RELATIONSHIP BETWEEN OIL AND STOCK MARKET VOLATILITIES

Project: International transmission and predictability of asset price volatility

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Contents

1 Introduction

In this particular paper, we will investigate the relationship between oil price volatility and the volatility of the S&P 500 price index from 2014 to 2024. Oil is an extremely important source of energy used in the production process of a wide range of products. This makes it crucial for the economic development of countries. An unexpected increase in oil prices could lead to a significant decrease in production by increasing production costs, resulting in a reduction in GDP growth. Furthermore, the globalization of markets has created additional factors that could significantly influence oil price volatility, making the study of oil price volatility even more important and identifying the factors causing this uncertainty. In our attempt to study one of the possible factors of oil uncertainty, we will use the uncertainty index of the S&P 500 as a highly significant indicator of market sentiment. Moreover, understanding the relationship between the two markets will help market participants as they encounter uncertainty in the market, and policymakers can develop more effective energy policies, allocate resources better, and enhance economic stability.

2 Literature Review

Examining oil price volatility is of paramount importance as it provides us with a clearer picture and understanding of changes in the level of uncertainty in the oil market. Given that this information is quite significant, it has attracted the attention of the scientific community in recent years. The use of the S&P 500 index volatility as a potential explanatory variable for oil uncertainty serves as an important reference point for the overall stock market against which all investments are compared, as well as a signal for the uncertainty prevailing in the entire market. It appears that on a global scale, financial indicators influence the fluctuation of oil prices, with the impact varying over time and the greatest influence coming from financial indices, highlighting the financialization of the oil markets, according to Chatziantoniou, Filippidis, Filis, Gabauer (2021). Another study by Xu, Ma, Chen, and Zhang (2019) also contributed by providing insights into the asymmetric relationship between volatility in oil and stock markets. Covering the period from 2007 to 2016 and including variables such as the SP& 500 for the stock market and WTI for oil, similar conclusions were drawn as in the previous reference.

Trying to empirically examine the transmission of uncertainty from stock markets to the oil and natural gas markets for the period 1999-2015, Jun Zhang, Chevallier, and Guesmi(2017) found that the oil and stock markets are interconnected. Additionally, their results indicate that the financialization of commodities remains after 2008, suggesting that the relationship between oil and stocks becomes closer over time. In a more recent study by Yang, Zhou, Du, Du, and Zhou (2023), a portion of their research focused on the relationship between price fluctuations in oil and uncertainty in prices in China and the United States. They found that the price uncertainty in the markets of both the United States and China is related to the uncertainty of oil prices, and this relationship is bidirectional. Additionally, the impact of oil market uncertainty on the stock markets of China and the United States seems to be more significant during crisis periods such as the Covid-19 pandemic. All this instability in the relationship between these two markets, influenced by factors such as the financialization of commodities, makes the addition of our research even more significant, providing a broader spectrum of the relationship between the variables. Below, a brief presentation of the data we used and the model on which our analysis relied will be provided.

3 Analysis of Data and Justification of Research Method

To conduct our research, we gathered daily price data for the S&P 500 and West Texas Intermediate (WTI) oil from the FRED database. Additionally, we obtained monthly data from the same source for the Gold ETF Volatility Index and the CBOE Silver ETF Volatility Index, which will serve as control variables in our analysis. Since we are examining the relationship between volatility on a monthly basis for both variables, with the help of Excel, we calculate the daily returns ($\log\left(\frac{p_t}{p_{t-1}}\right)$), except for one day where the price change was negative, so we utilized the following formula $\frac{p_t - p_{t-1}}{p_{t-1}}$ After obtaining the daily returns, we square them to compute the Realized Volatility developed by Andersen and Bollerslev (1998). Afterward, we multiply it by $\sqrt{252}$ for annualization and by 100 to convert it into a percentage. For the remainder of the analysis, we utilized the statistical software Stata. We applied the natural logarithm to all variables to address extreme values, as evident in the boxplots of the variables below. It's worth mentioning that regarding missing values in the returns, we replaced them with the most recent information available, which was the returns from one time period ago. Additionally, we will provide a table with descriptive statistics to provide an overview of our data. It's worth noting that we collected data for all variables from 2014 to 2024, except for the CBOE Silver ETF Volatility Index, for which data was available only until 2022. For this reason, we collected data from 2012 to 2022 to avoid missing values in our final analysis, which could potentially impact our results. Furthermore, returning to the outliers, we replaced them with the mean value for those prices that deviated more than $3 \cdot (Q_3 - Q_1)$ from the third quartile, that is, Q_3.

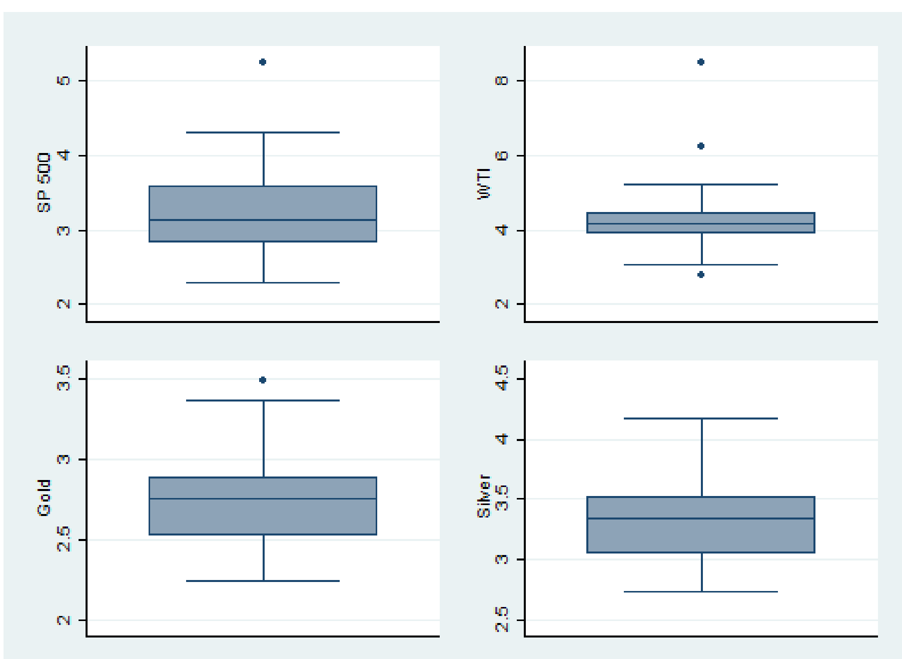

Figure 1: Box plots for the logarithmically transformed variables SP&500, WTI(Oil), GOLD, and SILVER.

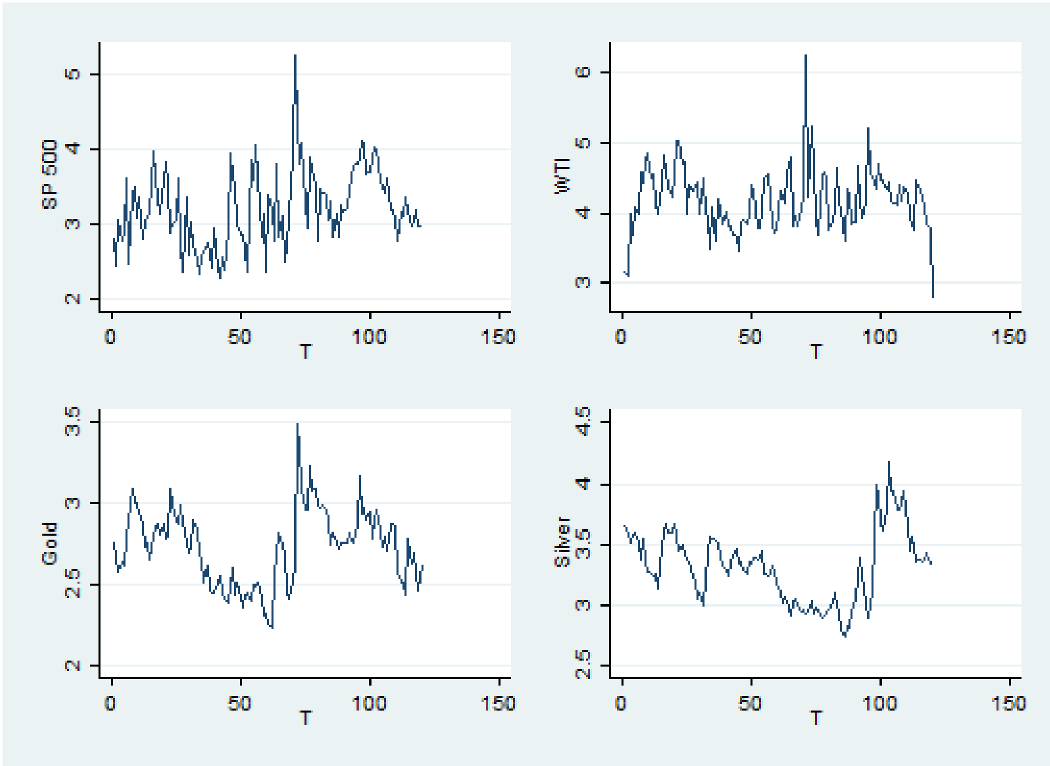

Figure 2: Annualised Volatility movement of Oil(WTI), SP&500, GOLD, SILVER.

Table 1: Descriptive statistics

VARIABLES	N	mean	sd	min	max
T	120	60.50	34.79	1	120
SP500_ln	120	3.209	0.518	2.283	5.239
WTI_ln	120	4.191	0.447	2.780	6.237
Gold_ln	120	2.736	0.233	2.240	3.492
Silver_ln	120	3.318	0.294	2.737	4.174

Note: Each unit of variable T corresponds to one month. (ln=Natural logarithm).

In our current empirical analysis, we will use an ARDL$(n, m_1, ..., m_n)$ model to study the realationship of oil price volatility with SP&500 volatility , which can be expressed as follows:

$$\Delta y_t = \alpha + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \sum_{k=1,t=0}^{m} \gamma_{k,i} \Delta x_{k,t-i} + \varepsilon_t$$

Where Δ is the first difference operator, and α, β, γ are the parameters to be estimated. Finally, n and m represent the lags of each variable. The dependent variable is the logarithm of oil (WTI_ln), and the independent variables are the logarithm of $SP\&500$ ($SP500\_ln$), as well as the logarithmic first difference of gold ($Gold$) and silver ($Silver$). All variables are measured in terms of volatility index. As stated by Anjum, Ghumro, and Husain (2017), one of the prerequisites of an ARDL model is the order of integration of the variables. It should not be $I(2)$ for any variable but can be $I(0)$ or $I(1)$ or a combination of these. It is worth noting that by the term order of integration, we mean how many times a time series needs to be differenced to become stationary. For this reason, we will proceed to conduct a Dickey-Fuller test to examine the degree of integration of each variable and will also use information criteria to determine the appropriate lag length for each variable.

4 Empirical Findings and their Interpretations

Before we proceed to examine the results of our estimations and see how they stand out in the existing literature, we will conduct some basic tests to ensure the validity of our estimations and minimize bias as much as possible. First of all, we start by checking the stationarity of our time series using a Dickey-Fuller test for unit root. Our findings were as follows: the variables WTI_ln and $SP500\_ln$ had an order of integration of $I(0)$ at a significance level of 1%, while the variables $Gold$ and $Silver$ had an order of integration of $I(1)$ at the same level of statistical significance. We also conducted a correlation table to ensure that our control variables are not highly correlated, in order to avoid problems of multicollinearity. Multicollinearity occurs when two or more independent variables have a high correlation, thereby reducing the effectiveness of our estimations. In our case, the correlation between Gold and Silver is low, which mitigates the risk of multicollinearity. To select the optimal lags for each variable in the ARDL model, we utilized the Bayesian Information Criterion (BIC). Unlike the AIC, which tends to favor models prone to overfitting, the BIC imposes a higher penalty based on the number of parameters in the model, Some of the mentioned can also be seen in tables 2 and 3 below.

Table 2: Dickey-Fuller test for unit root

DF	I(0)	DF	I(1)
SP500_ln	-5.730***		
WTI_ln	-6.648***		
Gold_ln	-3.437**	(d)Gold	-11.311***
Silver_ln	-2.703*	(d)Silver	-10.038***

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Correlation Table

Variables	WTI	SP&500	Gold	Silver
WTI	1.000			
SP&500	0.302	1.000		
Gold	0.430	0.264	1.000	
Silver	-0.109	0.004	-0.031	1.000

Correlation coefficients between 0.3 and 0.5 indicate low correlation.

Table 4: ARDL Regression model

Dependent variable: WTI_ln	ADJ	LR	SR
D.SP500_ln			0.376***
			(0.064)
D.Gold_ln			0.078
			(0.259)
LD.Gold_ln			0.691***
			(0.226)
D.Silver_ln			-0.031
			(0.104)
L.SP500_ln		0.441***	
		(0.082)	
L.Gold_ln		0.255	
		(0.187)	
L.Silver_ln		-0.037	
		(0.121)	
L.WTI_ln	-0.854***		
	(0.091)		
Constant			1.891***
			(0.546)
Observations	115	115	115
R-squared	0.523	0.523	0.523
ARDL Bounds Test	$F = 28.838$		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To begin with, before delving into explaining the coefficients, we conducted a Bound Test to determine whether there exists a long-run relationship between variables. We used the critical values from Pesaran/Shin/Smith (2001) to decide whether there is a presence of a long-run relationship between variables. The F-statistic ($F = 26.650$) was greater than the upper bound ($I_1 = 5.61$) at a significance level of 1%, indicating the presence of a long-run relationship between variables. Observing the table, we see that the SP&500 has a statistically significant average long-term and short-term impact on WTI oil at a significance level of 1%. The average long-term impact (0.441) of the SP&500 on WTI oil is greater than the average short-term impact (0.376). Specifically, a 1% increase in the volatility of the SP&500 corresponds to an average long-term increase of 0.441% and an average short-term increase of 0.376% in the volatility of Oil(WTI). Regarding control variables, we included the volatility of Gold and Silver, where Mensi, Lee, Vo, Yoon (2021) found that for a period from 2011 to 2019, short-term oil uncertainty is negatively dependent on Gold, while long-term oil uncertainty is negatively dependent on both Gold and Silver. In our study, we have several different levels of statistical significance, where only gold is statistically significant among the control variables, and it also has a positive long-term relationship with oil (WTI). This could be attributed, as the authors themselves suggest in their study, to the different market conditions prevailing, which change the dependency between variables. Additionally, the slight variations in periods could also account for the differences in dependency among variables. Finally, the constant term and the adjustment term are statistically significant at a significance level of 1%. The adjustment term measures the speed of adjustment back to the long-run equilibrium after a temporary shock. In our case, the value of -0.854 means that 85.4% of the imbalances that arose in the previous month are reversed back to the long-run equilibrium in the current month.

Regarding our findings and their relation to the relevant literature, Liu, Ji, and Fan (2013) found for the period from 2008 to 2012 that among the various uncertainty indices they examined, the primary source of short-term uncertainty in the oil market was the SP&500. However, they did not find any strong long-term equilibrium with the uncertainty indices under examination during this period of significant economic instability and recovery. Additionally, Liu, Tseng, Wu, and Ding (2020) find a positive correlation between the uncertainties of oil and the stock market (S&P 500), which changes over time. This changing correlation is attributed to factors such as economic events, geopolitical developments, and changes in market policy. Finally, they also identify a bilateral Granger causality between the two markets. With similar findings, Bašta and Molnár (2018) also found a strong correlation between the two uncertainties, which varies over time and exhibits a stronger relationship at higher time scales. Based on the above, we can conclude that our findings seem to align with the respective literature, as we found a statistically significant relationship between the two volatility indices. However, regarding the direction of this correlation, there seems to be no clear answer, as these indices are quite sensitive to factors that can influence their dynamic correlation.

5 Discussion of the results and concluding remarks

This particular study utilizes an ARDL model to determine the relationship between oil (WTI) volatility and the volatility of the SP&500, specifically whether changes in SP&500 volatility have any impact on oil (WTI) volatility. Using daily return data from 2014 to 2024 to calculate the Realized Volatility Developed by Andersen and Bollerslev (1998). We discovered a positive relationship between the two variables, both in the short term and the long term, with the long-term relationship being stronger. Specifically, an increase in SP&500 volatility results in an increase in oil (WTI) volatility. Understanding the interaction of the stock market with the oil market is crucial for the oil industry and consequently for the overall economy. For further research, we would recommend a more extensive study on the mechanisms that alter the dynamic correlations between the two volatilities. According to the literature, there is no stable correlation, even though the majority of the literature finds a positive relationship between these two markets.

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