The Impact of The Oil Price Volatility on The World's Stock Markets: How was the Influence of COVID – 19 During the Pandemic?

Abstract: Oil price volatility (OPV) serves as a critical determinant in shaping stock market dynamics, especially within economies that exhibit a significant dependency on energy imports. This analysis, focused on China, Germany, India, Japan, and the U.S., utilizes quantile regression to examine the differential effects of OPV on stock market returns during varying market conditions between March and August 2020. The results suggest that OPV's influence is not uniform, instead varying across quantiles, indicating its more pronounced role in certain market environments, such as periods of downturn or recovery. In both China and Germany, the negative impact of OPV is most substantial at lower quantiles, suggesting heightened market sensitivity to oil price fluctuations during periods of weaker returns or bearish market conditions. As stock market performance improves at higher quantiles, this sensitivity diminishes, indicating a reduced reactivity to OPV when market conditions stabilize. India similarly exhibits a strong negative correlation between OPV and stock returns in lower quantiles, reflecting its vulnerability to oil price shocks during underperforming market phases. However, this effect tapers off at higher quantiles, aligning with more resilient market phases. Japan and the U.S. demonstrate more moderate reactions to OPV, with a consistent negative influence across all quantiles. Despite the uniformity, this suggests that oil price volatility remains a relevant factor for market performance in these countries, even if the magnitude of its effect does not vary drastically across different market conditions. These findings highlight the importance of accounting for OPV, particularly in scenarios of economic stress, as its impact can be significantly magnified, with implications for investors and policymakers aiming to ensure market resilience. The significance of this research lies in its ability to inform strategies that can mitigate the adverse effects of OPV, contributing to more resilient financial systems globally.

Keywords: Oil Price Volatility, Stock Return, F=Government Bond, Exchange Rate.

1. Introduction

Oil price, and oil price volatility have a prominent economic impact on today's world. Its range of influence is so vast that even the stock market of a country is not out of reach of this. In addition, if there are any calamities happening in the world in a large span can be deadly for the entire economy of the world, saying more specifically the most significant countries as major economic hub. Covid – 19 pandemic can be counted as one of those calamites that the world ever encountered. Though it began from the late quarter of the year 2019, its concentrated impact been lethal in 2020.

There are number of studies has been conducted on the oil price volatility, even also finding out the impact on stock market, for example, [1] focuses on the relation between stock price returns and oil price returns covering the COVID -19 period. This relation is examined for major net oil-importing Asian countries. [2] Examine the impact of oil price shocks on stock returns in 12 oil importing European economies. These studies investigate investment and policy strategies with a variety of perspectives in different regions and at different times. Moreover, different findings of the previous studies motivate the need for investigation about the impact of oil price uncertainty in different stock and oil market conditions.

The main purpose of this study is to examine the impact of oil price volatility on the stock returns of five major oil-importing countries: China, Germany, India, Japan, and the U.S. Depending on the continent, and its economy, the impact of oil price volatility might influence uniquely. However, our point of concern is to create an overall image of the world economy, while the major oil importing countries are being counted in this study. As we are intended to find the influence of oil price volatility on stock market return of some selected countries, we have used Stock market return (STRETURN) as dependent variable, while oil price volatility (OPV), Government Bond (GBOND), and Exchange Rate (EXRATE) in USD. Thus, the USA is also included in the selected countries, so we used DXYRATE of USA to conduct the analysis. Here DXYRATE is an index (or measure) of the value of the United States dollar relative to a basket of foreign currencies, often referred to as a basket of U.S. trade partners' currencies.

There are number of studies conducted, and described the relationship between stock price, and oil price volatility in many possible ways. Some of those studies consider some linear models and/or conditional mean specifications such as vector autoregression to examine the relationship between the oil and stock markets. Although the conditional mean specification provides some useful information on the linear relationship, it may not fully explain other important characteristics of oil and stock prices. In particular, it is hard to capture the distributional heterogeneity because it summarizes the average relationship between an oil shock and stock prices. One of the main limitations of this specification is that it cannot consider the state, such as in the boom-and-bust cycle, of oil and stock markets. Unfortunately, these conditional mean-based time series models cannot capture the true relationship at lower and higher quantiles of data. In particular, stock markets may react asymmetrically to oil price volatility, and these reactions depend on the state of each stock market. Specifically, when the distribution of the considered time series is skewed and leptokurtic, it is difficult to uncover some interesting relationships across various quantiles of the time series variables. Therefore, it is crucial to provide a more comprehensive analysis of the relationship between oil price volatility and stock prices using a suitable econometric approach that captures the overall dependence structure of both the oil and stock markets. Moreover, investors and policymakers need a comprehensive understanding and an investigation of the potential differences in stock returns and oil price volatility across various quantiles to make sound decisions.

There are several interesting contributions of this study. We carry out empirical analysis to explore the stock markets' reactions considering various stock and oil market conditions. In this study, to provide a more comprehensive and precise picture of stock and oil prices' overall dependence, we employ the quantile regression [3] approach. These approaches help investigate the effects of oil price shocks on stock returns across various quantiles. In particular, the Quantile Regression approach can uncover some features in the relationship between stock returns and oil price volatility that are not apparent using the ordinary least squares (OLS) approaches. The Quantile Regression approach enables us to analyze uncertain oil price effects on stock prices according to stock market conditions and the size of oil price volatility. In this study, We have used the data from earlier March (2nd March 2020) to the last of August (8th August 2020) of the year 2020. A total of 147 observations has been used while conducting the research.

2. Literature Review

Many researchers found different types of insight from their conducted research while performing in unique ways. For example, [1] focuses on the relation between stock price returns and oil price returns covering the COVID-19 period. This relation is examined for major net oil-importing Asian countries. Utilizing daily data, they fit a DCC-GARCH model, and find evidence of a positive co-movement between oil price returns and stock price returns during the COVID-19 period. This indicates that falling oil prices act as a negative signal for the stock market. According to another study, the author examines the impact of oil price shocks on stock returns in 12 oil importing European economies using Vector Autoregressive (VAR) and Vector Error Correction Models (VECM) for the period 1973 – 2011. The results suggest the existence of a negative and significant impact of oil price changes on most European stock market returns. Furthermore, they find that stock market returns are mostly driven by oil supply shocks. [4] Examines the time-varying correlations between oil prices shocks of different types (supply-side, aggregate demand and oil-market specific demand as per Kilian (2009) who highlighted that "Not all oil shocks are alike") and stock market returns, using a Scalar-BEKK model. They consider the aggregate stock market indices from two countries, China and the US, reflecting the most important developing and developed financial markets in the world. The sample period runs from 1995 until 2013. The authors found that the stock market response to oil price shocks is different over time. More specifically, the evidence suggests that the US stock market is more responsive to oil price shocks compared to the Chinese stock market, as it exhibits a higher level of correlation with oil price shocks throughout the studied period. In addition, the US market is always positively related with the aggregate demand shocks, whereas this does not hold true for China. According to [5], Positive shocks to aggregate demand and to oil-market specific demand are associated with negative effects on the covariance of return and volatility. Oil supply disruptions are associated with positive effects on the covariance of return and volatility. The spillover index between the structural oil price shocks and covariance of stock return and volatility is large and highly statistically significant.

Some of the researchers viewed the circumstance from a different perspective, and found unique information. For instance, [6] showed that the magnitude, duration, and even direction of response by stock market in a country to oil price shocks highly depend on whether the country is a net importer or exporter in the world oil market, and whether changes in oil price are driven by supply or aggregate demand. They also showed that the relative contribution of each type of oil price shocks depends on the level of importance of oil to national economy, as well as the net position in oil market and the driving forces of oil price changes. But the most significant insight they found is that the effects of aggregate demand uncertainty on stock markets in oil-exporting countries are much stronger and more persistent than in oil-importing countries.

A research has been conducted on the USA, and 13 European countries described that the oil price shocks have a statistically significant impact on real stock returns contemporaneously and/or within the following month in the U.S. and 13 European countries over January 1986 – December 2005 [7]. Another research that has a similar context with our research provide support on the time-varying causal effect of the novel COVID-19 pandemic in the major oil-importing and oil-exporting countries on the oil price changes, stock market volatilities and the economic uncertainty using the wavelet coherence and network analysis, and found that the COVID-19 pandemic has a severe influence on oil prices, stock market indices, and the economic uncertainty. Their findings also provide evidence that the COVID-19 pandemic and oil price changes in oil-importing countries mirror those in oil-exporting countries and vice versa. They also found evidence on the COVID-19 pandemic has a profound immediate time–frequency effect on the US, Japanese, South Korean, Indian, and Canadian economic uncertainties. Those authors took the stand with the importance of a better understanding of oil and stock market prices in the oil-importing and oil-exporting countries, by saying that it is vital for investors and policymakers, especially since the novel unprecedented COVID-19 crisis has been recognized among the most serious ever happened [8].

Some researchers concludes that an increase in oil prices leads to decreasing stock return [9]. However, other researchers found that the oil price had no effect on stock prices [10], [11]. [12] examines the impact of oil price fluctuations and oil price volatility on the Korean economy, particularly the effects of crude oil prices, including the Asian Financial Crisis of 1997. The main conclusion of their study is that oil price fluctuations significantly affect the stock market. Specifically, they find that after an oil price shock and volatility, the stock market increases and then slows down after about 9 months. the impact of oil price fluctuations and oil price volatility on the Korean economy, particularly the effects of crude oil prices, including the Asian Financial

Crisis of 1997. The main conclusion of their study is that oil price fluctuations significantly affect the stock market. Specifically, they find that after an oil price shock and volatility, the stock market increases and then slows down after about 9 months.

To understand the connectivity between stock return, and oil price volatility we also used another two independent variables (Government Bond, and Exchange Rate) to better explain the regression model. The relationship between stock returns and government bonds has been a subject of extensive research. Generally, stocks and bonds are considered to have a negative correlation, especially during times of economic uncertainty or market stress. This negative correlation arises because bonds, especially government bonds, are viewed as safer investments compared to stocks, which are riskier. When the stock market is volatile, investors often shift their investments to bonds, causing bond prices to rise and stock prices to fall. For instance, Ilmanen (2003) in his study "Stock-Bond Correlations" published in *Financial Analysts Journal* explored the time-varying nature of stock-bond correlations. He found that this correlation tends to be negative during periods of economic downturns and high market volatility, which supports the "flight-to-quality" hypothesis. Similarly, Connolly, Stivers, and Sun (2005), in their paper "Stock Market Uncertainty and the Stock-Bond Return Relation" published in *Journal of Financial and Quantitative Analysis*, also documented the negative relationship between stock and bond returns during periods of increased market uncertainty.

Exchange rates can influence stock returns through the impact on the competitiveness of firms, especially for those heavily involved in international trade. When a country's currency appreciates, its exports become more expensive for foreign buyers, potentially decreasing demand for export-oriented firms' goods and negatively affecting stock prices. Conversely, a depreciating currency can boost export competitiveness but may lead to higher import costs. Bahmani-Oskooee and Sohrabian (1992) conducted an early study titled "Stock Prices and the Effective Exchange Rate of the Dollar" published in *Applied Economics*, where they analyzed the dynamic relationship between stock prices and exchange rates in the United States. They found that there is a bidirectional causality between stock prices and exchange rates, suggesting that movements in the stock market can predict changes in exchange rates and vice versa. Another study by Phylaktis and Ravazzolo (2005), "Stock Prices and Exchange Rate Dynamics" published in *Journal of International Money and Finance*, examined data from several Pacific

Basin countries and found that exchange rates and stock prices are cointegrated, indicating a long-term equilibrium relationship. As we used the data of Government Bond, and Exchange Rate to find out whether is there any influence on Stock Return by Government Bond, and Exchange Rate or not. According to the previous literature we can say that there is intrinsic connectivity and influential behavior between these variables and will be effective to count these for further part of the study.

3. Methodology

Quantile Regression Approach: Consider the following regression model to analyze how the impact of oil price uncertainty varies across different quantiles of stock returns:

$$STRETURN_t = \alpha + \beta_1 OPV_t + \beta_2 GBOND_t + \beta_3 EXRATE_t + \varepsilon_t$$

Here, ε_t denotes the error term, $STRETURN_t$ is the Stock Return at time t, OPV_t is the Oil Price Volatility at time t, $GBOND_t$ is the Government Bond Rate at time t, and $EXRATE_t$ is the Currency Exchange Rate of a country according to US dollar except USA, and $DXYRATE_t$ will be used instead of $EXRATE_t$ in terms of USA. We have used GBOND, and EXRATE to increase the explanatory power of the model. There are Five (5) countries included in the study, and the value of GBOND varies according to a country's currency itself. On the other hand, the value of STRETURN, and OPV is in USD for each of the country included in the study. From March 2020 to August 2020, we found the data of OPV about 147 days, and the value of the rest of the dependent, and independent variables came into account accordingly. All the data has been collected from Wall Street Journal's data sources. Now, we can then write the conditional quantile function of $STRETURN_t$ given the covariates as.

$$Q_{STRETURNt}(\tau|x_t) = \alpha(\tau) + \beta_1(\tau)\, OPV_t + \beta_2(\tau)\, GBOND_t + \beta_3(\tau)\, EXRATE_t$$

where $Q_{STRETURNt}(\tau|xt)$ denotes the τth conditional quantile of $STRETURN_t$, $0 < \tau < 1$, 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, in (3.2) by solving the following minimization problem:

$$\text{Min} \sum_{i=1}^{n} \rho_t\, (STRETURN_t - \alpha(\tau) - \beta_1(\tau)\, OPV_t - \beta_2(\tau)\, GBOND_t - \beta_3(\tau)\, EXRATE_t)$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the check function, and $I(\cdot)$ is an indicator function. In (3.2), $\beta_1(\tau)$ measures the marginal effects of oil price volatility at the τ quantile level. 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 (0.1, 0.2, 0.3), middle (0.4, 0.5, 0.6), and high quantiles (0.7, 0.8, 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.

Country	Variables	Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test	Level of Significance		
			1%	5%	10%
China	STRETURN	0.11610	0.739	0.463	0.347
	OPV	0.51860	0.739	0.463	0.347
	GBOND	0.73983	0.739	0.463	0.347
	EXRATE	0.45237	0.739	0.463	0.347
Germany	STRETURN	0.23466	0.739	0.463	0.347
	OPV	0.51860	0.739	0.463	0.347
	GBOND	0.05531	0.739	0.463	0.347
	EXRATE	1.07380	0.739	0.463	0.347
India	STRETURN	0.29394	0.739	0.463	0.347
	OPV	0.51860	0.739	0.463	0.347
	GBOND	1.08572	0.739	0.463	0.347
	EXRATE	0.48102	0.739	0.463	0.347
Japan	STRETURN	0.62144	0.739	0.463	0.347
	OPV	0.51860	0.739	0.463	0.347
	GBOND	0.79694	0.739	0.463	0.347
	EXRATE	0.79603	0.739	0.463	0.347
USA	STRETURN	0.35460	0.739	0.463	0.347
	OPV	0.51860	0.739	0.463	0.347
	GBOND	0.60963	0.739	0.463	0.347
	DXYRATE	1.00657	0.739	0.463	0.347

Table 1: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is used to test stationarity in a time series. The hypotheses for the test are: Null Hypothesis (H_0): The time series is stationary (i.e., no unit root). Alternative Hypothesis (H_1): The time series is non-stationary (i.e., it has a unit root). The

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test results across multiple countries reveal varying degrees of stationarity among key economic variables. In China, most variables such as STRETURN, OPV, and EXRATE demonstrate stationarity, as their KPSS statistics fall below the critical values at the 1%, 5%, and 10% significance levels. However, GBOND in China however at the boundary of stationarity, with a KPSS statistic that exactly matches the 1% critical value. Similarly, in Germany and India, most variables exhibit stationarity. For example, stock returns and OPV in both countries are stationary, indicating stable relationships over time. Nonetheless, notable exceptions arise with the EXRATE in Germany and the GBOND in India, which are both non-stationary, signifying the presence of a unit root and indicating potential time trends in these series. In Japan, the stock returns and OPV variables are stationary, but both government bonds and exchange rates display non-stationarity, suggesting that these variables are more prone to long-term movements and trends, rather than reverting to a constant mean over time. The USA also follows a similar pattern, with most variables, such as stock returns and government bonds, remaining stationary, while DXYRATE shows non-stationarity, implying the exchange rate index is subject to persistent fluctuations.

The stationarity of our main independent variables, STRETURN and OPV, across all countries is a positive outcome for econometric analysis. Since these variables are stationary, they do not exhibit unit roots, meaning their statistical properties, such as the mean and variance, are stable over time. This stability enhances the reliability of our regression results, as the absence of long-term trends or stochastic trends ensures that the relationships modeled are not driven by non-stationary behavior. Overall, the stationarity of these variables supports the integrity of your model, ensuring that the estimated coefficients reflect meaningful economic relationships rather than being distorted by non-stationary dynamics.

4. Results

4.1 CHINA

	STRETURN	OPV	GBOND	EXRATE
Mean	451.0785	80.68578	2.815510	7.030998
Median	415.8828	62.69000	2.844000	7.045900
Maximum	1112.928	325.1500	3.175000	7.169300
Minimum	375.0945	31.70000	2.492000	6.848400
Std. Dev.	125.2836	53.36292	0.169812	0.065184
Skewness	4.533483	1.555848	-0.095755	-0.442884
Kurtosis	23.43856	5.557492	2.096299	2.457347
Jarque-Bera	3062.161	99.36844	5.226777	6.609229
Probability	0.000000	0.000000	0.073286	0.036713

Table 2: Descriptive Statistics (China)

The STRETURN variable shows substantial variability with a mean of 451.08 and a high standard deviation of 125.28, indicating significant fluctuations and positive skewness. OPV also displays considerable variability with a mean of 80.69 and a standard deviation of 53.36, suggesting a right-skewed distribution with a higher peak and tails. In contrast, GBOND has a mean of 2.82 and a lower standard deviation of 0.17, reflecting relative stability and a nearly normal distribution. EXRATE has a mean of 7.03 with a standard deviation of 0.07, indicating a slight negative skew but overall normal distribution. The high Jarque-Bera statistics for STRETURN and OPV confirm significant departures from normality, while GBOND and EXRATE align more closely with normal distribution patterns.

	Quantile	Coefficient	t-Statistic	Prob.
OPV	0.100	-0.170291	-2.934685	0.0039
	0.200	-0.190995	-3.294224	0.0012
	0.300	-0.139760	-2.147202	0.0335
	0.400	-0.160340	-2.262748	0.0252
	0.500	-0.159191	-2.088427	0.0385
	0.600	-0.031069	-0.700389	0.4848
	0.700	-0.035244	-0.908697	0.3650
	0.800	-0.029434	-0.876581	0.3822
	0.900	-0.084345	-1.468459	0.1442
GBOND	0.100	34.47279	1.439552	0.1522
	0.200	36.81528	1.644402	0.1023
	0.300	54.94399	3.402139	0.0009
	0.400	47.44138	2.869325	0.0047
	0.500	45.39361	2.383443	0.0185
	0.600	76.08755	3.750530	0.0003
	0.700	88.96607	5.370088	0.0000
	0.800	95.18466	6.536723	0.0000
	0.900	66.00938	1.961706	0.0517
EXRATE	0.100	-49.84143	-0.809163	0.4198
	0.200	-146.4336	-2.023151	0.0449
	0.300	-256.6502	-7.924432	0.0000
	0.400	-278.9664	-8.901337	0.0000
	0.500	-327.6380	-8.097801	0.0000
	0.600	-345.0927	-8.019747	0.0000
	0.700	-334.9809	-7.656512	0.0000
	0.800	-348.8356	-7.575105	0.0000
	0.900	-441.7897	-3.871174	0.0002
C	0.100	673.3964	1.607640	0.1101
	0.200	1357.866	2.795019	0.0059
	0.300	2084.348	8.668203	0.0000
	0.400	2267.550	9.390340	0.0000
	0.500	2620.722	8.388097	0.0000
	0.600	2652.887	7.623077	0.0000
	0.700	2549.330	7.352869	0.0000
	0.800	2632520	7.325688	0.0000
	0.900	3380.165	3.745288	0.0003

Table 3: Quantile Regression Output (China).

The estimated coefficients for OPV across lower to median quantiles (0.100 through 0.500) range from -0.1703 to -0.1592, indicating a negative association between OPV and the dependent variable. Specifically, a 1-unit increases in OPV is associated with a decrease in the dependent variable by approximately 0.17 units at the 0.100 quantile and 0.16 units at the 0.500 quantile. The corresponding p-values (e.g., 0.0039 at the 0.100 quantile and 0.0385 at the 0.500 quantile) indicate statistical significance at conventional levels ($p < 0.05$), underscoring the relevance of OPV in explaining variations in the lower tail of the conditional distribution. However, at higher quantiles (0.600 through 0.900), the coefficients for OPV diminish substantially, ranging from -0.0311 to -0.0843, with p-values exceeding 0.10. This suggests that the effect of OPV on the dependent variable becomes insignificant as we move towards the upper end of the distribution, implying that the negative influence of OPV is concentrated primarily in the lower quantiles.

GBOND exhibits a consistently positive impact on the dependent variable across all quantiles, with coefficients ranging from 34.47 at the 0.100 quantile to 95.18 at the 0.800 quantile. This implies that for a 1-unit increase in GBOND, the dependent variable increases by approximately 34.47 units at the lower quantile and by as much as 95.18 units at the higher quantiles. The relationship between GBOND and the dependent variable becomes highly significant in mid-to-upper quantiles (0.300 through 0.800), with p-values as low as 0.0000 at the 0.700 quantiles. This indicates that bond-related factors are particularly influential in the central and upper portions of the conditional distribution, suggesting that GBOND has a stronger impact on the dependent variable at higher quantiles.

EXRATE is found to have a pronounced negative effect on the dependent variable, particularly in mid-to-upper quantiles. The coefficients range from -49.84 at the 0.100 quantiles to -441.79 at the 0.900 quantile, indicating that a 1-unit increase in the exchange rate results in a substantial decrease in the dependent variable, with the magnitude of the effect growing larger as we move to higher quantiles. The effect of EXRATE becomes highly significant starting at the 0.200 quantile, where the p-value is 0.0449, and remains significant throughout the distribution, with p-values approaching zero for quantiles 0.300 through 0.900. This implies that exchange rate fluctuations have a more substantial impact on the dependent variable in the mid and upper quantiles, potentially reflecting increased sensitivity to exchange rate changes at these levels.

The intercept term C provides a baseline measure of the dependent variable when all independent variables are held constant. The estimated intercepts increase across quantiles, from 673.40 at the 0.100 quantiles to 3380.17 at the 0.900 quantiles, reflecting an upward shift in the conditional distribution of the dependent variable as we move to higher quantiles. The intercept is statistically significant across most quantiles, with p-values as low as 0.0000 for quantiles 0.300 through 0.800, indicating a strong and consistent baseline effect that increases with the quantile level.

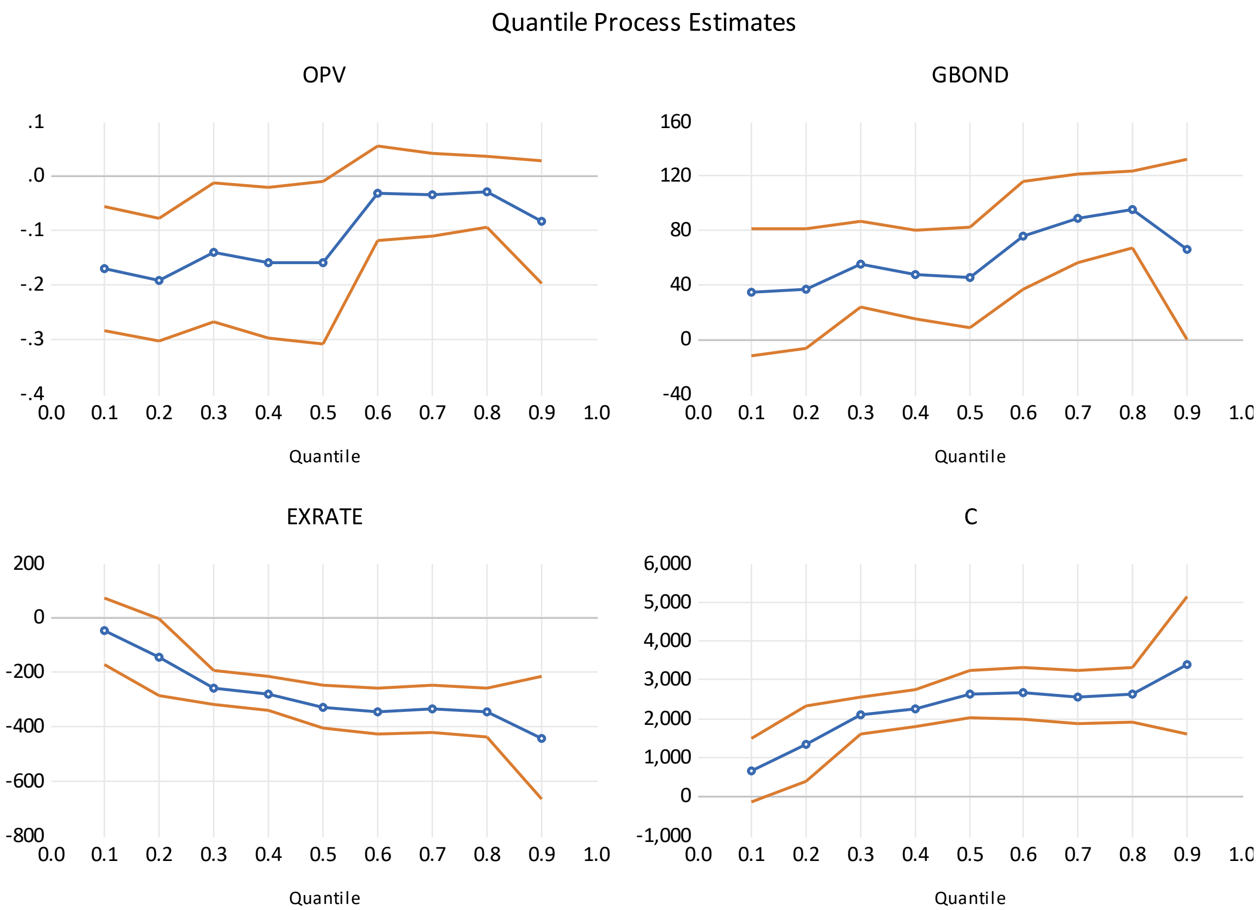

Figure 1: Regression Quantile Estimates (China)

4.2 GERMANY

	STRETURN	OPV	GBOND	EXRATE
Mean	10516.39	80.68578	-0.459435	1.119590
Median	10753.27	62.69000	-0.453000	1.113600
Maximum	12761.68	325.1500	-0.192000	1.193700
Minimum	7733.336	31.70000	-0.858000	1.069300
Std. Dev.	1085.764	53.36292	0.096145	0.035556
Skewness	-0.288353	1.555848	-0.931639	0.666005
Kurtosis	3.029699	5.557492	6.222344	2.234836
Jarque-Bera	2.042517	99.36844	84.86375	14.45333
Probability	0.360142	0.000000	0.000000	0.000727

Table 4: Descriptive Statistics (Germany)

The STRETURN variable has a mean of 10,516.39 and a standard deviation of 1,085.76, indicating significant variability with a slightly negative skew. The distribution is close to normal, as suggested by its kurtosis of 3.03 and a Jarque-Bera test that does not reject normality ($p = 0.36$). OPV shows a mean of 80.69 with a standard deviation of 53.36, presenting a high peak and right-skewed distribution. The high kurtosis and significant Jarque-Bera statistic ($p < 0.0001$) point to deviations from normality. GBOND has a mean of -0.46 and a standard deviation of 0.10, with a negatively skewed distribution and high kurtosis, indicating substantial deviations from normality and a significant Jarque-Bera statistic ($p < 0.0001$). EXRATE has a mean of 1.12 and a standard deviation of 0.04, showing a slight positive skew and near-normal distribution, with a significant Jarque-Bera statistic ($p = 0.0007$) suggesting minor deviations from normality.

	Quantile	Coefficient	t-Statistic	Prob.
OPV	0.100	-32.57253	-5.364339	0.0000
	0.200	-28.41947	-4.531581	0.0000
	0.300	-26.08543	-5.902008	0.0000
	0.400	-26.57871	-10.65225	0.0000
	0.500	-25.58246	-12.16100	0.0000
	0.600	-26.04799	-13.67718	0.0000
	0.700	-21.36096	-6.801916	0.0000
	0.800	-16.27584	-5.959529	0.0000
	0.900	-13.69439	-8.646681	0.0000
GBOND	0.100	1893.370	2.087664	0.0386
	0.200	2448.899	4.098174	0.0001
	0.300	2274.023	3.195812	0.0017
	0.400	2315.379	4.997843	0.0000
	0.500	2211.386	6.333768	0.0000
	0.600	2402.363	7.513643	0.0000
	0.700	2957.247	4.772919	0.0000
	0.800	3317.229	4.508170	0.0000
	0.900	2949.780	3.629823	0.0004
EXRATE	0.100	-8197.545	-2.213335	0.0285
	0.200	-8720.302	-2.173500	0.0314
	0.300	-9256.307	-2.816682	0.0055
	0.400	-11135.08	-5.507399	0.0000
	0.500	-10854.25	-5.992882	0.0000
	0.600	-11684.81	-8.055520	0.0000
	0.700	-12092.59	-9.129693	0.0000
	0.800	-12910.16	-9.885004	0.0000
	0.900	-14660.45	-11.10443	0.0000
C	0.100	22525.41	4.574731	0.0000
	0.200	23298.28	4.635911	0.0000
	0.300	23781.27	5.587478	0.0000
	0.400	26053.33	10.07808	0.0000
	0.500	25678.48	11.34457	0.0000
	0.600	26793.65	14.99711	0.0000
	0.700	27366.87	17.74960	0.0000
	0.800	28346.11	19.39826	0.0000
	0.900	30177.52	21.35281	0.0000

Table 5: Quantile Regression Output (Germany)

The coefficient estimates for OPV are consistently negative across all quantiles, ranging from -32.57 at the 0.100 quantile to -13.69 at the 0.900 quantile. This suggests that an increase in OPV is associated with a reduction in the dependent variable, with the magnitude of the effect being more pronounced at lower quantiles. For example, at the 0.100 quantile, a 1-unit increase in OPV results in a decrease of 32.57 units in the dependent variable, while at the 0.900 quantile, the decrease is 13.69 units. This indicates that OPV has a stronger negative impact on the lower quantiles of the distribution. The p-values for OPV are consistently 0.0000 across all quantiles, indicating that the negative effect of OPV is statistically significant throughout the distribution. This suggests that the operational factors represented by OPV have a significant downward influence on the dependent variable, regardless of the quantile.

The coefficients for GBOND are positive across all quantiles, ranging from 1893.37 at the 0.100 quantile to 3317.23 at the 0.800 quantile. This implies that increases in GBOND are associated with positive changes in the dependent variable, with the magnitude of this effect being larger at higher quantiles. For instance, at the 0.100 quantile, a 1-unit increase in GBOND is associated with a 1893.37-unit increase in the dependent variable, while at the 0.800 quantile, this impact increases to 3317.23 units. This suggests that the effect of GBOND is more pronounced in the upper quantiles of the conditional distribution. GBOND is statistically significant across all quantiles, with p-values ranging from 0.0386 at the 0.100 quantile to 0.0000 at the 0.300 to 0.900 quantiles. This indicates that government bond-related factors have a significant and positive impact on the dependent variable across the distribution, particularly in mid-to-upper quantiles.

The coefficients for EXRATE are negative across all quantiles, ranging from -8197.55 at the 0.100 quantile to -14660.45 at the 0.900 quantile, suggesting that increases in exchange rate levels have a deleterious effect on the dependent variable. The negative impact intensifies as we move towards the upper quantiles. For example, at the 0.100 quantile, a 1-unit increase in EXRATE leads to a reduction of 8197.55 units in the dependent variable, while at the 0.900 quantile, the reduction grows to 14660.45 units. This indicates that the detrimental effect of exchange rate increases is more substantial at higher quantiles. EXRATE is statistically significant across all quantiles, with p-values ranging from 0.0285 at the 0.100 quantile to 0.0000 at higher quantiles (e.g., 0.0000 at the 0.400 to 0.900 quantiles). This suggests that exchange rate fluctuations exert a consistently negative and significant effect on the dependent variable, with larger impacts in higher quantiles.

The intercept term C reflects the baseline value of the dependent variable when all covariates are held constant. The coefficients for C increase steadily across the quantiles, ranging from 22525.41 at the 0.100 quantile to 30177.52 at the 0.900 quantile. This suggests that the baseline level of the dependent variable rises as we move up the conditional distribution. For example, at the 0.100 quantile, the baseline value of the dependent variable is approximately 22525.41 units, while at the 0.900 quantile, it increases to 30177.52 units. This indicates a strong positive trend in the intercept across quantiles. The intercept is highly statistically significant across all quantiles, with p-values of 0.0000 in each case. This highlights the robustness of the baseline effect, which grows larger at higher quantiles, reflecting a broader upward trend in the conditional distribution.

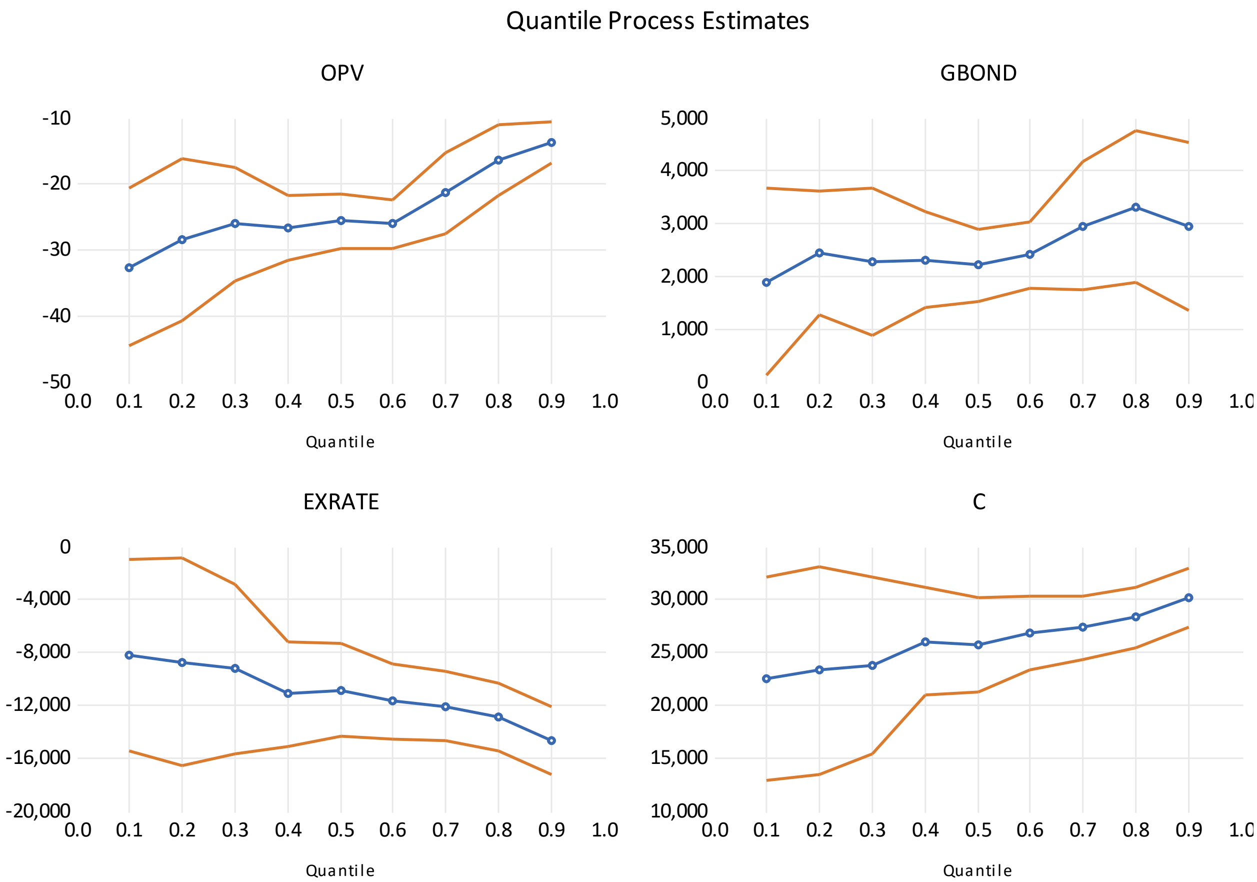

Figure 2: Regression Quantile Estimates (Germany)

4.3 INDIA

	STRETURN	OPV	GBOND	EXRATE
Mean	137.5078	80.68578	6.080799	74.78878
Median	136.3614	62.69000	6.074000	75.16000
Maximum	171.1488	325.1500	6.844000	76.95000
Minimum	99.70195	31.70000	5.749000	71.11000
Std. Dev.	17.88121	53.36292	0.245094	1.471696
Skewness	0.114450	1.555848	0.389956	-1.212214
Kurtosis	2.064584	5.557492	2.128807	3.596253
Jarque-Bera	5.680315	99.36844	8.374349	38.17938
Probability	0.058416	0.000000	0.015189	0.000000

Table 6: Descriptive Statistics (India)

The STRETURN variable shows a strong average return of 137.51 with a manageable standard deviation of 17.88, indicating relatively stable returns. Its distribution is close to normal, with skewness and kurtosis values supporting this, and a Jarque-Bera test p-value of 0.058 suggests near-normality. OPV displays a robust average of 80.69, although with a wider standard deviation of 53.36, reflecting a diverse range of values. The rightward skew and high kurtosis suggest a concentration of higher values, confirmed by a highly significant Jarque-Bera test ($p < 0.0001$), indicating a distinct distribution shape. GBOND averages 6.08 with a standard deviation of 0.25, showing a distribution that is fairly close to normal with only mild positive skewness and near-normal kurtosis. The Jarque-Bera test results ($p = 0.015$) show a slight deviation from normality, which is still within a reasonable range. Lastly, EXRATE has a high average of 74.79 and a standard deviation of 1.47, reflecting substantial variability. The negative skew and elevated kurtosis indicate a more pronounced distribution shape, with a very significant Jarque-Bera test ($p < 0.0001$), highlighting the unique characteristics of the data.

	Quantile	Coefficient	t-Statistic	Prob.
OPV	0.100	-0.206338	-3.483048	0.0007
	0.200	-0.251022	-3.695530	0.0003
	0.300	-0.243767	-7.788443	0.0000
	0.400	-0.244605	-8.495454	0.0000
	0.500	-0.219097	-7.497632	0.0000
	0.600	-0.211736	-6.628794	0.0000
	0.700	-0.155689	-2.764958	0.0064
	0.800	-0.095433	-4.109632	0.0001
	0.900	-0.108412	-3.607159	0.0004
GBOND	0.100	-6.716018	-0.475227	0.6354
	0.200	-2.198125	-0.169978	0.8653
	0.300	-1.483882	-0.395165	0.6933
	0.400	-0.716801	-0.226442	0.8212
	0.500	-4.125111	-1.317137	0.1899
	0.600	-5.317852	-1.692423	0.0927
	0.700	-9.438785	-2.063108	0.0409
	0.800	-13.86264	-4.454465	0.0000
	0.900	0.347253	0.031276	0.9751
EXRATE	0.100	-8.969938	-3.851447	0.0002
	0.200	-7.052204	-3.071379	0.0026
	0.300	-6.807221	-9.217623	0.0000
	0.400	-6.521842	-10.42638	0.0000
	0.500	-7.002870	-11.60186	0.0000
	0.600	-7.068245	-11.86625	0.0000
	0.700	-7.762421	-9.091643	0.0000
	0.800	-8.346094	-15.22276	0.0000
	0.900	-5.641756	-2.699454	0.0078
C	0.100	858.1310	3.384424	0.0009
	0.200	694.1434	2.846538	0.0051
	0.300	673.1207	8.986608	0.0000
	0.400	648.0351	10.28673	0.0000
	0.500	703.9219	11.54066	0.0000
	0.600	716.2616	11.87629	0.0000
	0.700	790.7281	9.089928	0.0000
	0.800	858.7726	15.45249	0.0000
	0.900	574.7545	2.615877	0.0099

Table 7: Quantile Regression Output (India)

The estimated coefficients for OPV display a consistent negative effect across all quantiles. These coefficients range from -0.2063 at the 0.100 quantile to -0.1084 at the 0.900 quantile. This indicates that as OPV increases, the dependent variable tends to decrease, with the effect being stronger at the lower end of the distribution. Specifically, at the 0.100 quantile, a one-unit rise in OPV results in a decline of 0.2063 units in the dependent variable. In contrast, at the 0.900 quantile, the reduction is 0.1084 units. This suggests that the negative influence of OPV diminishes as we move toward the higher quantiles. Given that the p-values across all quantiles are highly significant ($p < 0.01$), we can confidently assert that OPV exerts a statistically significant downward pressure on the dependent variable, irrespective of the quantile under consideration.

The coefficients for GBOND fluctuate across quantiles, generally showing negative effects. However, in the 0.900 quantile, the coefficient turns slightly positive at 0.3473, though this effect is statistically insignificant ($p = 0.9751$). For instance, in the 0.100 quantile, the coefficient is -6.7160, suggesting a potential negative relationship, but the lack of statistical significance ($p = 0.6354$) means we cannot confidently assert that this effect exists. A more noticeable negative impact occurs in the 0.700 quantile, where the coefficient is -9.4388, and this effect is significant ($p = 0.0409$). The strongest negative impact is observed at the 0.800 quantile, with a coefficient of -13.8626, which is highly significant ($p < 0.0001$). GBOND shows significant effects primarily in the higher quantiles, reflecting a stronger influence of government bonds on the upper end of the dependent variable's distribution.

The coefficients for EXRATE remain negative throughout the quantiles, with values ranging from -8.9699 at the 0.100 quantile to -5.6418 at the 0.900 quantile. This signifies that an increase in the exchange rate leads to a reduction in the dependent variable, and this effect is statistically significant across all quantiles. For example, at the 0.100 quantile, a one-unit rise in EXRATE decreases the dependent variable by 8.9699 units, while at the 0.900 quantile, this effect is reduced to 5.6418 units. Despite this reduction, the negative impact remains significant across all quantiles ($p < 0.01$), indicating that exchange rate fluctuations consistently exert a downward force on the dependent variable.

The constant term (C) captures the baseline level of the dependent variable when all predictors are held constant. The constant exhibits a positive effect across all quantiles, ranging from

858.13 at the 0.100 quantile to 574.75 at the 0.900 quantile. At the 0.100 quantile, the baseline value of the dependent variable is approximately 858.13 units, while at the 0.900 quantile, it decreases to 574.75 units. Despite this downward trend in higher quantiles, the constant remains highly significant ($p < 0.01$) across all quantiles.

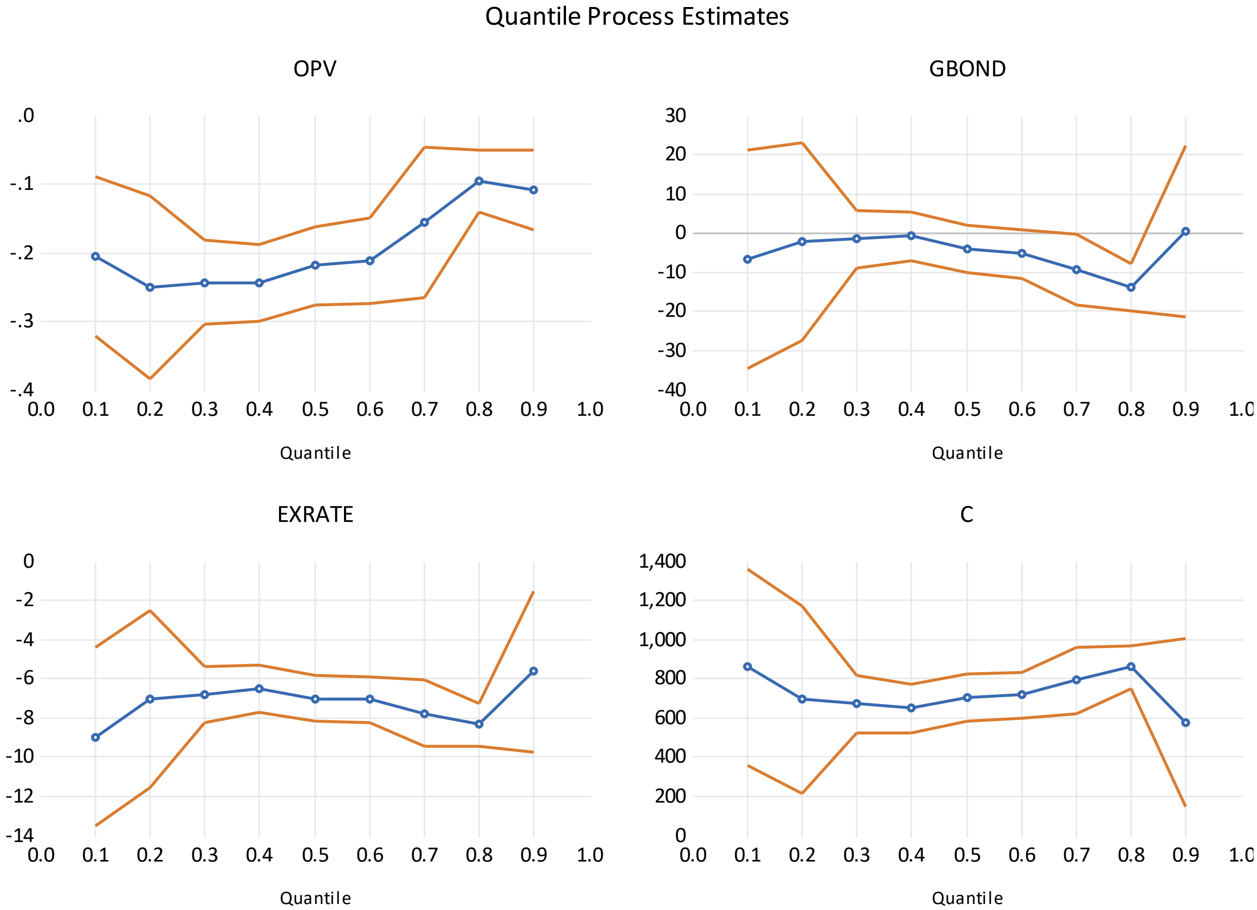

Figure 3: Regression Quantile Estimates (India)

4.5 JAPAN

	STRETURN	OPV	GBOND	EXRATE
Mean	198.6267	80.68578	-0.001075	107.5389
Median	206.0089	62.69000	0.011000	107.3100
Maximum	219.7458	325.1500	0.091000	112.1100
Minimum	149.5152	31.70000	-0.154000	102.3600
Std. Dev.	17.70435	53.36292	0.044821	1.605191
Skewness	-0.882434	1.555848	-1.410750	0.476014
Kurtosis	2.833164	5.557492	5.264172	3.671292
Jarque-Bera	19.24838	99.36844	80.15997	8.311571
Probability	0.000066	0.000000	0.000000	0.015673

Table 8: Descriptive Statistics (Japan)

STRETURN has a mean of 198.63 and a standard deviation of 17.70, indicating consistent returns with manageable variability. The distribution's slightly negative skew and normal-like kurtosis suggest a mostly typical distribution pattern. OPV displays a mean of 80.69 with a substantial standard deviation of 53.36, highlighting significant variability. The positive skew and high kurtosis suggest a tendency toward higher values, though the data deviates from normality, as noted by the Jarque-Bera test. GBOND shows a mean of approximately zero (-0.0011) and a standard deviation of 0.0448, reflecting minimal variation. The negative skew and higher kurtosis indicate some extreme values, with the Jarque-Bera test suggesting the distribution is not perfectly normal but still well within acceptable bounds. EXRATE reports a mean of 107.54 and a standard deviation of 1.61, indicating robust variability. The mild positive skew and elevated kurtosis suggest a few extreme values, with the distribution showing slight deviations from normality, but overall stability.

	Quantile	Coefficient	t-Statistic	Prob.
OPV	0.100	-0.457834	-12.67092	0.0000
	0.200	-0.427569	-14.82313	0.0000
	0.300	-0.390449	-18.08298	0.0000
	0.400	-0.378058	-20.70393	0.0000
	0.500	-0.372217	-19.78919	0.0000
	0.600	-0.330978	-4.668137	0.0000
	0.700	-0.250884	-5.042307	0.0000
	0.800	-0.189623	-8.200829	0.0000
	0.900	-0.181093	-9.247687	0.0000
GBOND	0.100	58.84643	4.791704	0.0000
	0.200	63.17874	5.350820	0.0000
	0.300	63.91361	5.668219	0.0000
	0.400	57.32264	5.072302	0.0000
	0.500	57.62175	4.370724	0.0000
	0.600	67.11466	3.887647	0.0002
	0.700	52.31858	2.357931	0.0197
	0.800	55.18524	2.640478	0.0092
	0.900	44.08974	1.840331	0.0678
EXRATE	0.100	-0.071346	-0.153403	0.8783
	0.200	-0.051018	-0.113602	0.9097
	0.300	-0.270918	-0.777272	0.4383
	0.400	-0.419920	-1.415968	0.1590
	0.500	-0.191214	-0.648142	0.5179
	0.600	0.061346	0.134566	0.8931
	0.700	-0.389346	-0.775574	0.4393
	0.800	-0.132573	-0.276748	0.7824
	0.900	0.611017	1.250364	0.2132
C	0.100	234.9050	4.739242	0.0000
	0.200	232.5209	4.931403	0.0000
	0.300	255.8448	6.909982	0.0000
	0.400	271.7346	8.603535	0.0000
	0.500	247.8319	7.871962	0.0000
	0.600	219.4569	4.335455	0.0000
	0.700	265.2599	4.844086	0.0000
	0.800	235.8887	4.539289	0.0000
	0.900	157.6828	2.984756	0.0033

Table 9: Quantile Regression Output (Japan)

The coefficient for OPV shows a pronounced negative relationship with the dependent variable across all quantiles. At the 0.100 quantile, the coefficient is -0.4578, indicating a substantial negative impact on the dependent variable. This effect becomes slightly less negative but remains significant through higher quantiles, reaching -0.1811 at the 0.900 quantile. All coefficients are statistically significant ($p < 0.0001$), which strongly suggests that increases in OPV consistently lead to a decrease in the dependent variable. The magnitude of the negative effect diminishes as we move to higher quantiles, reflecting that while OPV consistently reduces the dependent variable, the strength of this reduction lessens at the upper end of the distribution.

GBOND exhibits a positive and statistically significant effect across most quantiles, with coefficients ranging from 58.8464 at the 0.100 quantile to a peak of 67.1147 at the 0.600 quantile. This suggests that increases in government bonds are associated with higher values of the dependent variable, particularly in the lower to mid-range quantiles. However, at the 0.900 quantile, the coefficient decreases to 44.0897 and approaches statistical insignificance ($p = 0.0678$), indicating a weaker and less consistent effect at higher quantiles. Despite this, GBOND generally has a strong positive influence on the dependent variable in the lower to middle quantiles.

The impact of EXRATE on the dependent variable is minimal and not statistically significant across all quantiles. The coefficients vary from -0.0713 at the 0.100 quantile to 0.6110 at the 0.900 quantile, but all p-values are greater than 0.1, suggesting no significant relationship. This lack of significance implies that fluctuations in the exchange rate do not materially affect the dependent variable in any of the quantiles examined.

The constant term (C) captures the baseline level of the dependent variable when all other variables are held at zero. It is statistically significant across all quantiles, with values ranging from 234.9050 at the 0.100 quantile to 157.6828 at the 0.900 quantile. This consistent significance underscores that, irrespective of the quantile, the baseline level of the dependent variable is robust and significant, albeit decreasing as we move to higher quantiles.

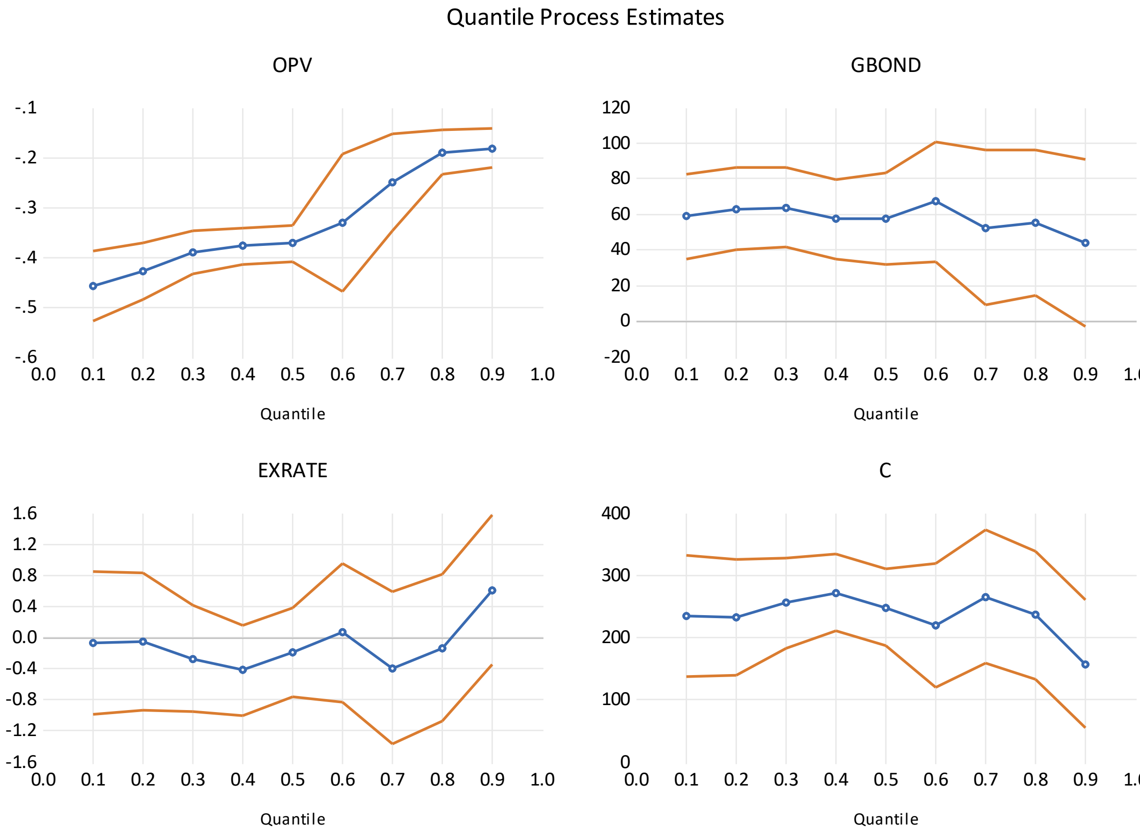

Figure 4: Regression Quantile Estimates (Japan)

4.6 USA

	STRETURN	OPV	GBOND	DXYRATE
Mean	25527.87	80.68578	1.456014	97.50415
Median	25864.78	62.69000	1.398000	97.80000
Maximum	29551.42	325.1500	2.140000	102.8200
Minimum	18591.93	31.70000	1.022000	92.14000
Std. Dev.	2395.585	53.36292	0.240748	2.579650
Skewness	-0.517224	1.555848	1.347880	-0.458749
Kurtosis	2.911516	5.557492	4.119302	2.335805
Jarque-Bera	6.602217	99.36844	52.18475	7.858116
Probability	0.036842	0.000000	0.000000	0.019662

Table 10: Descriptive Statistics (USA)

The STRETURN dataset exhibits a mean of 25,527.87 with a standard deviation of 2,395.59, reflecting considerable variability in returns. The negative skewness and near-normal kurtosis suggest a distribution with some negative skew and balanced tail behavior. For OPV, the mean is 80.69 and the standard deviation is 53.36, indicating significant variability and a positively skewed distribution with high kurtosis, highlighting the presence of outliers. The GBOND variable shows a mean of 1.456 and a standard deviation of 0.241, with positive skewness and high kurtosis suggesting a distribution with extreme values. Lastly, DXYRATE has a mean of 97.50 and a standard deviation of 2.58, with a slightly negative skew and low kurtosis, indicating a relatively stable distribution with minor deviations from normality.

	Quantile	Coefficient	t-Statistic	Prob.
OPV	0.100	-44.07624	-6.130659	0.0000
	0.200	-38.87158	-4.948450	0.0000
	0.300	-30.06620	-4.354714	0.0000
	0.400	-25.79335	-5.298099	0.0000
	0.500	-21.85356	-3.120304	0.0022
	0.600	-13.09158	-1.164718	0.2461
	0.700	-8.215607	-0.553793	0.5806
	0.800	-0.350495	-0.193908	0.8465
	0.900	-3.677436	-1.213711	0.2269
GBOND	0.100	1382.419	1.248856	0.2138
	0.200	2933.099	3.174201	0.0018
	0.300	4027.022	7.019458	0.0000
	0.400	4014.202	6.991828	0.0000
	0.500	4232.073	7.157708	0.0000
	0.600	5261.010	7.055240	0.0000
	0.700	5617.720	6.093901	0.0000
	0.800	6138.258	14.62475	0.0000
	0.900	5635.874	8.077517	0.0000
DXYRATE	0.100	-200.4166	-2.972263	0.0035
	0.200	-240.1797	-3.270023	0.0013
	0.300	-320.2987	-5.143759	0.0000
	0.400	-342.3085	-7.114321	0.0000
	0.500	-372.5459	-6.067507	0.0000
	0.600	-441.3594	-4.347823	0.0000
	0.700	-485.7243	-3.520274	0.0006
	0.800	-520.4129	-9.429019	0.0000
	0.900	-412.9730	-4.423093	0.0000
C	0.100	45439.38	7.137896	0.0000
	0.200	47081.23	7.537330	0.0000
	0.300	52895.52	10.01508	0.0000
	0.400	54899.50	13.34862	0.0000
	0.500	57409.99	11.25285	0.0000
	0.600	62224.73	7.518505	0.0000
	0.700	65831.24	5.827399	0.0000
	0.800	68256.29	14.13788	0.0000
	0.900	59087.57	7.519198	0.0000

Table 11: Quantile Regression Output (USA)

The OPV coefficient starts significantly negative at lower quantiles, indicating a stronger detrimental influence on the dependent variable for the lower percentiles. At the 10th quantile, the coefficient is estimated at -44.08 with a high t-statistic of -6.13 and a p-value of 0.0000, confirming its significance. This negative effect decreases as we move up the quantiles, with the 50th quantile coefficient declining to -21.85 (t-statistic -3.12, p-value 0.0022), showing a reduced but still significant effect. In higher quantiles (e.g., 70th to 90th), the coefficients diminish in magnitude, becoming statistically insignificant beyond the 60th quantile, implying that OPV primarily affects the lower end of the distribution.

The GBOND variable shows a positive and increasing influence on the dependent variable across the quantiles. Starting from the 10th quantile, GBOND has a coefficient of 1382.42 (t-statistic 1.25, p-value 0.2138), which is not significant. However, at the 20th quantile and higher, the effect becomes strongly significant, with the 30th quantile showing a coefficient of 4027.02 (t-statistic 7.02, p-value 0.0000). The positive effect continues to grow, reaching its peak at the 80th quantile, where the coefficient stands at 6138.26 (t-statistic 14.62, p-value 0.0000). This suggests that GBOND exerts a progressively stronger positive influence on the upper portions of the conditional distribution.

The DXYRATE variable shows a consistently negative influence across the quantiles. At the 10th quantile, DXYRATE holds a coefficient of -200.42 (t-statistic -2.97, p-value 0.0035), which is significant. This negative effect intensifies as we move higher in the distribution, reaching a coefficient of -372.55 at the median (50th quantile) with a t-statistic of -6.07 and a p-value of 0.0000. The effect peaks at the 80th quantile, with a coefficient of -520.41 (t-statistic -9.43, p-value 0.0000). However, the impact reduces slightly at the 90th quantile, where the coefficient is -412.97 (t-statistic -4.42, p-value 0.0000), indicating that DXYRATE consistently depresses the dependent variable, particularly in the middle to higher quantiles.

The constant term remains highly significant across all quantiles, reflecting substantial baseline levels of the dependent variable regardless of the quantile. For instance, at the 10th quantile, the constant is 45439.38 with a t-statistic of 7.14 (p-value 0.0000), increasing to 68256.29 at the 80th quantile with a t-statistic of 14.14 (p-value 0.0000). The constant's magnitude is slightly lower at the 90th quantile, at 59087.57 (t-statistic 7.52, p-value 0.0000).

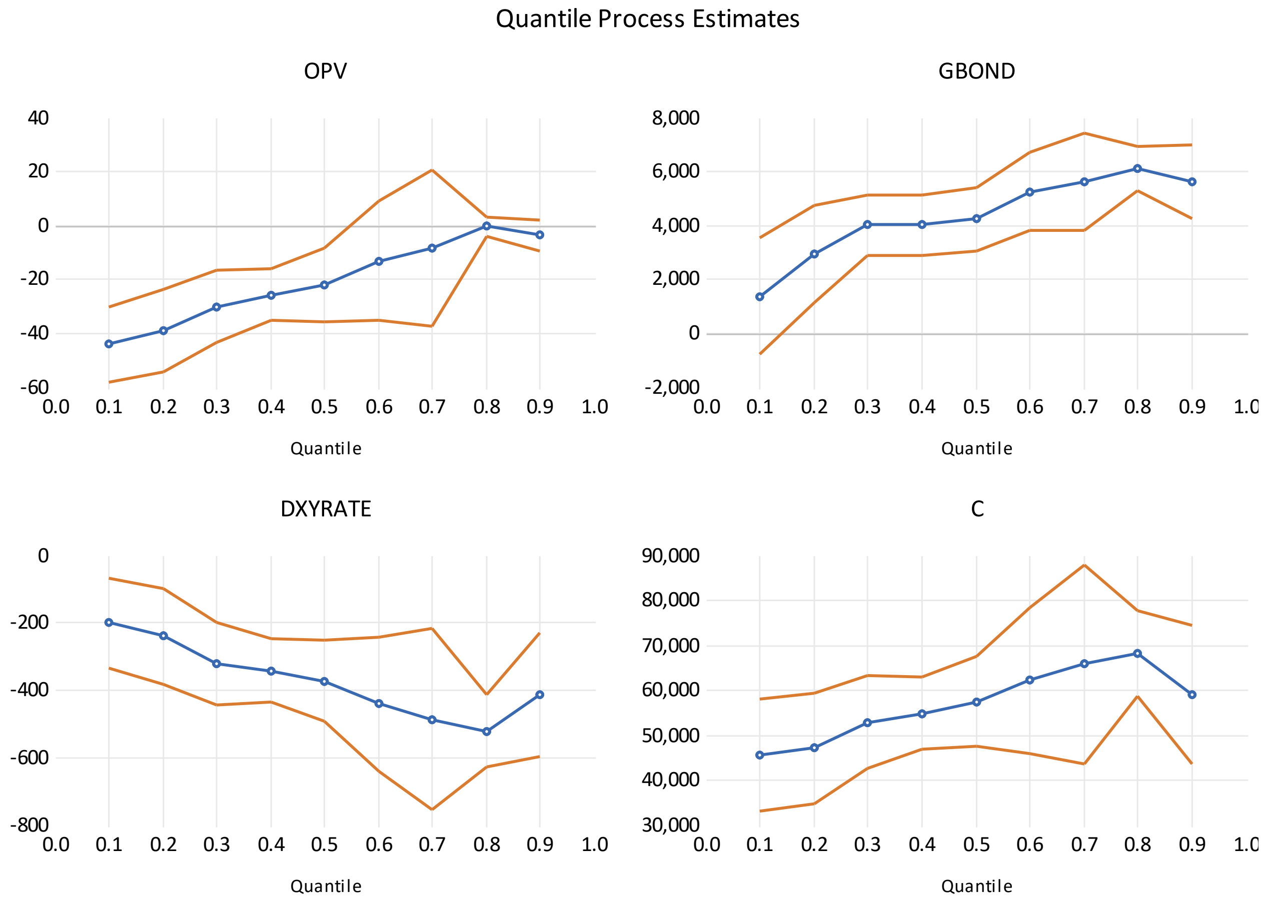

Figure 5: Regression Quantile Estimates (USA)

5. Conclusion

This research examined how oil price volatility (OPV) affects stock returns (STRETURN) in major oil-importing countries, especially during the COVID-19 pandemic. It also considered the roles of government bond rates (GBOND) and exchange rates (EXRATE) to provide a more complete picture of what influences stock markets. The findings indicate that oil price volatility generally leads to lower stock returns, particularly when the market is under stress or in a downturn. This effect is weaker in more stable or bullish market conditions, suggesting that stock markets are more sensitive to oil price shocks when they are already performing poorly. [5] Found that positive shocks to aggregate demand and to oil-market specific demand are associated with negative effects on the covariance of return and volatility. Oil supply disruptions are associated with positive effects on the covariance of return and volatility. The spillover index between the structural oil price shocks and covariance of stock return and volatility is large and highly statistically significant. One of the researchers also found that oil price has negative influence on Stock Return and conclude that an increase in oil prices leads to decreasing stock return [9] However, numerous authors like [10], [11], [13] established their findings as saying that the oil price had no effect on stock prices. On the other hand, our findings suggests that oil price volatility drives stock price in a downward way.

The relationship between government bonds and stock returns showed that higher bond rates often lead to higher stock returns, especially in normal or bullish market states. This could mean that investors move their money between stocks and bonds depending on market conditions; when stocks are more stable, bonds become an attractive investment, increasing their yields. This "flight-to-quality" is evident in countries like Germany and the USA, where stock and bond markets are closely linked.

Exchange rates also play a significant role. The study found that a weaker currency or more volatile exchange rates tend to reduce stock returns, especially in countries that depend heavily on exports. This is because currency depreciation can increase the costs of imports and reduce competitiveness in global markets, hurting stock prices. However, positive influence of exchange rate on stock return is also found, e.g., according to [14], oil price volatility and exchange rate volatility positively and significantly influence stock market returns in Nigeria. Though, the output of [14] is contradictory to ours, in terms of the way exchange rate impacts on stock price, but we can conclude that the presence of the influence of exchange rate is apparent on stock return. In this regard, our finding is supported.

Overall, this study used Quantile Regression to capture the varying impacts of these factors across different market conditions, offering valuable insights for investors and policymakers. Future research could benefit from analyzing more variables and longer periods to see how these relationships evolve post-pandemic and understand better the complex interactions between oil prices, exchange rates, and stock markets.

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