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The Volatility Spillover of Global Oil Price Uncertainty

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ABSTRACT

This manuscript, for the 1st time, analyses the volatility spillover of oil price uncertainty in the world using data from oil price uncertainty recently developed by Abiad and Qureshi (2023), spanning the time 1996-2019 on a monthly frequency. ARCH/GARCH (Autoregressive Conditional Heteroskedasticity and Generalized Autoregressive Conditional Heteroskedasticity) models are employed as an econometric tool. The findings suggest that ARCH model is more consistent than GARCH model in assessing the volatility of oil price uncertainty in the world. The results show that the volatility of oil price uncertainty is high in the world. The transition to renewable energy sources is proposed as a way to resist unexpected oil shocks since the production of renewables does not depend on the fluctuations of oil prices. Consequently, uncertainties in the oil price do not hinder economic activities.

Keywords: Oil Price, Uncertainty, Volatility, Autoregressive Conditional Heteroskedasticity, Generalized Autoregressive Conditional Heteroskedasticity
JEL Classifications: O13, O050, C01, C22

1. INTRODUCTION

Industrialization made oil the main source of world economic development, where oil price has been a core driver of global economy sustainability; meanwhile, price fluctuation has a significant impact on the global economy (Mati et al., 2023). Since oil has a significant role and share in production cost, it has been known as a core driver of modern economic activity (Miller and Ratti, 2009; Albulescu and Ajmi, 2021; Basher and Sadorsky, 2006). Therefore, oil price volatility is one of the main factors stunting growth and raising debt vulnerabilities (IMF, 2022). The source of oil price volatility is the supply and demand shock, which increases volatility during periods of international crises (Sánchez García and Cruz Rambaud, 2023).

On the other hand, the global economic and ecological situation shows that today is the beginning phase of new energy crises, because the trade-off between oil supply and CO_2 emissions forces to use and increase the share of renewable energy (Sadorsky, 2009; Boufateh and Saadaoui, 2020; Ready, 2018; Baumeister and Hamilton, 2019). In this phase, an increase in oil price will have a dual-dimensional effect. On one hand, it may decrease profit by increasing marginal production cost, which limits green innovative investment. On the other hand, forces substitute oil with alternative renewable energy sources. Since oil price shocks lead to the appreciation of clean energy stock prices (Kumar et al., 2012) and green bond prices (Azhgaliyeva et al., 2022). The world's existing ecological, economic, and political situation requires fossil fuel dependency and accelerates the development of renewable energy sources. However, the unprecedented increase in energy consumption retrained the oil price effect at a high level, which is a major source of uncertainty (Tunc et al., 2022). Therefore, this paper estimated the volatility spillover of global oil price uncertainty using econometric tools, especially ARCH/GARCH models.

2. LITERATURE REVIEW

In literature, estimating price fluctuation in oil market and finding appropriate methodology, as well as model type has been curtail debate among researchers. Some authors used spillover methodology to evaluate the volatility of oil and financial markets during economic and financial crises, which derives from VAR models for measuring the magnitude of interdependence between the volatility of variables, allowing to trace and decompose the origin and receiver of the spillover effect (Sánchez García and Cruz Rambaud, 2023). Consequently, developed GARCH (“sGARCH”) models are used to analyze volatility (Sánchez García and Cruz Rambaud, 2023), which is a good method for the development of accurate asset pricing models, hedging strategies, and forecasting (Malik and Hammoudeh, 2007).

A conditional variance model belonging to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family is used as a good tool for the estimation of oil price uncertainty; on the other hand, the Structural Vector Autoregressive model, SVAR, is preferable for the modelling of Uncertainty and Conflicts (Caporin et al., 2020). VHAR model is suggested as a suitable model for the evaluation of asymmetric propagation of volatility between long and short time horizons (Corsi, 2009), where this model is also taken as the best option for describing nonlinearities and long-range dependence in time series dynamics (Caporin et al., 2020).

On the other hand, some academics emphasize that multivariate GARCH family models have interpretative limitations and that they cannot quantify spillovers in sufficient detail where they propose to use a spillover index (the DY index) computed by developing vector autoregresssions (VARs) model (Baruník et al., 2015). As well as used alternative models to get accurate forecast, for instance vector Autoregressive (VAR) model, random walk (RW) model and HAR model as an alternative (Chatziantoniou et al., 2021). In practice used TVP-VAR model to identify shocks that cause price uncertainty.

But EGARCH and Realized Volatility specifications are known suitable methods to create an index for estimating price uncertainty, as well as Structural Vector Auto Regression and Vector Heterogeneous Auto Regression models admitted as empirical methodologies for estimating the bi-directional relationship of conflict and oil price uncertainty (Caporin et al., 2020). Some researchers applied bivariate VAR-GARCH-in-mean models to estimate oil price uncertainty and its effect on sectoral stock return (Caporale et al., 2015). Zheng Zhang and his colleagues filled the research gap in forecasting oil price volatility by developing OVX index, the GARCH-type models, and the stochastic volatility models (Zhang et al., 2023). They also argued that GARCH-type models perform better than stochastic volatility models in terms of the volatility forecast (Zhang et al., 2023).

This research used the oil price uncertainty (OPU) index Abiad and Qureshi (2023) offered. They conducted a research on developing an index of global oil price uncertainty (OPU) (Abiad and Qureshi, 2023.), by considering measures previously used to evaluate different types of uncertainty. OPU is known as a good measure to evaluate the effects of uncertainty on the price of oil, an important source of macroeconomic fluctuations, where it is flexibly applied to examine macroeconomic activity at the global and cross-country levels. For instance, OPU is admitted as the best complement for previously used measures of oil price volatility, such as the oil volatility index (OVX), since OPU is based on information mined from the top 50 news outlets, which are an online aggregator of global news (Abiad and Qureshi, 2023). Accurate expression of the shocks verbally explained by Romer and Romer (2010) in the oil market by calculated OPU index and a complete description of oil price fluctuations show its high scientific and practical importance.

The text-based approach by using the words: “oil,” “price,” and “uncertainty” substantiated that the calculated index almost completely explained shocks in the oil market and fluctuation in price. This approach has been used by several researchers up to Abiad and Qureshi (2023). For instance, Plante and Traum (2012) and Plante (2019) used the keyword “OPEC” to construct an index representing events that could affect the OPU index. Also used vector autoregression (VAR)-based analysis. OPU, offered by Abiad and Qureshi (2023), has the following advantages:

1. Geographically unrestricted measure of OPU, since the top 50 periodicals that account for the largest share of published articles in an online news aggregator have been a source of the database
2. Flexibly applied to examine macroeconomic activity at the global and cross-country level
3. It helps to understand the contextual factors that drive shock episodes and their impact in particular historical moments.

Unlike the authors, we used ARCH/GARCH models to investigate the volatility of oil price uncertainty in the world.

3. DATA AND METHODOLOGY

To study the volatility of oil price uncertainty in the world, the data of oil price uncertainty (*OPU*) in monthly frequency, measured in index[1], is applied over the period 1996-2019. The data is obtained from the Economic Policy Uncertainty portal (https://www.policyuncertainty.com/oil_uncertainty.html).

To investigate the volatility of oil price uncertainty in the world, we employ ARCH (Autoregressive Conditional Heteroskedasticity (Engle, 1982) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) (Bollerslev, 1986) models. An ARCH model is an econometric model for the variance of a time series. Engle (1982) used this model to estimate the means and variances of inflation in the U.K. Later Bollerslev (1986) extended the ARCH model (Equation 2) to the GARCH model (Equation 3).

1 The Energy-Related Uncertainty Indexes (EUI) has been created by Abiad and Qureshi (2023).

In order to build ARCH/GARCH models, there should be a presence of ARMA (Autoregressive Moving Average) (Box and Jenkins, 1970) process whose specification can be described as:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{1}$$

Where y is the dependent variable, p is autoregressive terms, ϕ_0 is constant, $\phi_1,\ldots\phi_p$ the coefficients of the autoregressive component, ε_t – error term, q is moving average terms, $\theta_1,\ldots\ \theta_q$ - the coefficients of the moving average component.

After verifying both the AR and MA processes, the ARMA specification should be tested for heteroskedasticity (Breusch and Pagan, 1979). If heteroskedasticity exists in the ARMA model, ARCH (Equation 2) and GARCH (Equation 3) models can be developed, which have the following specifications:

$$\sigma_t'^2 = \alpha_0' + \alpha_1' \varepsilon_{t-1}'^2 + \alpha_2' \varepsilon_{t-2}'^2 + \ldots + \alpha_n' \varepsilon_{t-n}'^2 \tag{2}$$

$$\hat{\sigma}_t^2 = \hat{\alpha}_0 + \hat{\alpha}_1\hat{\varepsilon}_{t-1}^2 + \hat{\alpha}_2\hat{\varepsilon}_{t-2}^2 + \ldots + \hat{\alpha}_j\hat{\varepsilon}_{t-j}^2 + \hat{\beta}_1\hat{\sigma}_{t-1}^2 + \hat{\beta}_2\hat{\sigma}_{t-2}^2 + \ldots + \hat{\beta}_m\hat{\sigma}_{t-m}^2 \tag{3}$$

$\sigma_t'^2, \hat{\sigma}_t^2$ - Conditional variance, ε' and $\hat{\varepsilon}$ are error terms, a', $\hat{a}$ and $\hat{\beta}$ are the coefficients of volatility, n, j and m are lag orders, $\alpha_0', \alpha_1', \ldots, \alpha_n' > 0, \hat{\alpha}_0, \hat{\alpha}_1, \ldots, \hat{\alpha}_j > 0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_m \geq 0, n \geq 0, j \geq 0, m \geq 0,\ 0 \leq \alpha_0' + \alpha_1' + \ldots + \alpha_q' < 1$.

The data is transformed into the natural logarithm. Furthermore, the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), the Phillips-Perron (PP) (Phillips and Perron, 1988) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) unit root tests are conducted to examine the stationarity, which is an important consideration of developing ARMA and ARCH/GARCH models.

As a check of diagnostics for the developed ARCH/GARCH model, the LM test for heteroskedasticity (Breusch and Pagan, 1979) is run.

4. RESULTS

Before estimating volatility, the data, used in natural logarithm form (*OPU_LOG*), is checked for unit root test. To this end, the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are run. The results are provided in Table 1.

Table 1: ADF, PP and KPSS unit root tests

Variable	ADF	PP	KPSS
	Level	Level	Level
EU_LOG	0.00	0.00	0.66

Source: Authors` estimations. ADF: Augmented dickey-fuller, PP: Phillips-perron, KPSS: Kwiatkowski-phillips-schmidt-shin

For the ADF, the P-values are reported and obtained with a specification adopting an automatic selection of BIC information criterion, including intercept. Maximum lags are set to 2. For the PP test, the P-values are reported, which are obtained with a specification adopting an automatic selection of Newey-West Bandwidth, including the intercept. For the KPSS, the test statistics are reported which were obtained with a specification adopting an automatic selection of the bandwidth and including intercept. In the ADF and PP tests, the null hypothesis is the presence of a unit root, while the null hypothesis in the KPSS test is the series stationarity. The null hypothesis is rejected for ADF and PP tests when the $P < 0.05$. The null hypothesis is accepted for the KPSS test when P-value is higher than 0.05.

Due to Table 1, energy uncertainty (*OPU_LOG*) is stationary in the level. On this occasion, the correlogram of energy uncertainty is run in the level. From the ACF (autocorrelation function) and PACF (partial autocorrelation function), the lag orders of AR and MA processes are identified.

Table 2 shows the existence of the ARMA process for energy uncertainty (*OPU_LOG*). According to the Parsimony principle, we fix the maximum lag order as 3 for both AR and MA processes. As a next step, ARMA specifications should be built with the different combinations of lag length [3 3], and the final specification is chosen relying on AIC, SIC and HQ criteria.

Table 3 contains the calculated ARMA models with lag length based on Table 2. It should be highlighted that the best specification must be chosen among Model 4, Model 5 and Model 6, because the coefficients are statistically significant in these specifications, and they have heteroscedasticity. AIC, BIC and HQ test results of Model 4 are lower than the other two models. However, ARCH/GARCH effects do not exist in Model 4[2]. Therefore, we rely on Model 5 (ARMA [3, 3]) to estimate ARCH/GARCH models.

The lag order of the ARCH model should be selected based on PACF from the correlogram of squared residuals, whereas the lag order for the GARCH model is considered from the ACF of the ARMA (3, 3) model (Table 4).

From Table 4, it can be clearly seen that the lag order for ARCH model is 1 whereas the GARCH effect (GARCH [1,1]) can be estimated with lag order 1.

Table 5 shows the mean and variance equations for employed ARCH (1) and GARCH (1,1) models. All coefficients of both mean and variance equations for the ARCH (1) model are statistically significant. Furthermore, the coefficients of constant and lagged squared residual (ε'^2 [−1]) in the variance equation are positive, and the coefficient of squared residual ε'^2 (−1) is <1, and there is no heteroscedasticity according to the LM-test result ($P = 0.44$).

The coefficients of the mean equation are significant; however, the coefficient of lagged squared variance is not statistically significant in the GARCH (1,1) model.

2 The results can be provided upon request.

Table 2: Autocorrelation and partial autocorrelation of energy uncertainty (*OPU_LOG*) in the level

Autocorrelation	Partial correlation		AC	PAC	Q-Stat	Prob
.|*****|	.|*****|	1	0.721	0.721	151.17	0.000
.|*****|	.|**|	2	0.649	0.270	274.28	0.000
.|****|	.|*|	3	0.598	0.138	379.05	0.000
.|****|	.|.|	4	0.551	0.070	468.23	0.000
.|****|	.|*|	5	0.549	0.132	557.14	0.000
.|****|	.|*|	6	0.540	0.096	643.35	0.000
.|****|	.|.|	7	0.522	0.053	724.20	0.000
.|***|	.|.|	8	0.472	−0.040	790.52	0.000
.|***|	.|.|	9	0.430	−0.031	845.97	0.000
.|***|	.|.|	10	0.432	0.066	902.16	0.000
.|***|	.|.|	11	0.410	0.007	952.76	0.000
.|***|	.|*|	12	0.437	0.103	1010.5	0.000
.|***|	.|*|	13	0.447	0.076	1071.3	0.000
.|***|	.|.|	14	0.414	−0.021	1123.6	0.000
.|**|	*|.|	15	0.336	−0.150	1158.1	0.000
.|**|	*|.|	16	0.288	−0.086	1183.6	0.000
.|**|	.|.|	17	0.289	0.031	1209.4	0.000
.|**|	.|.|	18	0.272	−0.011	1232.3	0.000
.|**|	*|.|	19	0.239	−0.076	1250.0	0.000
.|**|	.|.|	20	0.238	0.016	1267.6	0.000

Source: Authors\` estimations

Table 3: The estimated ARMA (p, q) models for energy uncertainty (*OPU_LOG*) and AIC, SIC and HQ test results

Coefficients	Model 1: ARMA (1, 1)	Model 2: ARMA (1, 2)	Model 3: ARMA (2, 1)	Model 4: ARMA (2, 2)	Model 5: ARMA (3, 3)	Model 6: ARMA (3, 2)	Model 7: ARMA (3, 1)	Model 8: ARMA (1, 3)	Model 9: ARMA (2, 3)
AR	0.94***	0.69***	0.57***	0.92***	0.90***	0.45***	0.48***	0.70***	0.64***
MA	−0.52***	0.10	0.62***	−0.53***	−0.50***	0.31***	0.32***	0.08	0.04
Constant	4.36***	4.41***	4.41***	4.34***	4.34***	4.41***	4.41***	4.41***	4.41
AIC	1.44	1.55	1.53	1.65	1.75	1.80	1.71	1.55	1.75
BIC	1.49	1.60	1.58	1.70	1.80	1.85	1.76	1.60	1.80
HQ	1.46	1.57	1.55	1.67	1.77	1.82	1.73	1.57	1.77
Breusch-Pagan test	0.81	0.75	0.81	0.00	0.00	0.00	0.26	0.75	0.00

Asterisks represent statistical significance *** for 1% level. AIC, BIC and HQ denote Akaike, Schwartz and Hannan-Quinn information criteria, respectively. For the Breusch-Pagan test, we report the P-values of Chi-square. According to the heteroscedasticity test, the null hypothesis is that there are no existing ARCH/GARCH effects up to the specified lag, whereas the alternative hypothesis means there are ARCH/GARCH effects up to the specified lag. The null hypothesis is rejected if the P-value of Chi-square is lower than 0.05 ($P < 0.05$)

Table 4: The correlogram of squared residuals of ARMA (3, 3) model

Autocorrelation	Partial correlation		AC	PAC	Q-Stat	Prob
.|*|	.|*|	1	0.210	0.210	12.832	0.000
.|*|	.|.|	2	0.100	0.058	15.748	0.000
.|.|	.|.|	3	0.013	−0.020	15.794	0.001
.|.|	.|.|	4	−0.050	−0.057	16.533	0.002
.|.|	.|.|	5	0.012	0.036	16.575	0.005
.|.|	.|.|	6	0.066	0.070	17.864	0.007
.|.|	.|.|	7	−0.030	−0.064	18.136	0.011
.|.|	.|.|	8	−0.003	0.000	18.138	0.020
*|.|	*|.|	9	−0.099	−0.093	21.070	0.012
*|.|	.|.|	10	−0.080	−0.036	22.987	0.011
.|.|	.|.|	11	−0.047	−0.017	23.665	0.014
.|.|	.|.|	12	0.045	0.068	24.265	0.019
.|.|	.|.|	13	0.000	−0.023	24.265	0.029
.|*|	.|*|	14	0.088	0.081	26.606	0.022
.|.|	.|.|	15	0.004	−0.017	26.611	0.032
.|.|	.|.|	16	0.018	0.017	26.715	0.045
.|.|	.|.|	17	0.024	0.016	26.893	0.060
.|.|	.|.|	18	−0.031	−0.053	27.181	0.076
.|.|	.|.|	19	0.060	0.072	28.283	0.078
.|.|	.|.|	20	0.057	0.018	29.293	0.082

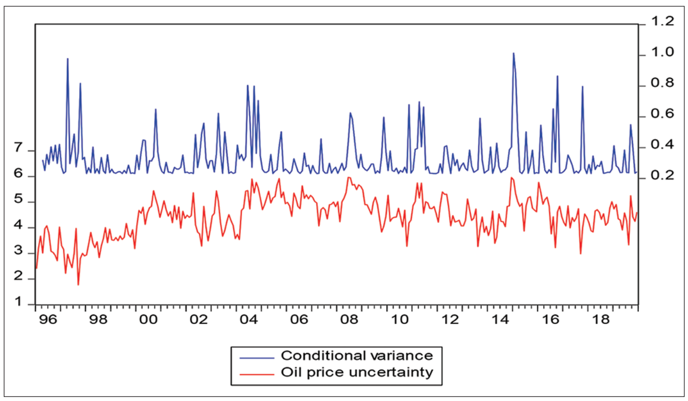
Source: Authors\` estimations

Table 5: The estimated ARCH (1) and GARCH (1,1) models

Coefficients	Model 1: ARCH (1)	Model 2: GARCH (1,1)
	Mean equation	
AR(1)	0.89***	0.89***
MA(1)	−0.58***	−0.58***
Constant	4.37***	4.36***
	Variance equation	
Constant	0.23***	0.19***
$\varepsilon'^2(-1)$	0.28**	
$\hat{\varepsilon}^2(-1)$		0.26**
$\hat{\sigma}^2(-1)$		0.12
LM-test for heteroscedasticity: P-value of Chi-square	(0.44)	(0.53)

P-values are in parentheses. Asterisks represent statistical significance *** and ** for 1% and 5% levels, respectively

Figure 1: The graph of actual value and volatility spillover of oil price uncertainty in the world during the period 1996-2019 in monthly frequency



For this reason, we might postulate that there is no GARCH effect, and we rely on ARCH (1) model in order to estimate the volatility of global oil price uncertainty. More specifically, the coefficient of global oil price uncertainty volatility is equal to 0.51 due to the ARCH (1) model. Consequently, it might be postulated that oil price uncertainty volatility in the world is higher than average (Figure 1).

5. CONCLUSION

It can be concluded that the role of oil in energy supply is decreasing slowly for several reasons, such as the global economic and ecological situation, a trade-off between oil supply and CO_2 emissions, and the geopolitical situation. All these are forcing the world to increase the share of renewable energy, but it is still a fact that renewable energy has not developed enough to replace oil fully; therefore, oil remains an important factor in the global economy. During the last two decades, oil-related shocks significantly increased in the global economy.

Different indicators were used to estimate the oil price volatility, and a special index was developed, which is better for capturing shocks and explaining price fluctuations. The OPU index is better at capturing shocks and provides a more complete description of oil price fluctuations since it is based on a wider range of information. We analyzed the volatility of oil price uncertainty in the global market based on the oil price uncertainty (*OPU*) index, calculated monthly frequency for 1996-2019.

ARCH/GARCH models are a good tool for estimating oil price uncertainty and evaluating shocks. The results substantiated that there is no GARCH effect since the coefficient of lagged squared variance is not statistically significant in the GARCH (1,1) model; therefore, we just rely on the ARCH (1) model in order to estimate the volatility of global oil price uncertainty. Since estimated coefficients are significantly different from zero, we can conclude that an ARCH effect exists there. Based on the outcomes of the ARCH model, global oil price uncertainty and volatility are high. It means that big errors at time t-1 have a larger variance of r_t at t. Therefore, it could be concluded that oil price volatility is high, and oil price uncertainty is not easily predictable.

Given the high volatility in oil price uncertainty, economic activities also lead to uncertainty. Unexpected and sudden shocks might distort economic complexity, which relies on oil. Moreover, oil export-based countries also lose economic profit as a result of such shocks. Therefore, the transition to renewable energy is the best solution to mitigate and avoid oil supply uncertainty. Renewable energy allows the nations to become energy-independent since energy generation is only associated with country-specific availabilities, not external sources.

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