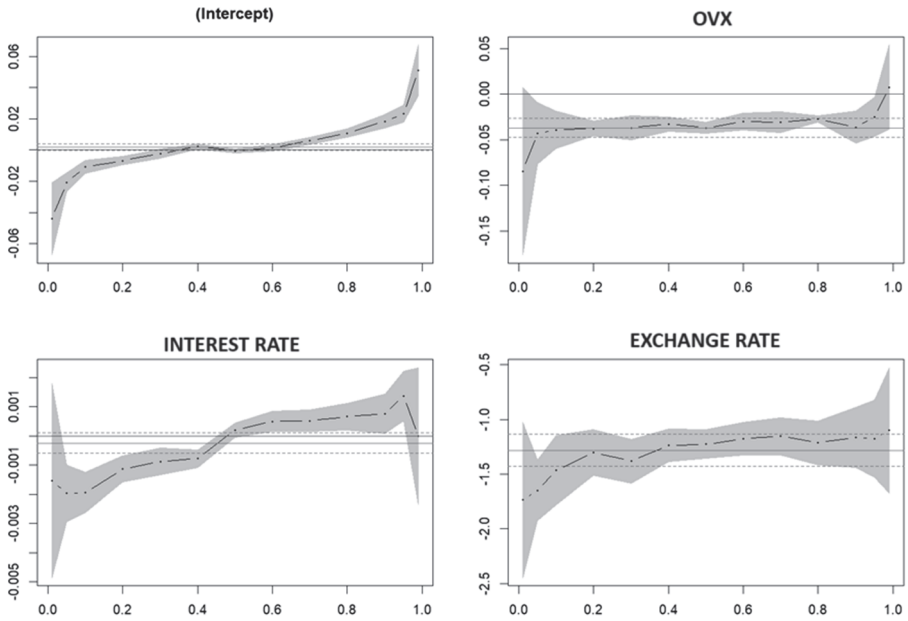


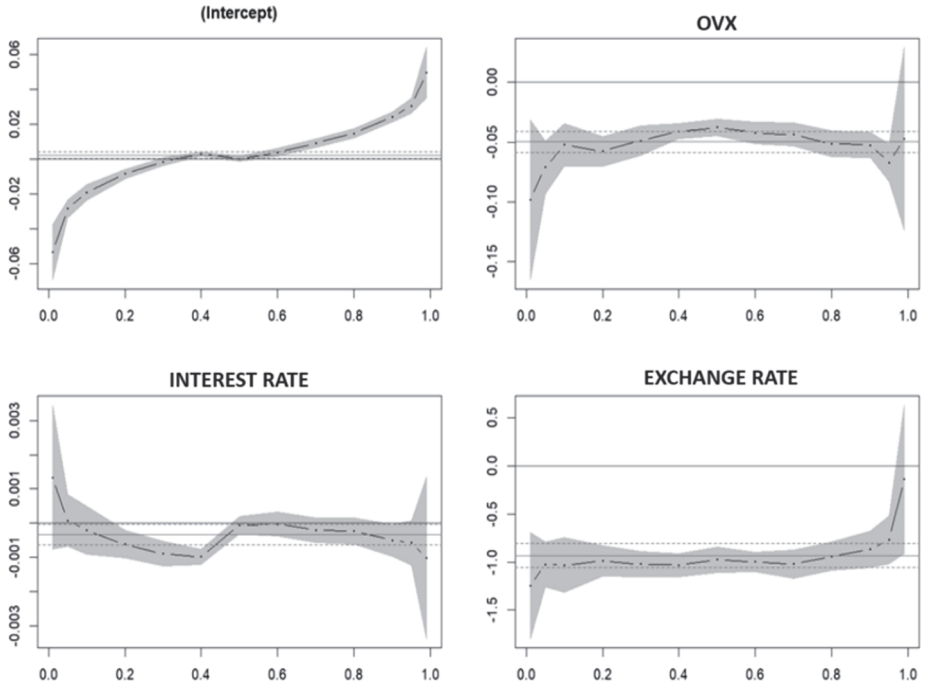
Figure 7 and Figure 8 show that oil price volatility has a significant negative effect on the pharmaceutical and healthcare sector (non-oil-intensive sectors) stock returns at all quantiles. Petroleum is used widely in health care – primarily as a transport fuel and feedstock for pharmaceuticals, plastics, and medical supplies – and few substitutes for it are available. This dependence theoretically makes healthcare vulnerable to petroleum supply shifts (Hess et al., 2011). The relationship between them is indirect; that is, higher oil prices raise the costs of production and transportation in these sectors, which in turn affects the profitability of the firms associated and, thus, their stock returns. Interest rate and exchange rate changes also affect the returns, mainly in the bearish and bullish periods. In the case of the exchange rate, since India is one of the largest exporters of pharmaceuticals and vaccine products, exchange rate changes have more impact on the stock returns and the negative effects are stronger in the bearish period.

Figure 9. Quantile regression results for realty.



It is evident from Figure 9 that oil price volatility has a significant and negative effect on the stock returns of the realty sector (non-oil-intensive sector) at all quantiles and is much stronger at the lower quantiles. Oil price volatility can be a signal of inflation expectation and economic instability and can lead to fluctuations in interest rates. Higher interest rates can increase borrowing costs for real estate companies, which can reduce their profitability and lower their stock return. Thus, from the figure it is clear that interest rate changes are strongly associated with realty sector stock returns.

Figure 10. Quantile regression results for metal.



As can be seen from the Figure 10, oil price volatility has a significant negative effect on the stock returns of the metal sector (oil-intensive sector) at all quantiles but it is much stronger in the bearish period. Metal and mining companies often require oil and other energy sources as inputs for their production processes. Higher oil prices or price volatility can increase the cost of production for metal companies, reducing their profit margins and stock returns.

Figure 11. Quantile regression results for IT.

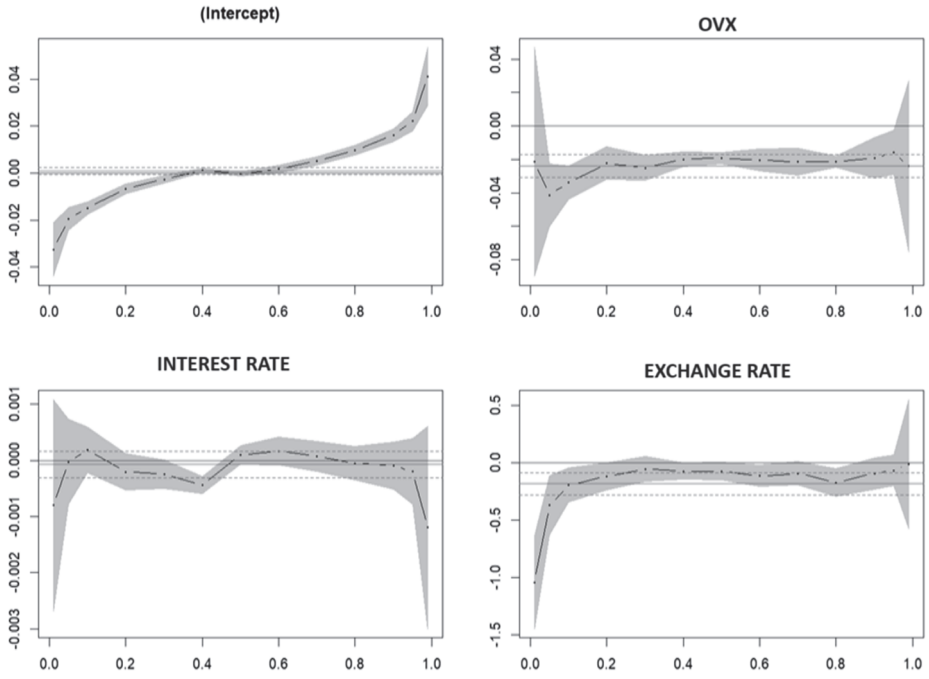
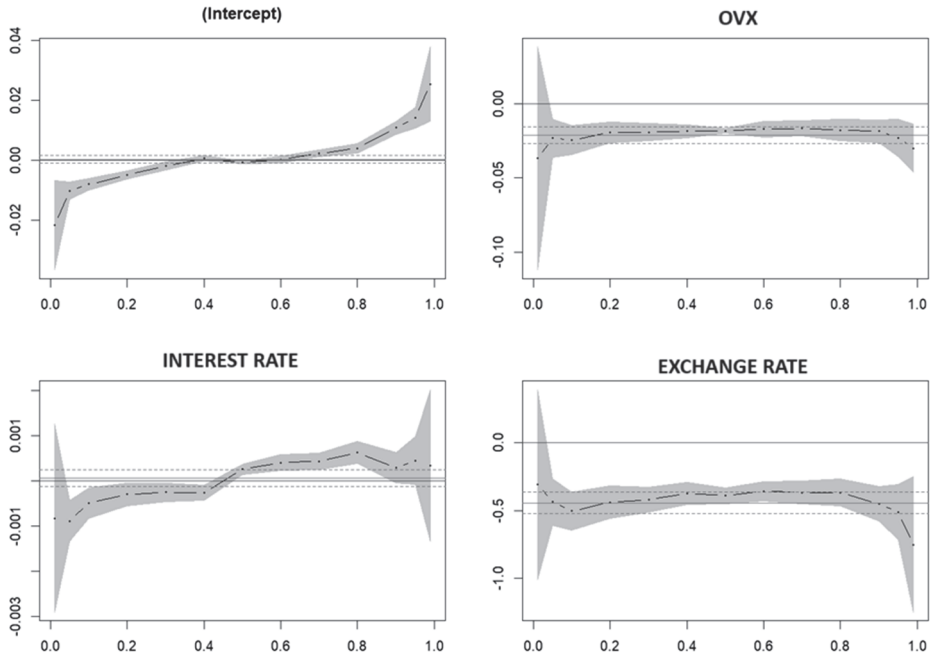


Figure 11 depicts the IT sector (non-oil-intensive sector). The impact of oil price volatility on stock returns is negative across all quantiles and more or less stable throughout, with a slightly stronger impact at the lower quantiles, i.e. in the bearish period. Such a result could be because IT is a non-oil-intensive sector; therefore, when the economy is in a bearish period, oil price volatility could be reflected in negative sectoral returns. However, as can be seen from the figure, exchange rate changes have stronger negative effects in the bearish period since India is a fast-growing software service exporter.

Figure 12. Quantile regression results for the FMCG sector.



As Figure 12 depicts, oil price volatility has a significant and negative effect on the stock returns of the FMCG sector (non-oil-intensive sector) at all quantiles, and its effect is more or less the same across all quantiles. Since the FMCG sector's demand is mostly inelastic, the oil price changes do not cause much change in the demand for these goods. This sector requires an agile logistics process. This leads to a rise in transportation and commercialisation costs, which reduces the profitability of the associated firms and, thus, the stock returns. Interest rate changes also significantly affect this sector and have stronger negative effects during the bearish period.

Table 3 and 4 report the results of the Wald test for quantile slopes of the 0.01 and 0.09 quantiles and the 0.05 and 0.99 quantiles. A quantile regression is particularly useful for capturing heterogeneous effects of independent variables on the dependent variable. By running an F-test for the equality of coefficients, we can identify whether these effects differ significantly across quantiles, providing insights into the conditional relationships between variables.

Table 3: Slope equality test for quantiles 0.01 and 0.99

SECTORS	Auto	Consumer	Metal	Finance	FMCG	Realty	Health	Pharma	IT	Bank	Nifty 50
β_1	0.481	0.734	0.407	0.572	0.883	0.141	0.361	0.255	0.959	0.548	0.359
β_2	0.001***	0.730	0.221	0.226	0.472	0.537	0.005**	0.008 **	0.804	0.716	0.321
β_3	0.232	0.698	0.054	0.577	0.396	0.25	0.019*	0.014 *	0.01395 *	0.8266	0.3523
F-statistic (combined)	0.004 **	0.958	0.035 *	0.515	0.751	0.120	0.002 **	0.004 **	0.053	0.931	0.357

Note: Significance levels: *** $p< 0.001$, ** $p< 0.01$, * $p< 0.05$, . $p< 0.1$

Table 4: Slope equality test for quantiles 0.05 and 0.95

	Auto	Consumer	Metal	Finance	FMCG	Realty	Health	Pharma	IT	Bank	Nifty 50
β_1	0.930	0.395	0.800	0.120	0.987	0.452	0.130	0.335	0.062	0.336	0.190
β_2	0.051	0.099	0.262	0.767	0.001**	0.000 ***	0.008 **	0.001***	0.766	0.717	0.036*
β_3	0.087	0.161	0.206	0.064	0.629	0.079	0.057	0.090	0.080	0.042*	0.034*
F-statistic (combined)	0.043 *	0.153	0.323	0.022 *	0.015 *	0.000 ***	0.0002***	0.000***	0.056	0.089	0.010**

Note: Significance levels: *** $p< 0.001$, ** $p< 0.01$, * $p< 0.05$, . $p< 0.1$

The null hypothesis is that the quantile slope coefficients are identical. It is evident from the table that for most of the sectors, the joint slope equality coefficient (F-statistic) is significant.

Overall it can be inferred that oil price volatility has a significant and negative effect on the stock returns of all sectors at all quantiles but it is much stronger in the bearish period. Regarding the statistical pattern of structure and degree of dependence, Hu (2006) also emphasises that the dependencies across the financial markets are left-tailed and unarguably asymmetric. Moreover, the strong lower-tail sensitivity could be an outcome of the fact that the influence of oil price shocks is more evident and tractable when markets are bearish than when markets are bullish (Zhu et al., 2016).

Further exchange rate and interest rate changes also affect the sectoral stock returns. This can be attributed to the flow-oriented theory, which states that exchange rate movements affect international competitiveness and trade balance, thereby influencing real economic variables such as real income and output. The exchange rate affects the values of the income and the costs of a company with considerable exports/imports and thus impacts the company's stock price.

As we can see from the analysis, oil price volatility affects the sectoral returns more when the economy is in the bearish period. In the normal and bullish periods, oil price volatility does not affect the stock returns greatly. Further interest rate and exchange rate changes substantially affect the sectoral returns in the bearish period as in the case of the pharmaceutical, healthcare, banking and finance, IT, FMCG, and consumer durables sectors. Thus, the impact of oil price volatility on sectoral returns is less than the influence of interest rate and exchange rate changes.

To capture the effect of systematic risk, market portfolio is added as one of the control variables in the quantile regression:

$$r_t = \alpha + \beta_1 OVX_t + \beta_2 IR_t + \beta_3 ER_t + \beta_4 MP_t + \varepsilon_t \quad (4)$$

Here, all other variables are the same as in Eq.(3); additionally, β_4 is the coefficient for market portfolio.

Table 5. Quantile regression results including market portfolio

QUANTILES													
SECTORS	**0.01**	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**	**0.99**
AUTOMOBILE													
Intercept	-0.024***	-0.018***	-0.011***	-0.007**	-0.003***	-0.001	0.000	-0.001***	0.002*	0.006***	0.012***	0.018***	0.029***
OVX	-0.014	-0.018**	-0.008	-0.006**	-0.003	0.000	-0.001	0.002	0.006	0.005	0.003	-0.003	-0.003
InterestRate	0.001	0.001***	0.0003***	0.0001	-0.000	-0.0001	-0.000	0.0002***	0.0003**	0.0001	-0.0003	-0.0007**	-0.002
ExchangeRate	-0.392	0.035	-0.062	-0.085 *	-0.096**	-0.060	-0.057.	-0.034	-0.08	-0.088*	-0.08	-0.039	0.108
Market Portfolio	0.930***	1.039***	1.003***	0.992***	0.988***	1.016***	0.995***	1.002***	0.995***	0.994***	1.015 ***	1.025***	1.167***
CONSUMER DURABLES													
Intercept	0.013***	-0.012***	-0.007***	0.004***	-0.002***	0.000	-0.000	-0.000	0.002**	0.005***	0.008***	0.012***	0.028***
OVX	0.011	-0.000	-0.002	-0.000	0.000	-0.001	0.002	0.001	-0.000	-0.005	0.001	0.007	0.017
InterestRate	-0.002***	-0.000	-0.001**	-0.000***	-0.000.	-0.000**	0.000	0.000*	0.000**	0.000*	0.001***	0.001	-0.000
ExchangeRate)	-0.430	-0.337**	-0.332***	-0.203***	-0.219***	-0.183***	-0.196***	-0.175***	-0.210***	-0.168**	-0.172*	-0.095	-0.175
Market Portfolio	0.792***	0.738***	0.718***	0.717***	0.697***	0.703***	0.707***	0.720***	0.702***	0.734***	0.716***	0.765***	0.859***
METAL													
Intercept	-0.013***	-0.012***	-0.007***	-0.004***	-0.002***	0.000	-0.000	-0.000	0.002	0.005***	0.008***	0.012***	0.028***
OVX	0.011	-0.000	-0.002	-0.000	0.000	-0.001	0.002	0.001	-0.000	-0.005	0.001	0.007	0.017
InterestRate	-0.002***	-0.000	-0.001**	-0.000**	-0.000	-0.000*	0.000	0.000**	0.000**	0.000**	0.001***	0.001	-0.000
ExchangeRate	-0.430*	-0.337**	-0.332***	-0.203***	-0.219***	-0.183***	-0.196***	-0.175***	-0.210***	-0.168**	-0.172*	-0.095	-0.175
Market Portfolio	0.792***	0.738***	0.718***	0.717***	0.697***	0.703***	0.707***	0.720***	0.702***	0.734***	0.716***	0.765***	0.859***
FINANCE													
Intercept	-0.017***	-0.010***	-0.007***	-0.004***	-0.002***	0.001**	-0.000	-0.001*	0.001	0.003***	0.007***	0.011***	0.017
OVX	-0.001	-0.001	-0.000	-0.001	0.002	0.000	-0.000	0.001	0.001	-0.000	0.005	0.007	0.020
InterestRate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000***	0.000***	0.000	-0.000	-0.000	-0.000
ExchangeRate	-0.246	-0.234**	-0.243***	-0.186***	-0.200***	-0.166***	-0.143***	-0.133***	-0.127***	-0.149***	-0.152***	-0.183*	-0.398
Market Portfolio	1.190***	1.221***	1.214***	1.188***	1.192***	1.191***	1.191***	1.196***	1.204***	1.220***	1.256***	1.252***	1.272
FMCG													
Intercept	-0.013***	-0.009***	-0.006***	-0.006***	-0.003***	-0.001	-0.000*	-0.001**	0.000	0.003***	0.006***	0.012***	0.024***
OVX	-0.004	-0.004	0.002	0.002	0.000	0.002	0.002*	0.001	0.001	-0.001	-0.002	0.006	0.028
InterestRate	-0.001**	-0.001**	-0.000**	-0.000**	-0.000	-0.000	0.000**	0.000***	0.001***	0.001***	0.001***	0.000	-0.000
ExchangeRate	0.313	0.162**	0.052	0.052	0.039	0.041	0.019	-0.021	0.0104	0.014	-0.049	-0.019	-0.087
Market Portfolio	0.644***	0.672***	0.652***	0.652***	0.661***	0.639***	0.643***	0.628***	0.648***	0.635***	0.649***	0.657***	0.741***
REALTY													
Intercept	-0.021***	-0.019***	-0.013***	-0.007***	-0.003*	-0.0004	0.000	0.000	0.004**	0.008***	0.014***	0.020***	0.041***
OVX	0.017*	0.009	0.004	0.005	0.010	-0.000	0.004**	0.005	0.002	0.006	0.016	0.020	0.053

InterestRate	-0.003***	-0.001*	-0.001**	-0.001**	-0.001***	0.006	-0.000	0.000*	0.000	0.000	0.000	0.001	0.000
ExchangeRate	-0.803	-0.445*	-0.184	-0.223*	-0.185*	-0.000	-0.275***	-0.373***	-0.393***	-0.374***	-0.283**	-0.487**	-0.684
Market Portfolio	1.145***	1.338***	1.353***	1.333***	1.298***	-0.230	1.264***	1.243***	1.229***	1.253***	1.316***	1.320***	1.105***
HEALTH													
Intercept	-0.032***	-0.016***	-0.013***	-0.009***	-0.006***	-0.002**	-0.000	-0.001	0.002**	0.006***	0.013***	0.022***	0.038***
OVX	-0.008	0.003	0.002	0.001	-0.001	-0.002	0.000	0.001	-0.002	0.003	0.003	0.013	0.017
InterestRate	0.001	0.000	0.000*	0.000**	0.000**	0.000	0.000*	0.000***	0.000	0.000	-0.000*	-0.001***	-0.002**
ExchangeRate	0.189	0.217	0.284**	0.157***	0.212***	0.189***	0.178***	0.162***	0.124**	0.119**	0.106	0.083	0.328**
Market Portfolio	0.607***	0.598***	0.618***	0.588***	0.583***	0.583***	0.592***	0.597***	0.603***	0.599***	0.623***	0.587***	0.449***
PHARMA													
Intercept	-0.042***	-0.016***	-0.015***	-0.010***	-0.006***	-0.003***	-0.000	-0.002**	0.002**	0.007***	0.014***	0.023***	0.046***
OVX	-0.014	0.001	-0.003	0.004	-0.001	-0.004	-0.001	-0.002	-0.002	0.006	-0.002	0.005	0.005
InterestRate	0.002**	0.000	0.001**	0.001***	0.000**	0.000	0.000	0.001***	0.000**	0.000	-0.000	-0.001**	-0.003***
ExchangeRate	0.259	0.257	0.277**	0.201***	0.237***	0.222***	0.216***	0.165***	0.157**	0.169***	0.161***	0.220	0.302
Market Portfolio	0.621***	0.666***	0.607***	0.603***	0.588***	0.587***	0.592***	0.595***	0.600***	0.621***	0.623***	0.574***	0.549***
IT													
Intercept	-0.027***	-0.015***	-0.011***	-0.007***	-0.003**	0.000	-0.000	0.001	0.003***	0.006***	0.012***	0.017***	0.032***
OVX	0.032	0.004	0.005	0.001	0.001	0.003	0.000	0.003	-0.001	-0.002	0.004	-0.002	-0.001
InterestRate	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000**	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.001
ExchangeRate	0.353	0.449**	0.466***	0.398***	0.342***	0.327***	0.331***	0.369***	0.369***	0.457***	0.351***	0.592***	0.630
Market Portfolio	0.888***	0.812***	0.793***	0.743***	0.722***	0.726***	0.710***	0.705***	0.742***	0.763***	0.747***	0.819***	0.805***
BANK													
Intercept	-0.016***	-0.011***	-0.008***	-0.005***	-0.003***	-0.001*	0.000	-0.001**	0.002**	0.004***	0.009***	0.011***	0.020***
OVX	-0.003	0.003	-0.001	-0.001	-0.001	0.002	0.002	0.002	0.001	0.003	0.009	0.010	-0.002
InterestRate	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000***	0.000*	0.000	-0.000	0.000	-0.000
ExchangeRate	-0.111	-0.191	-0.161**	-0.149***	-0.136***	-0.096**	-0.096***	-0.103**	-0.108**	-0.210***	-0.142	-0.237**	-0.299
Market Portfolio	1.213***	1.255***	1.247***	1.240***	1.224***	1.228***	1.227***	1.230***	1.237***	1.244***	1.285***	1.302***	1.306***

Note: Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Table 5 shows that after including market portfolio as one of the explanatory variables in the quantile regression analysis, market portfolio picks up most of the variations in sectoral returns, which is expected as systematic and non-diversifiable risk component drives sectoral returns. However, oil price volatility becomes insignificant in most of the cases. It could be due to the fact that oil price volatility affects the entire market as a whole, which is confirmed by Luo and Qin (2017) and Joo and Park (2021), and then spills over to a particular sector. Although fluctuations in oil price changes represent a source of systematic risk affecting aggregate market returns, the level of exposure to this risk differs among various sectors (Lee et al., 2012). Studies by Xiao et al. (2018) and Sreenu (2022) have shown that oil price volatility affects the sectoral returns. So this indirect channel of spillover could be the possible reason for the insignificance of oil price volatility when we include market portfolio as one of the control variables.

5. CONCLUSIONS

This paper examines the heterogeneous effect of oil price volatility on the Indian sectoral stock returns for the period January 2011 to September 2022 using the quantile regression method. The study aimed to analyse how oil price volatility affects sectoral returns during different market conditions: bearish, normal, and bullish periods. The results find that the total and sectoral stock returns are negatively affected by oil price fluctuations, and the negative effect is stronger during the bearish period. This finding is consistent with the results of Sreenu (2022), signifying that the uncertainty fluctuations in the crude oil market mainly hurt the Indian stock returns during unperforming periods, and also with those of Joo and Park (2021), whose results show that OVX has a statistically significant negative effect on the stock returns of oil-importing countries and this negative impact is stronger at the lower quantile levels than at the medium or higher quantile levels of stock returns. As expected, oil-intensive sectors, such as the automobile and metal sectors, are more affected by oil price volatility because of demand- and supply-side effects (Arouri, 2011). This finding is supported by Gogineni (2010), who concludes that sensitivity of industry returns to oil price changes depends on both the cost-side and demand-side dependence on oil and that the relative effects of these factors vary across industries. In the case of non-oil-intensive sectors, interest rate changes strongly affect some sectors more than oil price volatility, such as banking and finance, consumer durables and the

FMCG sectors. Similarly exchange rate changes have a greater impact than oil price volatility in the case of the pharmaceutical and IT sectors. Furthermore, one of the findings of this study is that market portfolio picks up most of the variations in sectoral returns, as it is a systematic and non-diversifiable risk component. Initially, the oil price volatility affects the entire market as a whole, as confirmed by Luo and Qin (2017) and Joo and Park (2021), and then spills over to a particular sector. This implies that there exists an indirect channel through which oil price volatility affects sectoral returns.

Crude oil price uncertainty is a significant problem faced by India due to many political and economic conditions at the global level. Since India is a huge oil import-dependent country, stockholders are very apprehensive about the influence of this ambiguity on the sectoral stock market. Consequently, this study has significant and valuable inferences for investment choices, risk management, and portfolio diversification. For those investors who have invested in energy intensive sectors such as the automobile and metal sectors, over and above hedging against normal market risk, it is also important to hedge against oil price volatility risks. The method of quantile regression is considered superior to ordinary regression in order to capture heterogenous dependence; however, it requires a large amount of data to obtain reliable estimates, and the model specification should be appropriate to obtain unbiased estimates.

Moreover, as India is an emerging market with distinctive growth opportunities and challenges, it represents a valuable case study for analysing the response of industry portfolios to oil price shocks. Investigating how the Indian industry portfolio reacts to fluctuations in oil prices can provide crucial insights into the behaviour of emerging market economies and their resilience to external economic factors. The Indian market may exhibit unique volatility patterns in response to oil price changes which can differ from those observed in other global markets. Understanding these patterns can assist international investors in evaluating the risk-return profile of Indian assets during periods of oil price uncertainty.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

Ahmadi, M., Manera, M., & Sadeghzadeh, M. (2016). Global oil market and the US stock returns. *Energy*, *114*, 1277-1287.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., & De Gracia, F. P. (2018). Oil volatility, oil and gas firms and portfolio diversification. *Energy Economics*, *70*, 499-515.

Arouri, M. E. H. (2011). Does crude oil move stock markets in Europe? A sector investigation. *Economic Modelling*, *28*(4), 1716-1725.

Arouri, M. E. H., & Rault, C. (2012). Oil prices and stock markets in GCC countries: Empirical evidence from panel analysis. *International Journal of Finance & Economics*, *17*(3), 242–253.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics*, *34*(2), 611–617.

Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global Finance Journal*, *17*(2), 224–251.

Belhassine, O., & Karamti, C. (2021). Volatility spillovers and hedging effectiveness between oil and stock markets: Evidence from a wavelet-based and structural breaks analysis. *Energy Economics*, *102*, 105513.

Binder, M., & Coad, A. (2011). From Average Joe's happiness to Miserable Jane and Cheerful John: using quantile regressions to analyze the full subjective well-being distribution. *Journal of Economic Behavior & Organization*, *79*(3), 275-290.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*(3), 623–685.

Broadstock, D. C., Wang, R., & Zhang, D. (2014). Direct and indirect oil shocks and their impacts upon energy related stocks. *Economic Systems*, *38*(3), 451–467.

Brown, S. J., & Otsuki, T. (1990). Macroeconomic factors and the Japanese equity markets: The CAPMD project. In E. J. Elton & M. Gruber (Eds.) *Japanese Capital Markets*. New York: Harper & Row.

Cboe Global Markets. (2024). *Cboe Crude Oil ETF Volatility Index (OVX)*. https://www.cboe.com/us/indices/dashboard/OVX/

Chowdhury, S. S. H., & Irfan, M. (2022). A study on the time-varying volatility connectedness between the sectors in the Indian stock market. *Montenegrin Journal of Economics, 18(3),* 77–88.

Choi, S. Y., & Hong, C. (2020). Relationship between uncertainty in the oil and stock markets before and after the shale gas revolution: Evidence from the OVX, VIX, and VKOSPI volatility indices. *PloS one*, *15*(5), e0232508.

Degiannakis, S., Filis, G. & Arora, V. (2018). Oil prices and stock markets: A review of the theory and empirical evidence. *Energy Journal, 39*(5), 85–130. https://doi.org/10.5547/01956574.39.5.sdeg

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158-171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134.

Diebold, F. X., & Yılmaz, K. (2015). *Financial and macroeconomic connectedness: A network approach to measurement and monitoring.* Oxford University Press, USA.

Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *The American economic review*, *70*(5), 960-971.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of business & economic statistics*, *20*(3), 339-350.

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, *42*(6), 1137–1159.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International review of financial analysis*, *20*(3), 152-164.

Ferson, W. E., & Harvey, C. R. (1995). Predictability and time-varying risk in world equity markets. *Research in Finance, 13*, 25–88.

Gogineni, S. (2010). Oil and the stock market: An industry level analysis. *Financial Review*, *45*(4), 995–1010. https://doi.org/10.1111/j.1540-6288.2010.00282.x

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy, 91*(2), 228–248.

Hess, J., Bednarz, D., Bae, J., & Pierce, J. (2011). Petroleum and health care: Evaluating and managing health care's vulnerability to petroleum supply shifts. *American Journal of Public Health*, *101*(9), 1568–1579.

Hu, L. (2006). Dependence patterns across financial markets: A mixed copula approach. *Applied Financial Economics*, *16*(10), 717–729.

Jammazi, R., Ferrer, R., Jareño, F., & Shahzad, S. J. H. (2017). Time-varying causality between crude oil and stock markets: What can we learn from a multiscale perspective?. *International Review of Economics & Finance*, *49*, 453–483.

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance, 51*(2), 463–491.

Joo, Y. C., & Park, S. Y. (2021). The impact of oil price volatility on stock markets: Evidences from oil-importing countries. *Energy Economics*, *101*, 105413.

Kaneko, T., & Lee, B. S. (1995). Relative importance of economic factors in the US and Japanese stock markets. *Journal of the Japanese and International Economies, 9*(3), 290–307.

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.

Kilian, L., & C. Park. (2009). The Impact of Oil Price Shocks on the US Stock Market. *International Economic Review, 50*(4), 1267–1287.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, 33–50.

Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, *15*(4), 143–156.

Koenker, R., Portnoy, S., Ng, P. T., Zeileis, A., Grosjean, P., & Ripley, B. D. (2018). Package 'quantreg'. *Reference manual available at R-CRAN: https://cran. rproject. org/web/packages/ quantreg/quantreg. pdf*.

Lee, B. J., Yang, C. W., & Huang, B. N. (2012). Oil price movements and stock markets revisited: A case of sector stock price indexes in the G-7 countries. *Energy Economics*, *34*(5), 1284–1300.

Lu, F. B., Hong, Y. M., Wang, S. Y., Lai, K. K., & Liu, J. (2014). Time-varying Granger causality tests for applications in global crude oil markets. *Energy Economics*, *42*, 289-298.

Luo, X., & Qin, S. (2017). Oil price uncertainty and Chinese stock returns: New evidence from the oil volatility index. *Finance Research Letters*, *20*, 29–34.

Maghyereh, A. I., Awartani, B., & Sweidan, O. D. (2019). Oil price uncertainty and real output growth: New evidence from selected oil-importing countries in the Middle East. *Empirical Economics*, *56*, 1601–1621.

Malik, F., & Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis*, *18*(3), 95-100.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic modelling*, *32*, 15-22.

Nandha, M., & Faff, R. (2008). Does oil move equity prices?. A global view. *Energy Economics*, *30*(3), 986–997.

Ready, R. C. (2018). Oil prices and the stock market. *Review of Finance*, *22*(1), 155-176.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics*, *21*(5), 449–469.

Nath Sahu, T., Bandopadhyay, K., & Mondal, D. (2014). An empirical study on the dynamic relationship between oil prices and Indian stock market. *Managerial Finance*, *40*(2), 200-215.

Silvapulle, P., Smyth, R., Zhang, X., & Fenech, J. P. (2017). Nonparametric panel data model for crude oil and stock market prices in net oil importing countries. *Energy Economics*, *67*, 255–267.

Smyth, R., & Narayan, P. K. (2018). What do we know about oil prices and stock returns?. *International Review of Financial Analysis*, *57*, 148–156.

Sreenu, N. (2022). Impact of crude oil price uncertainty on Indian stock market returns: Evidence from oil price volatility index. *Energy Strategy Reviews*, *44*, 101002.

Spiro, P. S. (1990). The Impact Of Interest Rate Changes On Stock Price Volatili. *Journal of Portfolio Management*, *16*(2), 63.

Umar, Z., Jareño, F., & Escribano, A. (2021). Static and dynamic connectedness between oil price shocks and Spanish equities: A sector analysis. *The European Journal of Finance*, *27*(9), 880–896.

Vo, M. (2011). Oil and stock market volatility: A multivariate stochastic volatility perspective. *Energy Economics*, *33*(5), 956-965.

Wei, Y., Qin, S., Li, X., Zhu, S., & Wei, G. (2019). Oil price fluctuation, stock market and macroeconomic fundamentals: Evidence from China before and after the financial crisis. *Finance Research Letters*, *30*, 23–29.

Xiao, J., Zhou, M., Wen, F., & Wen, F. (2018). Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market conditions: Evidence from oil volatility index. *Energy Economics*, *74*, 777–786.

Youssef, M., & Mokni, K. (2019). Do crude oil prices drive the relationship between stock markets of oil-importing and oil-exporting countries?. *Economies*, *7*(3), 70.

Zhang, D. (2017). Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. *Energy Economics*, *62*, 323–333.

Zhu, H., Guo, Y., You, W., & Xu, Y. (2016). The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. *Energy Economics*, *55*, 30–41.

Received: March, 03, 2024
Accepted: August, 24, 2024