INTERNATIONAL TRANSMISSION AND PREDICTABILITY OF ASSET PRICE VOLATILITY

Investigating the Relationship Between Oil and Natural Gas Volatilities and Prices

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Contents

1 Abstract

This assignment delves into the relationship between oil and natural gas prices, with a specific focus on how natural gas volatility impacts oil volatility. Over a 10-year period, daily price data for both assets were collected, facilitating the computation of monthly annualized volatility for both of the aforementioned asset prices. The model we choose to evaluate this relationship is a simple ARMA(1, 1) model, by incorporating both autoregressive and moving average components, this model enables us to capture the complex interplay between the two commodities while accounting for underlying trends.The findings from our analysis hold significance for the development of robust risk management strategies within the energy sector, providing stakeholders with valuable insights into the interplay between the volatilities of oil and natural gas. However, it should be noted that at the end of the day, this article is just an assignment, and its results serve more as a general guideline about the movements of the volatilities of these two assets rather than a definitive conclusion.

2 Introduction

In our effort to assess the relationship between oil and gas price volatilites over the period of interest (2013-2013), The choice of variables and models lay the foundation for our analysis, enabling us to gain valuable insights into the dynamics between oil and gas prices. Leveraging daily price data extracted from the FRED database over a comprehensive 10-year span, this investigation centers on the renowned BRENT oil price index and the Henry Hub natural gas price index.

Our analysis begins with a thorough exploration of the relationship between these two assets. We first compute the monthly annualized volatilities of both oil and natural gas prices, laying the groundwork for subsequent analysis. Moving into the analytical phase, we employ a simple Ordinary Least Squares regression model to examine the relationship between the variables. Furthermore, we enhance the robustness of our analysis by incorporating certain control variables, sampled on a monthly basis.

In seeking a deeper understanding of the underlying dynamics, we employ a simple Autoregressive Moving Average (ARMA) model. This modeling technique allows us to uncover potential patterns and dependencies that may not be readily apparent from the initial analysis. By examining the temporal dependencies and interactions between the variables of interest, the ARMA model provides valuable insights into their behavior over time.

Through this comprehensive approach, we aim to enhance our understanding of the underlying mechanisms driving the observed phenomena. By gaining insight into the intricate relationship between oil and natural gas prices, we can facilitate more informed decision-making and policy formulation in relevant domains.

In the subsequent sections, we asses the assignment's framework. In the third section, we provide a brief overview of the previous literature that informed the writing of this assignment. Following that, the fourth section delves into a comprehensive exploration of the datasets utilized, elucidating the rationale behind their selection and providing a methodological background. Lastly, the fifith section centers on the empirical examination of our analysis results.

3 Literature review

The presentation as well as the analysis performed itself are based on a number of studies which have previously gone into similar endeavours. In this section of the assignment we will go into a brief presentation of the contents of those articles taken into consideration subsequently laying the foundation for my own work.

Serletis and Herbert (1999) conducted a comprehensive analysis of the industrial price of oil and natural gas, revealing an autocorrelation between these commodities in the first order. Their findings not only underscored the substitutable nature of oil and natural gas in industrial production but also provided crucial insights into the underlying patterns driving their correlation. **Ewing et al. (2002)**: Covering the period from April 1996 to October 1999, analyze the close prices of oil and natural gas. They observe that natural gas volatility does not react to its own volatility, while oil price volatility is influenced by its own volatility. Additionally, it highlights the impact of natural gas sector-led shocks on natural gas volatility and the indirect influence of crude oil returns on natural gas volatility. **Regnier (2007)**: compares the volatility levels between production-refinery oil and natural gas prices and domestic sale prices from January 1945 to August 2005. The study concludes that crude oil, refinery oil, and natural gas prices exhibit approximately 95% more volatility than domestic sale prices, providing insights into the differential volatility patterns across different segments of the energy market.

Xiuzhen X. ,Zheng W.,Umair M., (2022) examines how oil price volatility affects the asymmetrical response of gasoline prices. Utilizing a vector autoregressive approach, it investigates theories like oligopolistic coordination and Bayesian updating to explain this phenomenon. The findings suggest that higher oil price volatility decreases the degree of asymmetry in gasoline price responses, supporting these theories. By analyzing various measures of volatility and response, the research confirms prior findings of a negative correlation between oil price volatility and gasoline price asymmetry. Overall, this study enhances our understanding of the dynamics between oil and gas price volatilities, offering valuable insights into their relationship. Furthermore **Radchenko S., (2005)** looks at how changes in oil prices affect gasoline prices, focusing on why gasoline prices might rise more quickly than they fall when oil prices change(asymetric response). It considers different reasons for this, like how companies work together and how people shop for gas. including various economic variables in their analysis, like inflation rate or fluctuations in energy commodity taxation(through the use of dummy variables). The study finds that when oil prices change a lot, the difference between how fast gas prices go up and down gets smaller. The analysis distinguishes between explanations and concludes that oligopolistic coordination theory is the most likely explanation. This also confirms **Peltzman, S., (2000)** finding of the negative relationship between oil price volatility and gasoline price asymmetry.

Finally **O Saltik, S Degirmen, M Ural (2016)**: delves into the critical role of accurately forecasting crude oil and natural gas price return volatility for policymakers, production companies, and traders, emphasizing its impact on economic indicators like growth rates, inflation, and unemployment. Employing various econometric models such as GARCH, IGARCH, EGARCH, and FIGARCH, the research explores the intricate relationship between oil and gas prices, shedding light on their volatility patterns and market dynamics. Through empirical analysis, the study determines optimal hedge strategies and identifies significant implications for derivative markets, offering insights into risk management and decision-making processes amidst volatile energy markets.

4 Data & Methology

4.1 Data

As previously mentioned, the main datasets utilized in this assignment are the Brent oil prices and the Henry Hub natural gas spot prices, obtained from the FRED database. Spanning approximately a decade, the data frequency is daily. During this period, the Brent oil price dataset contained 68 missing observations, while the Henry Hub gas spot price dataset had 82 NA observations. To maintain dataset balance, missing values were addressed by initially replacing them with zero and subsequently employing linear interpolation between non-null values. The table1 below provides descriptive statistics for both datasets.

Table 1: Descriptive Statistics for Brent Oil and Henry Hub Natural Gas Prices

Statistic	**Brent Oil Price**	**Henry Hub Natural Gas Price**
Count	2609	2609
Mean	68.03	3.32
Standard Deviation	22.04	1.51
Minimum	9.12	1.33
25th Percentile	50.88	2.49
50th Percentile (Median)	64.99	2.87
75th Percentile	81.66	3.74
Maximum	133.18	23.86

Note: Descriptive statistics of datasets of Brent oil price and Henry Hub natural gas spot price datasets obtained from FRED database.

The selection of these specific datasets stems from their prominence in existing literature and their reliability as benchmarks. The Brent oil price is widely recognized as a standard for global oil prices, providing a comprehensive overview of the international oil market. Similarly, the Henry Hub natural gas spot price serves as a key index due to its strategic location and extensive connections with other U.S. markets, offering valuable insights into natural gas supply and demand dynamics.

Moreover, the availability of extensive data for both indexes during our period of interest (2013-2023) further justifies their selection. This abundance of data enables a robust analysis of price movements and volatility patterns over the specified time frame. Additionally, both indexes are denominated in U.S. dollars per barrel, ensuring consistency in currency measurement for comparative analysis.

The following graphs1,2 illustrate the price trends of these indexes throughout the designated period, providing visual insights into their respective trajectories and fluctuations.

The Brent oil price exhibits significant volatility, characterized by numerous and intense fluctuations throughout the specified time period. In contrast, the Henry Hub natural gas price appears relatively stable over time, with consistent trends until a sudden spike in

February 2021 (**Putin's legacy**). Following this spike, although there are fluctuations, the natural gas price seems to stabilize again after February 2023. This observation suggests differing volatility patterns between the two indexes, with oil prices demonstrating greater instability compared to natural gas prices during the analyzed period.

Figure 1: Brent crude oil price (2013-2013) source: FRED

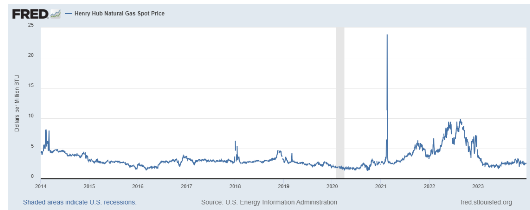

Figure 2: Henry Hub natural gas spot price (2013-2013) source:FRED

In the preprocessing phase of our data, we first take the first log differences. This is done to standardize our data and ensure stationarity in the time series of each of these two prices. Subsequently, we calculate the returns of each of the two assets as the percentage change of the first log differences. Next, we resample our data to compute the monthly returns, from which we derive the standard deviations (volatilities). Finally, in our last step, we annualize these standard deviations by multiplying them with the square root of twelve.

As our As our control variables, I have selected the the World Industrial Production Index (WIP) and the Global Economic Conditions Index (GECON) proxies for worldwide economic activity, inspired by **Xiuzhen X. ,Zheng W.,Umair M. (2022** who in their work, used these two indexes along with certain other metrics to account for global economic growth over the period of interest in their model. In addition, **Radchenko (2005)** emphasized the significance of inflation in influencing certain asset prices. While this study originally omitted any metric to adjust for inflation due to its short time horizon and perceived lack of necessity, I have chosen to incorporate the Consumer Price Index (CPI) as a measure of inflation's impact. This decision stems from the notable fluctuations experienced during our specific time period, highlighting the importance of considering inflationary effects on asset pricing dynamics. The data for the CPI, like oil and gas prices, were collected from the FRED database, while proxies for global economic growth were sourced from Professor Christiane Baumeister's website.

In tabel 2 I present summary statistics for both the monthly annualized volitilities, as well as the control variables.

To assess potential multicollinearity issues, we employ two robustness measures. Firstly, we examine the correlation matrix among all variables, providing insights into the strength and direction of their relationships. Secondly, we calculate the Variance Inflation Factor (VIF), offering a quantitative assessment of multicollinearity. Both measures are presented in the following tables34:

Table 2: Summary statistics of oil and gas volatility, GECON, WIP, and CPI

	Oil Volatility	**Gas Volatility**	**GECON**	**WIP**	**CPI**
Count	120	120	120	120	120
Mean	0.080	0.172	-0.063	131.944	2.719
Std. Dev.	0.069	0.149	0.605	6.985	2.311
Min	0.021	0.046	-4.424	116.662	-0.227
25%	0.050	0.090	-0.191	125.426	1.335
Median	0.069	0.133	-0.033	132.647	2.029
75%	0.086	0.203	0.216	137.007	3.174
Max	0.695	1.300	1.309	144.472	8.968

Note: The descriptive statistics of all key variables used in our model. These statistics include the mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile, and maximum values. These metrics offer insights into the central tendency, variability, and range of the data, facilitating a deeper understanding of the characteristics and dynamics of these economic indicators

Table 3: Correlation Matrix of Key Variables

	Gas Volatility	**Oil Volatility**	**GECON**	**CPI**	**WIP**
Gas Volatility	1.000	-0.001	-0.048	0.086	0.168
Oil Volatility	-0.001	1.000	-0.827	-0.063	-0.171
GECON	-0.048	-0.827	1.000	-0.046	0.064
CPI	0.086	-0.063	-0.046	1.000	0.781
WIP	0.168	-0.171	0.064	0.781	1.000

Note: Correlation matrix of all variables, presents the extend to which the variables influence each other (created using python).

Table 4: Variance Inflation Factor (VIF) of Variables

Variable	**VIF**
Gas Volatility	2.397
Oil Volatility	7.564
GECON	3.313
CPI	2.822
WIP	9.262

Note: Variance inflation factor of all variables, showing the extent to which the variance of an estimated regression coefficient is increased due to multicollinearity in the model. In other words, it quantifies how much the variance of the estimated coefficients is inflated because of correlations among the predictor variables, typically if it is smaller than 5 it indicates an acceptable level of multicollinearity. Also it is important to mwntion that a VIF value below 10 indicates accepatale level of multicollinearity, indicating no severe issues may arise in our models.(created using Python).

Looking at the correlation matrix we can see that that the correlation between most variables is relatively small, indicating that there should be no concern for multicollinearity issues arising amongs most variables. The only exception to this are the relationship between CPI and WIP which boast a relatively high correlation value of 0.781 as well as the relationship between GECON and oil volatility whose correlation value is equal to -0.827. To further investigate this issue we compute the VIF of all variables, the results of which are presented in the table 4. We can clearly observe that most of the variables variance does not inflate over the threshold of five, the only exceptions to this being the WIP and oil volatility which while boasting values above five still do not exceed the ultimate threshold of ten. However, it was decided to exclude 'WIP' from the model to preempt potential multicollinearity issues in our estimations going forward.

4.2 Methology

We'll begin our analysis with a standard Ordinary Least Squares (OLS) regression model, a widely used technique for estimating the relationship between dependent and independent variables. OLS regression provides a simple and intuitive framework for understanding how changes in the independent variables relate to changes in the dependent variable. Past studies have indicated a significant relationship between oil prices and their lagged values, prompting our interest in exploring this further.

To address this, we will not only employ OLS regression but also supplement our analysis with an Autoregressive Moving Average (ARMA) model of order (1,1). By incorporating lagged values of the dependent variable into the model, ARMA (1,1) allows us to capture the temporal dependencies inherent in the data. This approach enables us to better understand how past oil price fluctuations influence current volatility, thus providing insights into the dynamics of oil markets.

Through this combined approach, we aim to enhance our understanding of the relationship between oil prices and their historical trends, thereby facilitating more robust analyses and informed decision-making.

I will now briefly present the characteristics of an ARMA(1, 1) in order to facilitate a better understanding of the model and the subsequent results it produces.

The ARMA model is comprised of two main components, the first being the Autoregressive component (AR) and the Moving Average (MA) component. The autoregressive component of the ARMA(1,1) model describes the linear relationship between the current value of the time series and its past values. In an AR(1) model, the current value of the time series y_t is modeled as a linear combination of its previous value $y_t - 1$ and a random error term ϵ_t:

$$y_t = \phi_1 y_{t-1} + \varepsilon_t \tag{1}$$

Here, ϕ_1 is the autoregressive parameter, which represents the impact of the previous value on the current value of the time series.

The moving average component of the ARMA(1,1) model describes the relationship between the current value of the time series and past forecast errors. In an MA(1) model, the current value of the time series y_t is modeled as a linear combination of its previous value $y_t - 1$ and a random error term $\epsilon_t - 1$, respectively:

$$y_t = \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{2}$$

Here, θ_1 is the moving average parameter, which represents the impact of the previous forecast error on the current value of the time series.

Combining the AR and MA components, the ARMA(1,1) model can be represented as:

$$y_t = \phi_1 y_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{3}$$

This equation captures both the autoregressive relationship between past and current values and the moving average relationship between past forecast errors and current values. In summary, the ARMA(1,1) model accounts for both the temporal dependencies in the data (autoregressive component) and the impact of past forecast errors (moving average component). By estimating the parameters ϕ_1 and θ_1 from the data, we can make forecasts and analyze the behavior of the time series over time.

5 Empirical Findings

As mentioned earlier in the text in processing my data I begin by taking the first log differences for both oil and natural gas prices, next the daily returns for both assets are computed as taking the percentage change of the first log differences. Afterwards, I resample the daily returns to calculate the monthly returns and monthly standard deviations for both oil and gas prices. The monthly returns are calculated as the mean of the daily returns within each month, while the monthly standard deviations represent the volatility of returns for each asset over each month. The resulting monthly standard deviations are then annualized by multiplying them by the square root of 12, which represents the number of months in a year.

The following graph 3 presents the monthly annualized volatilites of both assets plotted against the time parameter t, which represent the months of the 10-year period under examination(120):

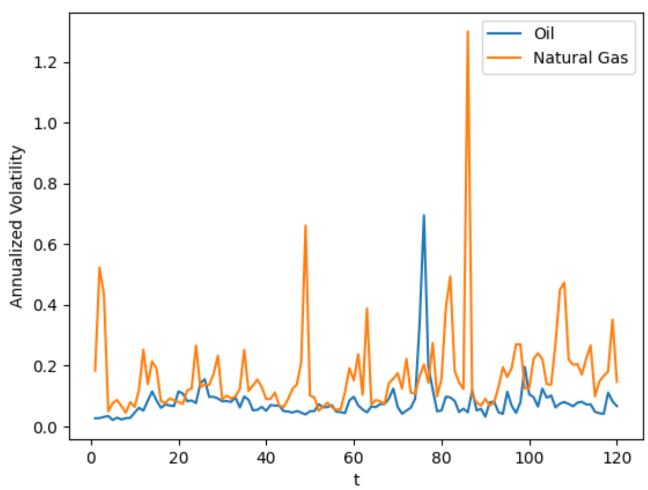

Figure 3: monthly annualized volatilities plotted against time parameter t(created using Python library: statsmodels.api)

Although oil prices appeared to undergo higher and more intense fluctuations compared to natural gas prices, the analysis of monthly annualized volatilities reveals a surprising stability in oil volatility. This discrepancy can be attributed to the characteristic behavior of oil prices, which tend to dissipate quickly over time, resulting in lower estimated monthly volatility. In contrast, the fluctuations in natural gas prices seem to persist for longer dourations and are absorbed at a slower rate. This observation leads us back to **Putin's Legacy** particularly noting a significant increase in natural gas volatility around the 80'th time period, coinciding with a pronounced spike and subsequent fluctuations experienced by natural gas prices in February 2021. The ensuing instability in prices further supports the notion of natural gas volatility persisting over time, contrasting with the relatively transient nature of oil price fluctuations.

The abrupt decline in oil prices amid the COVID-19 pandemic is clearly depicted in the diagram, with the most pronounced spike in oil volatility occurring shortly before the 80'th time period, which aligns closely with the onset of the pandemic.

Overall, there do seem to be some common trends in the volatilities of the two assets, particularly in their response to significant events or periods of market turbulence. Despite the differences in their inherent characteristics, both oil and natural gas exhibit fluctuations that can be influenced by similar external factors such as geopolitical tensions, economic conditions, and shifts in demand and supply dynamics. Understanding these common trends and their underlying drivers can provide valuable insights for investors and policymakers seeking to navigate the complexities of energy markets and manage associated risks effectively.

Before we go further into our analysis we need to first asses whether the time series are stationary or not, normally we would expect them to be, since we took 1st log differences beforehand, but in order for us to come to the definative conclusion that they are we implement an **Augmented Dickey-Fuller (ADF) test**. The null hypothesis of the ADF is that a unit root is present in the time series, which indicates non-stationarity.

The test statistic of the ADF for oil price volatility came back equal to -6.2418 with a corresponding p-value of **4.6769e-08**. Since the p-value is much smaller than the significance level of 0.05, we can reject the null hypothesis, at a 95% confidence level ,and hence conclude that the time series has a unit root (i.e., it is non-stationary). Therefore, based on the ADF test results, we can conclude that the time series is stationary. For gas price volatility te ADF test statistic came back equalt to **-9.3638** with a corresponding p-value of **7.6966e-16**. Hence once again we can reject the null hypothesis and assume that both time series are stationary at a 95% confidence level.

The table 5 contains the results of the simple OLS regression. Additionally, the subsequent section within the table presents various diagnostic tests and statistics relevant to the model. Namely these diagnostics are the the Omnibus test which evaluates the overall goodness-of-fit of the regression model by examining the skewness and kurtosis of the residuals, with significance indicating potential issues such as non-normality or outliers. The Durbin-Watson statistic assesses autocorrelation in the residuals, where values close to 2 suggest no autocorrelation. The Jarque-Bera (JB) test examines the normality of the residuals, with significance indicating departure from normality. Skewness measures asymmetry, with positive values indicating a longer right tail and negative values indicating a longer left tail. Kurtosis measures the heaviness of the tails, with higher values suggesting more outliers. The Condition Number assesses multicollinearity, with high values indicating high correlation among independent variables and potential instability in parameter estimates. Overall, by evaluating these model diagnostics, we can establish the validity and reliability of our regression results.

Table 5: Regression Results of simple OLS model

	coef	**std err**	t	$P > \|t\|$	**[0.025**	**0.975]**
const	0.0841	0.007	12.784	0.000	0.071	0.097
gas_annualized_volatility	-0.0147	0.024	-0.620	0.536	-0.062	0.032
GECON	-0.0948	0.006	-16.243	0.000	-0.106	-0.083
CPI	-0.0029	0.002	-1.906	0.059	-0.006	0.000
Omnibus:	82.193	**Durbin-Watson:**	0.982			
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	453.361			
Skew:	2.415	**Prob(JB):**	3.58e-99			
Kurtosis:	11.206	**Cond. No.**	25.0			

Note: Results of the OLS regression model estimation for oil price monthly annualized volatility. Coefficients are reported with standard errors, z-values, and p-values. 95% confidence intervals are provided for coefficient estimates.

The results of the OLS regression model estimation for oil price monthly annualized volatility indicate several important findings. Firstly, the intercept term (const) is statistically significant at the 95% confidence level, suggesting that there is a baseline level of volatility in oil prices that is not explained by the independent variables included in the model. Secondly, the coefficient for gas annualized volatility is negative but not statistically significant, indicating that changes in gas prices do not have a significant effect on oil price volatility. Thirdly, the coefficients for GECON and CPI are both statistically significant at the 95% confidence level and have negative values, implying that higher levels of global economic growth (GECON) and consumer price index (CPI) are associated with lower oil price volatility. Finally, the diagnostic tests, such as Omnibus, Durbin-Watson, Jarque-Bera (JB), skewness, and kurtosis, provide insights into the overall fit, autocorrelation, normality, and distribution of residuals in the model. The Cond. No. value indicates the absence of severe multicollinearity issues among the independent variables. Overall, these results suggest that global economic conditions and consumer price levels play a significant role in explaining oil price volatility, while gas prices do not have a statistically significant impact in this particular model.

Since this does not coincide neither with existing literature nor with the movement we can observe in the above grah 3, we will next look at the ARMA(1, 1) model to compare results and delve deeper into the temporal dynamics of oil price volatility. This approach allows us to assess the potential influence of past values of oil prices on current volatility, which has been shown to hold a significant relationship in previous studies.

The followng table 6 presents the results of the ARMA(1, 1) model in the same variables used in OLS:

Table 6: Regression Results using ARMA(1,1) Model

Variable	**Coef**	**Std Err**	**z**	$P > \|t\|$	**[0.025**	**0.975]**
const	0.0911	0.014	6.299	0.000	0.063	0.119
gas_annualized_volatility	-0.0447	0.018	-2.500	0.012	-0.080	-0.010
GECON	-0.0959	0.005	-21.067	0.000	-0.105	-0.087
CPI	-0.0036	0.003	-1.279	0.201	-0.009	0.002
ar.L1	0.5178	0.172	3.018	0.003	0.181	0.854
ma.L1	0.0189	0.185	0.103	0.918	-0.343	0.381
sigma2	0.0010	0.000	9.097	0.000	0.001	0.001
Ljung-Box (L1) (Q)	0.00	**Jarque-Bera (JB)**	1739.03			
Prob(Q)	0.99	**Prob(JB)**	0.00			
Heteroskedasticity (H)	3.77	**Skew**	3.09			
Prob(H) (two-sided)	0.00	**Kurtosis**	20.59			

Results of the ARMA(1, 1) model estimation for oil price monthly annualized volatility. Coefficients are reported with standard errors, z-values, and p-values. 95% confidence intervals are provided for coefficient estimates.

The results from the ARMA(1,1) model indicate that the coefficients of the variables are statistically significant. The constant term has a coefficient of 0.0911 with a standard error of 0.014, suggesting a significant impact on the dependent variable. The coefficient for gas annualized volatility is -0.0447, indicating a negative relationship with the dependent variable something which coencides with the notion of asymetric responses of gas prices to oil price volatility which has already been assessed by previous articles on the subject, although it is only marginally significant (p = 0.012). GECON shows a highly significant negative relationship with a coefficient of -0.0959, indicating that an increase in GECON (improuvement of general economic conditions) leads to a decrease in oil price volatility and hence a relative stabilization of oil prices. However, the coefficient for CPI is not statistically significant (p = 0.201). The AR and MA parameters (ar.L1 and ma.L1) are also estimated, with ar.L1 showing a significant positive relationship, coenciding with existing litterature, specifically **Ewing et al. (2002)** whose work already assessed the fact that oil price volatility is influenced by its own past values. On the other hand ma.L1 is not significant. Additionally, the Ljung-Box test for autocorrelation (L1) and Jarque-Bera test for normality indicate that the model residuals are well-behaved, suggesting no significant issues with autocorrelation or heteroskedasticity. Overall, the ARMA(1,1) model provides valuable insights into the relationship between the variables, with significant coefficients and satisfactory diagnostic tests.

The differences between the results of the OLS and ARMA(1,1) models can be attributed to several factors. OLS assumes independence among observations and a linear relationship between variables, potentially overlooking temporal dependencies and nonlinear patterns present in the data that ARMA(1,1) captures through its autoregressive and moving average components. Moreover, OLS may be sensitive to multicollinearity, while ARMA(1,1) explicitly addresses autocorrelation, offering more stable coefficient estimates. Additionally, differences in error term assumptions between the two models can impact their performance, with ARMA(1,1) providing more flexibility in handling non-normality and heteroscedasticity.

Overall, the ARMA(1, 1) model would be deemed to be a better fit than the simple

OLS, since the presence of temporal dependencies has already been established by previous litterature, and is also reflected in the statistically significant AR(1) components in the model. Additionally the previously computed variance inflation factor of oil price volatility(7.564) has already incenarated possible issues with multicollinearity in the dependent variable something which the ARMA model mittigates through the usage of the MA component. Furthermore, as a final nail in the coffin the results obtained from the ARMA model are more in sink with what the results of existing litterature have already established leading us to conclude the supremacy of the ARMA model against the OLS in the estimations of these particular relationships.

6 Conclusion

In conclusion, the findings from both the simple OLS and ARMA(1,1) models offer valuable insights into the dynamics of oil and natural gas price volatilities. While the OLS model provides a traditional framework for assessing linear relationships, the ARMA(1,1) model incorporates temporal dependencies and captures nonlinear patterns inherent in the data. The significant coefficients and satisfactory diagnostic tests in the ARMA(1,1) model suggest its superiority in explaining the relationships among the variables. However, it's important to acknowledge the limitations of this assignment, recognizing that the results serve as more of a general guideline rather than definitive conclusions. Future research should aim to incorporate additional relevant variables such as unemployment rates or further indexes of global financial well-being. Moreover, employing more sophisticated models like GARCH that account for conditional heteroskedasticity and non-linearity could provide further insights into the complexities of energy markets. Ultimately, by refining our methodologies and expanding the scope of analysis, one can deepen our understanding of the factors driving volatility in oil and natural gas prices.

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