Does solar activity affect the price of crude oil? A causality and volatility analysis (2007-2020)[1]

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Abstract: This study examines how solar activity affects the oil volatility index. To test whether solar phenomena affect the oil volatility price index, the Granger and Step-by-Step causality techniques are applied. Furthermore, we employ the autoregressive distributed lag order model (ARDL), which introduces as exogenous variables the Dow Jones Equity REIT index, the 3-month U.S. Government bond, the Oil Volatility Index, and the spread. As part of the model, we also include a solar variable, namely, the solar wind velocity, which is one of the most significant features of the solar wind plasma. According to the results, the solar wind velocity "Granger causes" and "step-by-step causes" the oil volatility price index. All variables analyzed provide useful information for the modelling of the oil volatility index, which shows that solar activity does indeed influence the market for oil prices.

JEL codes: C22, C58, C50, C51

Keywords: oil volatility index, solar wind, ARDL, macroeconomic variables

1. Introduction

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As a primary source of energy, crude oil is one of the most closely watched indicators in the global economy. There are however a number of factors that contribute to the formation of crude oil prices which are complex and multifaceted, including factors related to economics, geopolitics, and the environment. The potential impact of solar activity on economic activity has also been examined in recent years, with some researchers suggesting that solar activity may affect the economy (e.g. Daglis et al., 2019; Daglis et al. 2020).

The term solar activity usually refers to the variations in the sun's magnetic field and the emission of radiation and charged particles that affect the Earth's climate and environment (e.g. Gerontidou et al., 2018). It has been widely argued that changes in solar activity could impact global temperature patterns and weather phenomena such as hurricanes and droughts, which could have a negative impact on energy demand and supply.

The purpose of this study is to investigate whether there is a causal relationship between solar activity and the price of crude oil, given the potential links between solar activity and energy markets. These findings have important implications for policymakers seeking to understand the complex drivers of crude oil prices and the potential impact of solar activity on the energy market.

The present work aims to provide a comprehensive econometric analysis quantifying the impact of solar events on oil markets, thereby enabling a new, but crucial approach. In this context, to the best of our knowledge, this paper contributes to the literature in the following ways: (a) it is the first in the literature to argue that solar activity may affect the oil market, broadening the potential channels for the oil market effect, (b) it is the first in the literature to quantify the solar impact on the oil market via econometric analysis, (c) it offers a deeper understanding of the factors that shape global energy markets and, thus, helps to inform decision-making.

The paper is structured as follows: Section 2 presents the theoretical framework; section 3 describes the methodology used; section 4 presents the data and the results and, finally, section 5 concludes the paper.

2. Theoretical Framework

As far as we are aware, none of the approaches in the literature examine solar activity in the context of the oil market. This paper is the continuation of previous works on the impact of solar phenomena on the economic and financial system. More precisely, the results of these studies indicate that solar and geomagnetic space weather affect the performance of the US telecommunications sector (Daglis et al., 2020) as well as the financial select sector fund price index (Daglis et al., 2020).

In brief, due to solar events, the geomagnetic activity is disrupted, negatively impacting the infrastructure and performance of these industries. In this context, a disruption or destruction to the oil pumping system could also negatively impact the oil market prices. According to Chang and Lin (2006), there have been 242 accidents involving storage tanks over the last 40 years (1960-2003). Human error accounted for only 30% of the problems (Galván and Gomes, 2013), meaning that other possible factors may have played an important role as well. An example of such a factor might be the ionization of the atmosphere (Carpenter, 1996).

The oil pumping process can be adversely affected by ionization in an indirect manner (Changa and Linb, 2006). Oil pumping systems may be affected through fire triggers by bound charges, electromagnetic pulses, electrostatic pulses, and earth currents, with the ionization of the atmosphere being one of the most serious effects of oil pumping hinder (Carpenter, 1996). It is important to note that, despite the indirect nature of the fire trigger (through ionization of the atmosphere), the risk associated with indirect effects is greater than the risk associated with direct fire triggers, such as lightning strikes (Changa and Linb, 2006).

Despite the fact that oil pumping activity is strongly affected by ionization, which can be caused by solar events, there has been no research on this particular topic, including the effects of solar activity on oil pumping systems. In conclusion, solar activity, as captured by the solar wind, may lead to ionization of the atmosphere, which may create a variety of problems, including those associated with oil pumping and disposal. According to the supply and demand theory (Groenewegen, 2008), pumping and maintenance activities affect the supply of oil on the market, thereby influencing its price.

3. Methodology

Our paper uses "Granger causality" as well as "step-by-step causality" to test whether solar wind causes oil volatility index.

3.1 Granger causality

Using the Granger causality test, we test the hypothesis that the times series are not Granger causal, which means that the volatility of the solar wind's velocity (Vsw) does not have predictive power over the oil volatility index (OVX). In order to capture the long-run relationship between two variables, Engle and Granger (1987) recommended the use of an Error Correction Model (ECM) in the model if two variables are cointegrated. The ECM Granger non-causality test involves fitting the model:

$$\Delta y_t = a_0 + \sum_{i=1}^{m} a_{1i}\Delta y_{t-i} + \sum_{i=0}^{m} a_{2i}\Delta x_{t-i} + \lambda\mu_{t-1} + \varepsilon_t \quad \textbf{(1)}$$

where Δ is the first difference operator, Δy_t and Δx_t are stationary time series and ε_t is the white noise error term with zero mean and constant variance. Also, μ_{t-1} is the lagged value of the error term of the co-integration regression:

$$Y_t = c_1 + c_2 X_t + \mu_t \quad \textbf{(2)}$$

The next step is to use the state-of-the-art step-by-step causality introduced by Dufour and Renault (1998) and extended by Dufour et al. (2006) to study the exact timing pattern of the causality relationship.

3.2 Dufour and Renault causality

Based on the literature, Granger causality test may fail to unveil the potential timing pattern of a causal relationship. To overcome this problem, Dufour and Renault (1998) introduced the notion of *step-by-step* or *short-run* causality based on the idea that two time series X_t and Y_t could interact in a causal scheme via a third variable Z_t. More precisely, despite the fact that X_t could not cause Y_t one period ahead, it could cause Z_t one period ahead i.e. Z_{t+1}, and Zt could cause Yt two periods ahead i.e. Y_{t+2}. Therefore, $X_t \rightarrow Y_{t+2}$, even though $X_t \nrightarrow Y_{t+1}$.
For testing the step by-step causality, consider the following model:

$$Y_t = a + \sum_{k=1}^{p} \pi_\kappa Y_{t-k} + \sum_{q=0}^{Q} \beta_q X_{t-q} + u_t \quad \textbf{(3)}$$

where: Y_t is an (1xm) vector of variables, a is a (1xm) vector of constant terms; X_t is a vector of variables and u_t is a (1xm) vector of error terms such that $E(u_t u_s) = \sigma_{ii} I if t = s and E(u_t u_s) = \sigma_{ij} I if t \neq s,$ where I is the identity matrix. Based on Dufour et *al.* (2006), the model described in (3) corresponds to horizon h=1 and we will test for the existence of non-causality in horizon *h*. In the next sub-section, we use an autoregressive distributed lag (ARDL) model to examine whether the variables employed provide useful information regarding the modeling of OVX.

3.3 ARDL (p, q) Model

An ARDL model is used in this study, as it is considered one of the most appropriate techniques. The ARDL(p,q) model contains *p* lags of the dependent

(y_t) and also q lags of the independent variable (x_t), and has the following general form:

$$y_t = b_0 + \sum_{i=1}^{p} b_i\, y_{t-i} + \sum_{i=0}^{q} a_i\, x_{t-i} + \varepsilon_t \quad \textbf{(4)}$$

4. Empirical Analysis

4.1 Data and variables

The solar wind velocity (derived from the Goddard space flight center, space physics data facility) was used in our analysis. It was chosen because plasma velocity is considered to be one of the most significant characteristics of solar wind streams (Gerontidou et al., 2018). The macroeconomic variables used are: the Dow Jones equity reit index (djreit) which measures publicly traded real estate investment trusts in the Dow Jones, the 3-month US government bond (3Musgov), the Chicago Board Options Exchange also known as (Cboe) Volatility Index (Vix), and the spread (10-year US government bond minus 3-month government bond). Oil volatility index (OVX) is the dependent variable. All data are presented in a weekly format and cover the period between week 21 of the year 2007 and week 18 of the year 2020. The descriptive statistics of the time series are shown in Table 1, below.

Table 1: Descriptive statistics of the time-series

Variable	Min	Mean	Std	Max
OVX	17,7600	184,5135	92,1979	1005,5700
Vsw	279,0000	2046,7095	394,0497	3145,0000
Vix	9,4860	19,8099	9,6733	72,0260

djreit	92,4720	283,8645	71,0156	432,5480
3Musgov	0,0020	0,7828	1,0930	4,9700
Spread	-0,4960	1,8581	0,9999	3,7900

4.2 Results

As mentioned above, to test the causal relationship between solar activity and oil volatility, the present study uses Granger causality and step-by-step causality. A summary of the results can be found in Tables 2 and 3, respectively.

Table 2: Granger causality results.

Order	F-stat	P-value
1	26.247	$3.916*10^{-7}$

The results show that the Vsw variable Granger causes OVX with a lag equal to 1.

Table 3: Step-by-step causality results

Order	F-stat	P-value
5	7.5853	0.006043
18	12.044	0.000553

According to the results, in lags 5 and 18, the Vsw step-by-step causes the OVX.

Furthermore, we construct an ARDL model, in which we include macroeconomic variables that have been shown to influence the volatility of oil, thereby testing how these variables affect the oil volatility.

Tables 4 and 5 below summarize the results of the model estimation. Besides the coefficients and standard error, Tables 4 and 5 present the heteroscedasticity and autocorrelation consistent standard errors (HACSE) and the Jackknife heteroscedastic-consistent standard errors (JHCSE). When lags are included for a variable, the name is followed by ".l1". The constant term, Vsw, and Djreit are in levels, while OVX, VIX, 3Musgov, and spread are lagged. Both OVX and Vsw have been multiplied by 100, and djreit is included in the first difference, also multiplied by 100.

Table 4: ARDL model with robust HC standard errors

Variable	Coefficient	Std.Error	JHCSE	t-JHCSE stat	P-Value
Constant	-0.325677	0.11110	0.15110	-2.16	0.0314
OVX.l1	0.647526	0.02712	0.19100	3.39	0.0007
Vsw	0.035904	0.00405	0.01146	3.13	0.0018
vix.l1	0.027934	0.00263	0.01207	2.31	0.0209
3Musgov.l1	-0.095367	0.02196	0.03501	-2.72	0.0066
djreit	-0.086378	0.01886	0.03870	-2.23	0.0259
spread.l1	-0.126197	0.02512	0.04228	-2.98	0.0029

According to Table 4, all variables are statistically significant. As can be seen from the table above, the coefficients for the OVX, VIX, and Vsw are positive, which indicates that they increase the value of the OVX. By contrast, 3Musgov, djreit, and spread have negative coefficients, which reduce the OVX value.

Table 5: ARDL model with robust HAC standard errors

Variable	Coefficient	Std.Error	HACSE	t-HACSE stat	P-Value
Constant	-0.325677	0.11110	0.14710	-2.21	0.0271
OVX.l1	0.647526	0.02712	0.08775	7.38	0.0000
Vsw	0.035904	0.00405	0.00977	3.67	0.0003
vix.l1	0.027934	0.00263	0.00752	3.72	0.0002
3Musgov.l1	-0.095367	0.02196	0.04101	-2.33	0.0203
Djreit	-0.086378	0.01886	0.04237	-2.04	0.0419
spread.l1	-0.126197	0.02512	0.05501	-2.29	0.0221

Similarly, according to Table 5, all variables are statistically significant, the coefficients for the OVX, VIX, and Vsw are positive, while the 3Musgov, djreit, and spread have negative coefficients.

Moreover, the number of observations for the models equals 684, R-squared = 0.800, Adj.R-squared = 0.798, Log-likelihood = -362.722, F-stat = 452.7, P-value (F-stat) = 0.000, residual sum of squares (rss) = 115.662065, indicating that the independent variables adequately model the dependent variable.

5. Conclusion

As part of this study, we examined the impact of solar phenomena on oil volatility. In order to test the causal pattern of Vsw on OVX, we performed Granger and step-by-step causality tests. Based on the results, there is indeed a causal relationship, which means that the solar activity, and more specifically, the solar wind, causes the oil volatility index.

Additionally, we developed an ARDL model. The empirical results indicate that macroeconomic variables provide useful information regarding the predictive ability of the oil volatility index. These results are consistent with previous studies (e.g. Bakas and Triantafyllou, 2019). Accordingly, solar activity, which is statistically significant, is also useful for modeling the oil volatility index performance.

These results clearly show that solar phenomena, in particular the solar wind, may have an adverse effect on the oil market as a result of oil pumping malfunctions caused by atmospheric ionization. According to the findings of the present study, more information channels must be taken into consideration in the analysis of markets, and more specifically in the analysis of the oil market. Further research could include additional variables that express solar and geomagnetic phenomena, such as solar flares.

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