ECO4121 Term Paper
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**The Leverage Effect on Volatility in Brent Crude Oil Spot Prices**

## 1. Introduction

Crude oil has been an important commodity around the globe as it is the raw material of many petroleum products and organic materials. It has contributed to over a third of the world's energy consumption and hence closely related to socio-economic development. Crude oil now has been traded in markets both as spot oil and via derivatives contracts. Its price and volatility have crucial implications for investors, hedgers, speculators, and governments. Brent is considered the global crude oil benchmark (Dowling et al., 2016), thus focusing on Brent prices provides us with a proxy to study the global crude oil price.

The leverage effect or asymmetric effect refers to the relationship between returns and volatility: volatility increases when the stock price falls (Figlewski & Wang, 2000). However, previous literature suggest that the relationship does not always apply to crude oil prices. Zavadska, Morales, and Coughlan (2020) examined the data from 7th December 1988 to 31st December 2013 and divided the data using multiple structural breaks. They found that the leverage effect is not significant during the Gulf war (1990-1991), the Asian financial crisis (1996-2000), and the terrorism attack (2001-2002). Zhang et al. (2008) even found the inverse leverage effect and attributed it mainly to the non-renewable property of the oil and non-trivial supply and demand.

This research is going to update the Brent oil spot price after 2005 and model the spot price level and volatility using ARMA-ARCH type models. The models aim to describe the crude oil spot price evolving pattern and check whether the leverage or asymmetric effect exists in the Brent crude oil spot price.

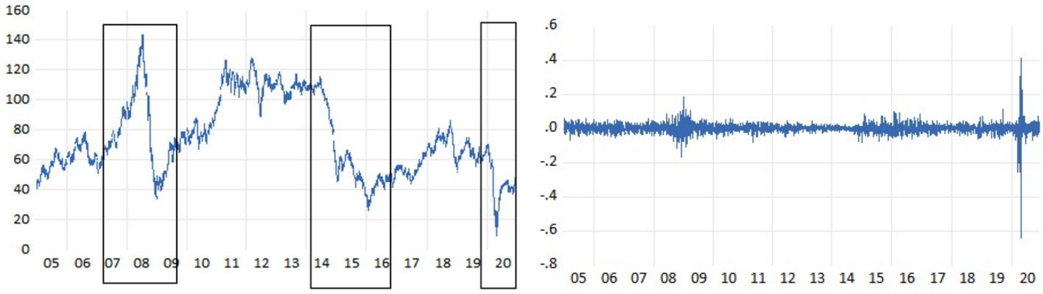
## 2. Data and Methodology

The closing spot prices for the Europe Brent crude oil market were collected on a trading-daily basis from the US Energy Information Administration (EIA) and are shown in US dollars per barrel. The whole data sample spans from 4th Jan 2005 to 30st Nov 2020, which offers 4,030 observations. The inter-day return series {rt} is defined in terms of the close-to-close prices on consecutive trading days.

$$r_t = lnp_{t,close} - lnp_{t-1,close} \quad (1)$$

Fig. 1

*Time series Eviews plot of Brent crude oil prices (left, the columns are drawn by the author) and daily return (right)*




Note: 2007-2009: Global Financial Crisis; 2014-2015: Russian Financial Crisis; 2020: Global Pandemic

The study begins with an analysis of the properties of the price data series. It is followed by the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. As shown in Table 1, the inter-day return series is tested to be stationary while the daily price series did not pass the test.

Table 1

*Unit root and stationary tests*

| Variable | ADF | PP |
|---|---|---|
| $p_t$ | -0.5610 | -0.6213 |
| $r_t$ | $-14.4463^{***}$ | $-64.7659^{***}$ |

Note: ADF and PP statistics adopt t-Statistic for judgment, and $^{***}$ indicates statistical significance at the 1 percent level of significance.

This is followed by the level modeling by autoregressive moving average (ARMA) equations and volatility modeling using the generalized autoregressive conditional heteroskedasticity (GARCH) and threshold-GARCH (T-GARCH) strategies.

## 2.1 ARMA modeling

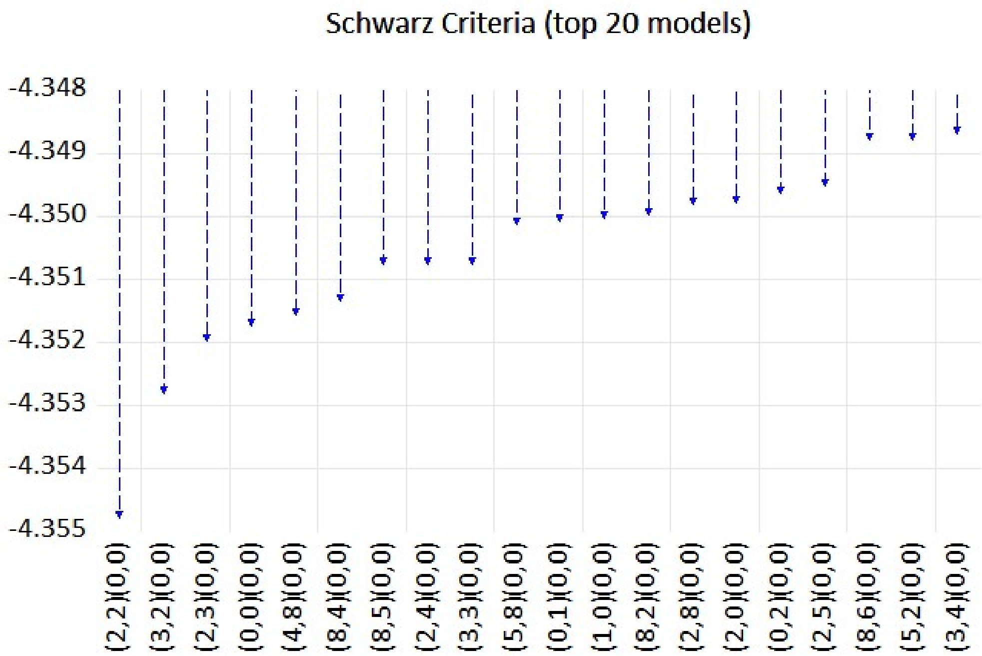
ARMA model is very important in modeling time-series data (Pourahmadi, 1992). Generally, suitable parameters are specified for ARMA (p, q), where p is the dimension of the autoregressive component, and q is the dimension of the moving average component of the model (Ives et al., 2010). The ARMA model of order (p, q) for the level of inter-day return can be expressed as follows (Box and Jenkins, 1976):

$$r_t = \mu + \sum_{i=1}^{p} \phi_i \, r_{t-i} + \sum_{j=1}^{q} \psi_j \, \varepsilon_{t-j} \quad (2)$$

Regarding the data sample in this study, a recursive algorithm is used and the suitable model is selected according to Schwarz (1978) Information Criterion (SIC). Fig. 2 shows the best 20 ARMA model specifications and ARMA (2,2) is shown to be the best.

Fig. 2

*Best 20 ARMA model specifications according to Schwarz Criteria*




2.2 ARCH-type modeling

The ARCH model was presented by Engle (1982) suggesting that the variance of the residuals at the time $t$ depends on the squared error terms from past periods. This study makes use of the GARCH model presented by Bollerslev (1986) and the T-GARCH model by Zakoian (1994) to model the volatility. The GARCH (p, q) is presented as follows:

$$r_t = \alpha + \beta' x_t + \varepsilon_t \quad (3)$$

where, $\varepsilon_t|\Omega_t{\sim}iid\ N(0, h_{t)}$, and

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i h_{t-i} + \sum_{j=1}^{q} \gamma_{j\varepsilon_{t-j}^2} \quad (4)$$

The simplest form of the GARCH model is the GARCH (1, 1), which is commonly used in research in oil markets, as it is generally simpler and of better performance (Salisu & Fasanya, 2013).

To include the leverage or asymmetric effect in our analysis, T-GARCH (1,1) is employed. The variance equation is specified as follows:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \theta\varepsilon_{t-1}^2 d_{t-1} + \beta h_{t-1} \quad (5)$$

where, $d_t$ takes the value of 1 when $\varepsilon_t$ is smaller than 0, and 0 otherwise. This implies that positive and negative shocks have heterogeneous effects. Positive shocks take an impact of $\alpha$, while negative shocks have an impact of $\alpha + \theta$.

## 3. Empirical results

As shown in Table 2, the coefficients of the ARCH- and GARCH-term in Model (2) are significant. The data series shows strong evidence of volatility clustering, where large changes in level tend to cluster together, which is consistent with existing literature (Charles and Darné, 2014). The statistical result verifies the evident volatility spikes during the negative shocks like the global financial crisis (2007-2009); Russian financial crisis (2014-2015), and global pandemic (2020), as shown in Fig. 1.

The coefficient before the threshold term is positive and significant in model (3). The value of the coefficient implies that on average, negative shocks increase the crude oil inter-day return volatility 0.0902 more than the impact of positive shocks, which is 0.0274. The finding that negative news has a larger impact on the volatility of oil than good news is consistent with the findings of Salisu and Fasanya (2013).

Table 2

*Estimation results*

| | (1) | (2) | (3) |
|---|---|---|---|
| | ARMA | ARMA-GARCH | ARMA-TGARCH |
| Variable | $r_t$ | $r_t$ | $r_t$ |
| $\phi_1$ | 0.2698$^{***}$ | 1.9700$^{***}$ | 0.0701 |
| | (0.0173) | (0.0013) | (0.3075) |
| $\phi_2$ | -0.9251$^{***}$ | -0.9968$^{***}$ | 0.6620$^{**}$ |
| | (0.0175) | (0.0012) | (0.2796) |
| $\psi_1$ | -0.2979$^{***}$ | -1.9705$^{***}$ | -0.0495 |
| | (0.0184) | (0.0005) | (0.3064) |
| $\psi_2$ | 0.9003$^{***}$ | 0.9978$^{***}$ | -0.6538$^{**}$ |
| | (0.0203) | (0.0003) | (0.2745) |
| $\alpha$ | | 0.0852$^{***}$ | 0.0274$^{***}$ |
| | | (0.0044) | (0.0058) |
| $\beta$ | | 0.9120$^{***}$ | 0.9217$^{***}$ |
| | | (0.0047) | (0.0044) |
| $\omega$ | | 4.E-06$^{***}$ | 4.E-06$^{***}$ |
| | | (8.E-07) | (7.E-07) |
| $\theta$ | | | 0.0902$^{***}$ |
| | | | (0.0079) |

Note: $\mu, \phi_1, \phi_2, \psi_1, \psi_2$ are the parameters of ARMA (2,2), defined in Eq. (2); $\alpha, \beta, \omega, \theta$ are parameters of ARCH-type models specified in Eq. (3) (4) (5); $^{***}$, $^{**}$ indicate that the statistical significance at the 1 and 5 percent level of significance, respectively.

## 4. Conclusion

In the paper, we investigate the inter-day return volatility pattern of Brent oil spot price using the updated data from 2005 to Nov 2020. The study finds volatility clustering behavior which is consistent with the previous study. As for the leverage or asymmetric effect where there exist contradictory results in different literature, this study verifies that there is a positive leverage effect in the inter-day return volatility where volatility increases when the stock price falls.

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