THE VOLATILITY OF WORLD CRUDE OIL PRICES

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Abstract

The role of oil in an economy is very crucial. This article measures the world oil price uncertainty based on conditional standard deviations. It focuses on the volatility of crude oil price in United Kingdom, Texas, and Dubai markets, from January, 1980 to May, 2010. It finds the evidence that asymmetric leverage effects are not found. It also finds that volatility process in returns to its mean only evidenced in Dubai. These findings have some important implications for Indonesia. The government might use the dynamic of oil price in Dubai market as a benchmark to set up its state budget to realize fiscal sustainability.

Keywords: Oil price, volatility, asymmetric leverage, fiscal sustainability
JEL classification numbers: C22, Q43

Abstrak

Peran minyak dalam ekonomi adalah sangat penting. Artikel ini mengukur ketidakpastian harga minyak dunia berdasarkan pada standar deviasi bersyarat. Artikel ini berfokus pada volatilitas harga minyak mentah di pasar Inggris, Texas, dan Dubai, selama periode Januari 1980 sampai Mei 2010. Hasil analisis menemukan bukti bahwa dampak *leverage* yang asimetris tidak ditemukan. Hasil analis juga menemukan bahwa proses volatilitas return terhadap rata-ratanya hanya terjadi di Dubai. Temuan ini memiliki beberapa implikasi penting bagi Indonesia. Pemerintah dapat menggunakan dinamika harga minyak di pasar Dubai sebagai patokan untuk mengatur anggaran negara dalam rangka mewujudkan kesinambungan fiskal.

Keywords: Harga minyak, volatilitas, asymmetric leverage, fiskal berkesinambungan
JEL classification numbers: C22, Q43

INTRODUCTION

Oil is arguably the most influential physical commodity in the world and plays a prominent role in an economy. It is not a surprise, therefore, that the price of oil changes attracts a considerable degree of attention for many decades. Various attempts have been undertaken to explain the behaviour of the oil price as well as to assess the macroeconomic consequences of oil price shocks especially since oil crisis in 1970s.

The oil price shocks was repeated in early 2000s. The wide price fluctuations in 2000s, when crude oil price index has increased 272 percent between January 2000 and March 2008, and fluctuations by more than USD 20 a barrel in mid 2008 reinforce the idea that oil prices are volatile. The lates one, in early February 2011, the world oil price touched USD100 per barrel.

The volatility of oil prices has prompted governments, especially in developing countries, to intervene in the oil market in various ways. Most countries in the world have been conducting some policies including price-smoothing schemes for end users, fuel tax adjustments, price controls, and subsidies for lower income class, or even incentives for diversification away from oil.

At the same period, the world witnessed the most marked commodity price boom of the past century. The price of metals, food grains, and other commodities rose sharply, and over a sustained period. Like commodity booms in earlier decade, this one was associated with strong global growth, but was exceptional in its duration and in the range of commodities affected. By mid 2008, metals and minerals were 296 percent higher and internationally traded food prices 138 percent higher — mainly due to higher grain prices.

The high food commodity and oil prices have significant political impacts. Haiti, for example, faced serious internal governmental problems. China, Vietnam, and India imposed some protections to their international trades. Indonesia, among others, desired to develop the national food and energy security (Sugiyanto, 2008). Coupled with the financial crisis that erupted in September 2008 and the subsequent global economic downturn, some developing countries have suffered dramatic increase in poverty incidence (World Bank, 2009).

The recent sharp increase in oil price raises the question as to the nature i.e. permanent or temporary. Knowledge of oil price fluctuation under market-oriented energy policy is very important. The greater oil price volatility would increase a household's income risk and a potential output loss for business. For the government, the greater oil price volatility would increase subsidies. In short, the oil price shocks would deteriorate the whole economy by meant various channels (Rodriguez and Sanchez, 2005).

In the case of Indonesia, oil price is set by the government. It is under government subsidy since 1970s. Despite the fact that Indonesia is exporting oil, the country also imports oil from other countries. The surplus of importing value over the exporting value makes Indonesia a net oil importing country. Despite these facts, the repercussions from price increase in the world market could not be avoided from spillover to the local market.

Being a government control item, the event of oil price surge has inflicted a soaring fuel subsidy bill to the government. This situation pressured the Indonesia's government to review its policy on oil prices and finally decides implement oil price increase in the local market. The government's decision to slowly liberalize the local oil market has triggered mixed responses from the public, particularly households and business units.

The main objective of this paper is to understand the nature of dependence of the conditional variance on past volatility in oil prices. The conditional standard deviation is interpreted as a measure of uncertainty. The rest of this paper proceeds as follows. The next section describes the oil prices behaviour. This is followed by exploring previous empirical evidences. The methodological framework and the data are delivered in the proceeding section; the penultimate section discusses empirical results; and the last section concludes and points to some directions for future research. Some policy implications for Indonesia are also drawn.

Oil Prices Fluctuation

The world oil price fluctuation has very long history. Crude oil prices behave much as any other commodity with wide price swings in times of shortage or oversupply. The crude oil price cycle may extend over several years responding to changes in demand as well as OPEC and non-OPEC supply. Table 1 below presents some major factors that have influenced the world oil markets and therefore the oil price.

Let us start explaining the oil price dynamics within 1970s. In 1972, the price of crude oil was about USD 3.00 per barrel, increased 50 percent compared to the beginning decade. By the end of 1974, the price of oil had quadrupled to over USD 12.00. After embargo, the world crude oil price was relatively flat ranging from USD 12.21 per barrel to USD 13.55 per barrel.

Table 1: Some Major Influencing Factors on the World Oil Markets and Oil Price

No.	Year	Moment
1	1973-1974	• Oil embargo began (October 19-20, 1973) • Oil embargo ended (March 18, 1974)
2	1979-1982	• Iranian revolution; Shah deposed • OPEC raised prices 14.5% on April 1, 1979 and OPEC raised prices 15% • Iran took hostages; President Carter halted imports from Iran • Saudis raised marker crude price from 19 $/bbl to 26 $/bbl • Kuwait, Iran, and Libya production cut drop OPEC oil production to 27 million b/d • Saudi Light raised to USD 28/bbl, Saudi Light raised to USD 34/bbl • First major fighting in Iran-Iraq War
3	1983-1986	• Libya initiated discounts • OPEC cut prices by USD 5/bbl and agreed to 17.5 million b/d output • Norway, United Kingdom, and Nigeria cut prices • OPEC accord cut Saudi Light price to USD 28/bbl
4	1990-1991	• Iraq invaded Kuwait • Operation Desert Storm began • Persian Gulf war ended
5	1996-2001	• U.S. launched cruise missile attacked into southern Iraq following an Iraqi supported invasion of Kurdish safe haven areas in northern Iraq. • Prices rose as Iraq's refusal to allow United Nations weapons inspectors into "sensitive" sites raises tensions in the oil-rich Middle East. • OPEC raised its production ceiling. This was the first increase in 4 years. • World oil supply increased by 2.25 million barrels per day in 1997, the largest annual increase since 1988. • Oil prices continued to plummet as increased production from Iraq coincides with no growth in Asian oil demand due to the Asian economic crisis and increases in world oil inventories following two unusually warm winters. • Oil prices tripled between January 1999 and September 2000 due to strong world oil demand, OPEC oil production cutbacks, and other factors, including weather and low oil stock levels. • Oil prices fell due to weak world demand (largely as a result of economic recession in the United States) and OPEC overproduction. • Oil prices declined sharply following the September 11, 2001 terrorist attacks on the United States, largely on increased fears of a sharper worldwide economic downturn (and therefore sharply lower oil demand).
6	2002-2010	• Political instability within various oil producing nations • Rising costs of oil • Speculator entered the oil market • Global financial crisis • European sovereign debt crisis

Source: http://www.eia.doe.gov/emeu/cabs/chron.html, http://www.wtrg.com and Kuper (2002)

In 1979 and 1980, events in Iran and Iraq led to another round of crude oil price increases. The Iranian revolution resulted in the loss of 2 to 2.5 million barrels per day of oil production between November 1978 and June 1979. The combination of the Iranian revolution and the Iraq-Iran War caused crude oil prices to more than double increasing from USD 14 in 1978 to USD 35 per barrel in 1981.

From 1982 to 1985, OPEC attempted to set production quotas low enough to stabilize prices. These attempts met with repeated failure as various members of OPEC produced beyond their quotas. During most of this period, Saudi Arabia acted as the swing producer cutting its production in an attempt to stem the free fall in prices. Crude oil prices plummeted below USD 10 per barrel by mid-1986 in accordance with world economic recession.

The price of crude oil spiked in 1990 with the lower production and uncertainty associated with the Iraqi invasion of Kuwait and the ensuing Gulf War. From 1990 to 1997 world oil consumption increased 6.2 million barrels per day. Asian consumption accounted for all but 300,000 barrels per day of that gain and contributed to a price recovery that extended into 1997. Declining Russian production contributed to the price recovery.

The price increases came to a rapid end in 1997 and 1998 when the impact of the economic crisis in Asia was either ignored or severely underestimated by OPEC. In December, 1997 OPEC increased its quota by 2.5 million barrels per day (10 percent) to 27.5 MMBPD effective January 1, 1998. The rapid growth in Asian economies had come to a halt. In 1998 Asian Pacific oil consumption declined for the first time since 1982. The combination of lower consumption and higher OPEC production sent prices into a downward spiral. In response, OPEC cut quotas by 1.25 million b/d in April and another 1.335 million in July. Price continued down through December 1998.

With minimal Y2K problems and growing US and world economies the price continued to rise throughout 2000. Russian production increases dominated non-OPEC production growth from 2000 forward and was responsible for most of the non-OPEC increase since the turn of the century. In the absence of the September 11, 2001 terrorist attack this would have been sufficient to moderate or even reverse the trend. In the wake of the attack crude oil prices plummeted. Spot prices for the U.S. benchmark West Texas Intermediate were down 35 percent by the middle of November. The oil prices were moving into the USD 25 range by March, 2002.

During much of 2004 and 2005 the spare capacity to produce oil was under a million barrels per day. A million barrels per day is not enough spare capacity to cover an interruption of supply from most OPEC producers. In a world that consumes over 80 million barrels per day of petroleum products that added a significant risk premium to crude oil price and was largely responsible for prices in excess of USD 40-50 per barrel.

Throughout the first half of 2008, oil regularly reached record high prices. On February 29, 2008, oil prices peaked at USD 103.05 per barrel, and reached USD 110.20 on March 12, 2008, the sixth record in seven trading days. Prices on June 27, 2008, touched USD 141.71/barrel, for August delivery in the New York Mercantile Exchange (after the recent USD 140.56/barrel), In January 2009, oil prices rose temporarily because of tensions in the Gaza Strip. From mid January to February 13, oil fell to near USD 35 a barrel. As of May 2010, crude oil prices have started to decline again due to the 2010 European sovereign debt crisis. On May 17, 2010 the price for a barrel of crude oil fell below USD 70 a barrel to USD 69.41.

While the evolution of commodity prices is relatively stable, that of oil prices is more volatile (Reigner, 2007). Various attempts to explain the behaviour of the oil price have been undertaken in the past few years. Three main approaches can be identified in this vast literature: first, Hotelling's (1931) notion of oil as exhaustible resource; second the ascertainment that the global macroeconomic situation is an important factor, and, thirdly, the notion that additional factors such as OPEC announcements as well as speculation affect the price of oil.

Regarding the first approach, Hotelling's (1931) seminal paper proposes the notion that oil is exhaustible and that the price of oil, in optimum, grows at the rate of interest. Various extensions of this rule have been suggested and are still subject of scientific debates, see e.g. Sinn (2008). In particular Krautkraemer (1998), however, provides evidence of frequent failure of empirically testing Hotelling-type hypotheses. Dvir and Rogoff (2009) epitomize this skepticism: they apply the storage rather than a Hotelling resource extraction model in order to model oil price behaviour.

Papers such as Slade (1982) and Pindyck (1999) deal with oil price behaviour in the very long run. These papers deal with the question as to whether the price of oil follows a deterministic trend. While Slade (1982) finds evidence of quadratic trends in real oil prices, Pindyck (1999) argues that the oil price fluctuates around a long-run trend. The trend itself is - due to changes in demand, extraction costs and new site discoveries – stochastically fluctuating over time. Livornis (2009) provides an excellent survey of this literature and expresses a less pessimistic view on the significance of the Hotelling rule.

In contrast to this line of research, Krichene (2002) and Dees et al. (2007) argue that the price of oil is determined by global economic conditions and employ demand and supply frameworks in order to explain the oil price. Krichene (2002) uses a structural multiple equation model of the global oil market and focuses on the calculation of demand and supply elasticity. Among the more salient findings of this paper is that short-run demand and supply of oil is very price inelastic and that long-run oil supply elasticity significantly decreased after the first oil crisis 1973/74.

Dees et al. (2008), in contrast, use a country-by country approach and explicitly incorporate geological factors as well as OPEC behaviour in their oil supply function. The model is generally able to reproduce responses of the global oil market to changes in OPEC behaviour. The papers by Kaufmann et al. (2004) and Dees et al. (2008) also focus on the role of OPEC behaviour, but do not explicitly model oil supply. Both papers make use of an error correction approach and show that variables such as OPEC capacity utilization and OPEC quotas Granger cause real oil prices but not vice versa.

While these results are more of very general character, Kaufman and Ullmann (2009) show that the 2008 oil price hike can be explained by a combination of fundamental factors and speculative behaviour, and Miller and Ratti (2009), finally, provide evidence of the existence of oil price bubbles.

The unstable world oil price pumps dozen empirical studies dealing with its impacts on economic activity in all aspects. Sadorsky (1999), among others, tested the relationship between oil price and stock market. In developing countries, Sari (2006) simultaneously examined the link of oil price, stock returns, interest rates, and output in Turkey. Gronwald et al. (2009) analyzed the oil price fluctuation in Kazakhstan related to economic growth. Mohammad (2010) observed the impact of oil prices volatility on export earning in Pakistan. Aliyu (2009) connected the oil price to exchange and inflation rates in Nigeria. In general the found a negative impact generated from oil price volatility.

Bacon and Kojima (2008) investigated the degree of oil price volatility Ghana, Chile, India, Philippine, and Thailand during July 1999-March 2007. They observed some adverse impacts on exchange rates and fiscal condition. Dealing with world oil price fluctuation, they point out some policies including the role of hedging, strategic stocks, price-smoothing scheme, and reducing the importance of oil consumption to achieve energy security.

In the case of Indonesia, the world crude oil price is used as basic assumption to set up budget state in current year. Kuncoro (2010) found that the increase in oil price marginally induces fiscal stance for about 0.02 percent. His study implied that the primary balance surplus is vulnerable to maintain fiscal sustainability. This finding would suggest that price smoothing based on long-term trends would have imposed a considerable fiscal drain.

To summarize, the price of oil is affected by numerous factors and subject to a considerable degree of volatility. Hamilton (2008) nicely summarizes these findings: "Changes in the real price of oil have historically tended to be permanent, difficult to predict, and governed by very different regimes at different points in time". Thus, deriving future predictions is a very difficult task. In any case, expecting the oil price to begin a stable increase in the near future would definitely be hazardous.

METHODS

The brief literature review above suggests the potential for some interesting hypotheses about potential linkages among energy commodities, macroeconomic variables, and more importantly dependency across energy markets. The purpose of this section is to develop an analytical framework within which these can be clearly stated as a set of formal propositions. We focus on the oil market.

From an econometric point of view, neglecting the exact nature of the dependence of the variance of the error term conditional on past volatility will result in loss of efficiency. The ARCH models are developed to model time-varying conditional variances (see Bollerslev et al., 1994). ARCH models consist basically of two equations, one for the mean and one for the conditional variance. The mean equation can be univariate or may contain other variables (multivariate). GARCH model addresses the issues of heteroscedasticity and volatility clustering by specifying the conditional variance to be linearly dependent on the past behaviour of the squared residuals and a moving average of past conditional variance. Formally, the model can be expressed as follows:

$$y_t = \beta x_t + \varepsilon_t \tag{1}$$

The mean equation may also include the conditional variance or the conditional standard deviation (ARCH-in-Mean models). The specification for the conditional variance may allow for asymmetric effects. Here we start with a symmetric univariate specification.

In applications using monthly data the error variance depends on past volatilities going back a number of periods. For these applications GARCH (Generalised ARCH) models are developed. The GARCH model depicts conditional variance of a price series to depend on a constant, past news about volatility and the past forecast variance. The GARCH(p,q) model has p ARCH terms and q GARCH terms (the values of p and q are determined by the Schwarz Information Criterion):

$$\sigma_t^2 = \omega + \alpha \sum \varepsilon_{t-p}^2 + \beta \sum \sigma_{t-q}^2 \tag{2}$$

It is commonly assumed that the innovations ε_t are Gaussian. If this assumption is violated the usual standard errors are not consistent and the quasi-maximum likelihood covariances and standard errors described by Bollerslev and Wooldridge (1992) have to be used.

The simplest GARCH model is the GARCH(1,1) model that in many applications provides a good description of the data. The error variance depends on all past volatilities with geometrically declining weights as long as $\beta_t < 1$. Well-defined conditional variances require that the parameters ω, α, β are non-negative. In many applications the estimates for $\alpha + \beta$ in the GARCH(1,1) model are close to unity, which means that the model is not covariance stationary. In that case the model can be used only to describe short-term volatility.

It is notable that in the symmetrical model, the conditional variance is a function of the size and not of the sign of lagged residuals. One way to allow for asymmetries is the Threshold GARCH (TARCH) model:

$$\sigma_t^2 = \omega + \alpha \sum \varepsilon_{t-p}^2 + \beta \sum \sigma_{t-q}^2 + \gamma \delta \varepsilon_{t-p}^2 \quad (3)$$

where $\delta = 1$ if $\varepsilon_t < 0$, and 0 otherwise.

An alternative and popular model that allows for asymmetric shocks to volatility is the Exponential GARCH (EGARCH) model:

$$\begin{aligned} \ln(\sigma_t^2) &= \omega + \alpha \sum \left| \varepsilon / \sigma \right|_{t-p} \\ &\quad + \beta \sum \ln(\sigma_{t-q}^2) + \gamma [\varepsilon / \sigma]_{t-p} \end{aligned} \quad (4)$$

The coefficient γ in the last term of equations (3) and (4) measures the leverage effects. In theory there may be many leverage effects, Eviews only allows for one. In this model, good news ($\varepsilon_t < 0$) and bad news ($\varepsilon_t > 0$) have different effects on the conditional variance. Good news has an impact of α, while bad news has an impact of $(\alpha + \gamma)$.

According to Swaray (2002), the strength of ARCH-class models as compared with time-series models, lie in their ability to allow the conditional variance of underlying processes to vary over time. Also the information that is used in forming conditional expectations is similar to that used to predict the conditional mean (i.e. variables observed in previous periods). Hence, the GARCH model maintains the desirable forecasting properties of a traditional time-series but extends them to the conditional variance (Holt & Aradhyula, 1990).

RESULTS DISCUSSION

Data of world crude oil prices are presented by UK Brent (light blend), WTI Midland Texas, and Dubai (medium) in USD per barrel (fob). The sample periods chosen for this study extend from January 1980 to the May 2010. The total observation is 365 sample points. The data are provided by the International Financial Statistics (IFS) online service (International Monetary Funds, 2010). The raw data are then transformed into first log-differenced to obtain volatility measurement. Figure 1 delivers the crude oil prices volatility in three markets.

Table 2 presents the elementary statistics covering mean, median, and extreme values. The average of first log-differenced is close to each other, around 2 percent for the three markets. However, the median values are far enough from the respective mean especially in Texas and Dubai. Similarly, the absolute (maximum and minimum) values are not identical to each other. Those preliminary indicate non normal distribution. We will re-check more convincingly later.

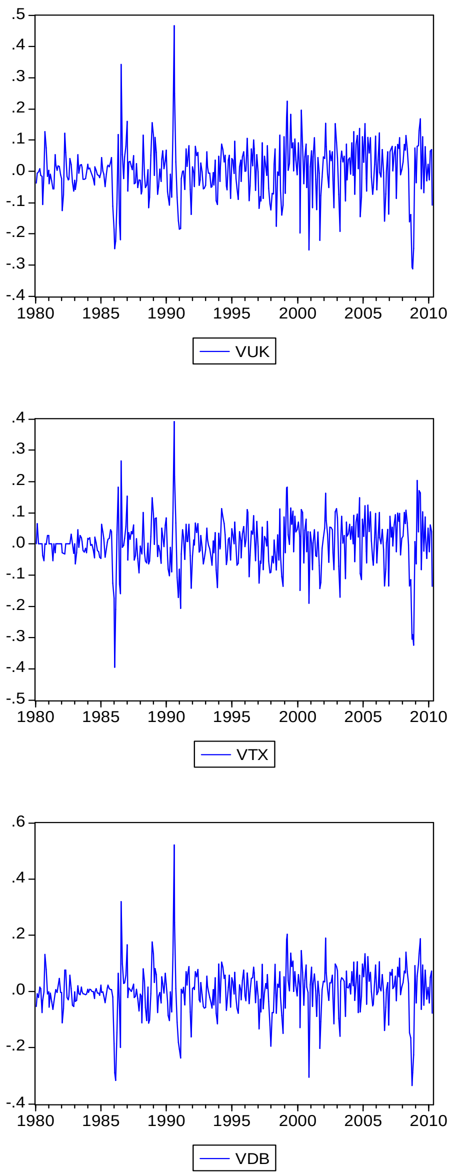
The Table also delivers standard deviation ranging from 0.082 to 0.089. Statistically, a set data is said to be relatively volatile if its CV (ratio of standard deviation to its mean) is more than 50 percent. Based on the empirical rule, the crude oil price in UK is the most volatile indicated by the highest CV, followed by that in Dubai and Texas markets. This finding supports to the theoretical background in the previous section that the oil prices are not stable.

The log-differenced oil prices are asymmetrically distributed (bell-shaped) indicated by the high value of Jarque-Bera tests. The null hypotheses that the series data is normally distributed can be rejected in 95 percent confidence level. The lower tail of the distribution is thicker than the upper tail (indicated by the negative values of skewness in Texas and Dubai) and the tails of the distribution are thicker than the normal (indicated by the kurtosis coefficient greater than the thick tails can be modelled by assuming a "conditional" normal distribution for returns; where conditional normality implies that returns are normally distributed on each month, but that the parameters of the distribution change from month to month. Also, as evidenced in Table 2, the volatility (standard deviation) of oil price returns exhibits "clustering" i.e. bursts of high volatility separated by periods of relative tranquility.

The correllograms of the log-differenced oil prices and of the squared log-differenced oil prices for 12 lags suggests strong dependence in the mean of variance. There is only a few insignificant in the longer lags but substantial dependence in the volatility. This time-varying nature of variance is referred to in statistics as heteroscedasticty. The persistence of volatility is an indication of autocorrelation in variances.

The Ljung-Box *Q*-statistic test can be used to check for autocorrelation in variance. Under the null hypothesis that a time series is not autocorrelated, $Q(p)$ is distributed $\chi^2(p)$, where p denotes the number of autocorrelations used to estimate the statistic. For p = 12, the $Q(p)$ statistic for squared oil price returns is 53.3, 58.7, and 94.8 respectively, which rejects the hypothesis that variances of monthly returns are not autocorrelated. They seem that the price volatility in the three oil markets is persistent at least in one year.

The price volatility in the three oil markets typically is indifferent each other presented by the correlation matrices. The correlation is high even close to unity. The highest oil price volatility correlation is more than 0.94 between Dubai and UK. The oil price volatility in Dubai market is lowest correlated with that in Texas (0.89) compared to the others. The long distance between Dubai and Texas might be the source of explanation.



Source: Data processed.

Figure 1: Crude Oil Prices Volatility

Table 2: Descriptive Statistics

	VUK	*VTX*	*VDB*
Mean	0.001772	0.001894	0.001936
Median	0.001748	0.000287	0.005566
Maximum	0.466400	0.391112	0.521421
Minimum	-0.313472	-0.395148	-0.335434
Std. Dev.	0.089002	0.081742	0.086547
Skewness	0.042534	-0.393327	-0.026617
Kurtosis	5.926260	6.838412	8.323111
Jarque-Bera	129.9819	232.8422	429.7982
Probability	0.000000	0.000000	0.000000
CV (%)	5022.69	4315.84	4470.40

Source: Data calculation.

Table 3: Causality Test

Null Hypothesis:	Obs	F-Statistic	Probability
VTX does not Granger Cause *VUK*	352	1.80577	0.04616
VUK does not Granger Cause *VTX*		1.66045	0.07431
VDB does not Granger Cause *VUK*	352	1.28950	0.22293
VUK does not Granger Cause *VDB*		0.70846	0.74325
VDB does not Granger Cause *VTX*	352	1.61119	0.08687
VTX does not Granger Cause *VDB*		1.78951	0.04874

Source: Data estimation.

Correlation does not necessary present causation. The traditional Granger test could be employed to identify the direction of causality. The test is done for 12 lags as suggested from partial autocorrelation. Table 3 identifies how great the oil price volatility in one market affects to the oil price volatility in the other markets. Regardless to the significance, Table 3 preliminary suggest the existence of oil price volatility co-movement.

Does the high volatility of the data mean non stationary? Table 4 shows the results of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests for the underlying data series in levels and first differences. According to Swaray (2002) the Phillips–Perron (PP) test can be more appropriate in this case because of the evidence of heteroscedasticity assumed in the error process of the price series examined. We assume that the level of the oil price is not stationary.

Formal unit-root tests (including a constant, no trend, and 12 lags) to log-oil price data reject the hypothesis of a unit root at 5% (the ADF test statistic equals -1.7, 5% critical value equals –2.8693). The similar results are obtained by implementing PP unit root tests. However, these tests have only little power if errors are not homogeneous (Kim and Schmidt, 1993). Furthermore, the power of unit root tests depends more on the span of the data, which in our case is only 30 years, than on the number of observations (Perron and Shiller, 1985). Moreover, the presence of structural breaks reduces the power of unit root tests also (Perron, 1989). More details on unit roots, structural breaks, and trends can be found in Stock (1994).

The same method imposed to the log-differenced oil price data gives the opposite conclusion. The ADF test statistic equals from -13.1 to -14.6 and the PP test statistic ranges from -12.3 to 14.2 implying the series data have a unit roots. The occurrence of unit roots in the price series of these commodities gives a preliminary indication of shocks having permanent or long lasting effect, thus making it very difficult for traditional price stabilization policies to survive.

Stationary is required to perform co-integration. Co-integration is an important concept to analyze the data behaviour. Using Johansen's maximum likelihood approach (Johansen, 1988; 1991), we test the bivariate among the three oil price markets volatility with 4 lags in all the cases. The trace and Max-Eigen value (λ *max*) statistics for testing the rank of co-integration are shown in Table 5.

The results of both tests deny the absence of co-integrating relation oil prices volatility series. Furthermore, both tests suggest the presence of one co-integrating equation at 5 percent level or better between the non stationary prices of crude oil which means that the linear combinations of them are stationary and, consequently, prices tend to move towards this equilibrium relationship in the long-run. This is complement to the result of correlation and causality analysis.

Furthermore, does the stationary of oil prices change imply that it will return to its mean value? The following section presents empirical results for a monthly time series data. The results of GARCH estimation model will clearly answer this question. The Schwarz Information Criterion for GARCH model suggests that $\alpha = 1$ and $\beta = 1$. The GARCH model results are in Table 6.

The ARCH Lagrange Multiplier test indicates that there is no autoregressive conditional heteroscedasticity up to order 12 in the residuals. An alternative test is the Ljung-Box Q-statistic of the standardized squared residuals. At the twentieth lag Q equals from 7.4 to 13.8, indicating that the standardized squared residuals are serially uncorrelated. From these tests, we conclude that the GARCH volatility model is adequate.

Table 4: Unit Root Tests

	ADF Test		PP Test	
Level	*t*-stat	5% level	*t*-stat	5% level
Log (OP UK)	-1.676441	-2.869285	-1.459409	-2.869263
Log (OP TX)	-1.766282	-2.869285	-1.450294	-2.869263
Log (OP DB)	-1.771291	2.869285	-1.272295	2.869263
First log-diff.	t-stat	5% level	t-stat	5% level
VUK	-14.64803	-2.869285	-14.19856	-2.869285
VTX	-13.78728	-2.869285	13.25763	-2.869285
VDB	-13.09016	-2.869285	12.28922	-2.869285

Source: Data estimation.

Table 5: Multiple Co-integration Tests

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.315899	313.6462	29.68	35.65
At most 1 **	0.246502	177.3519	15.41	20.04
At most 2 **	0.190216	75.7447	3.76	6.65

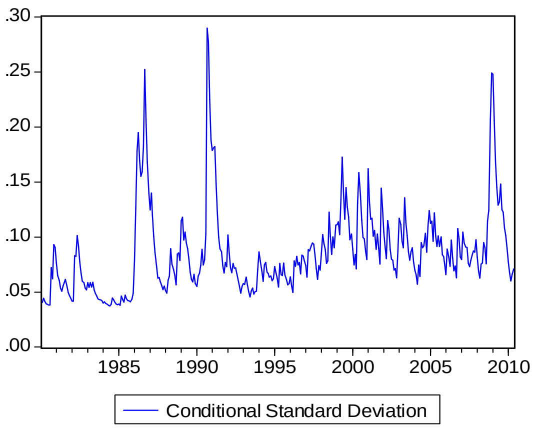
Notes: (1) *(**) denotes rejection of the hypothesis at the 5%(1%) level, (2) Trace test indicates 3 cointegrating equation(s) at both 5% and 1% levels.
Source: Data estimation.

Table 6: GARCH Model Estimates

	VUK		*VTX*		*VDB*	
	Coeff.	*Z*-stat	Coeff.	*Z*-stat	Coeff.	*Z*-stat
Constant	-0.002380	-0.67879	-0.003018	-1.25735	0.005142	1.25949
ω	0.000450	3.25528	0.000106	1.64696	0.003935	10.52062
α	0.348587	6.75545	0.351480	7.23237	0.501573	7.96304
β	0.647337	13.07202	0.703594	17.81267	-0.022678	-0.39833
Diag. test	Value	Prob.	Value	Prob.	Value	Prob.
$\alpha + \beta = 1$	0.01415	0.9054	3.57608	0.0594	42.0631	0.0000
	0.01415	0.9053	3.57608	0.0586	42.0631	0.0000
J-B test	20.70801	0.0000	15.70913	0.0000	132.11880	0.0000
ARCH	0.97428	0.47312	0.73163	0.72034	1.04797	0.40418
LM(12)	11.73505	0.46719	8.88609	0.71263	12.59086	0.39947
Q(12)	11.3580	0.4980	7.4229	0.8289	13.8170	0.3130

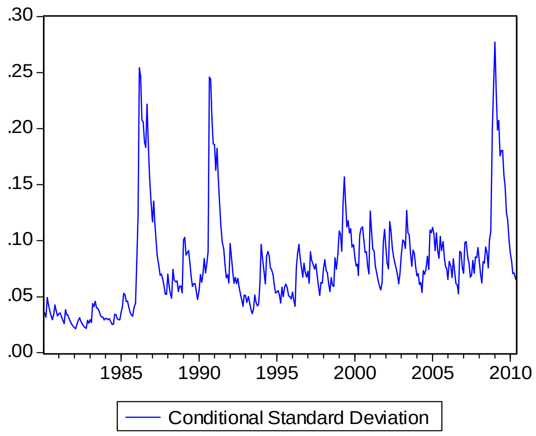
Source: Data estimation.

The Wald test for ($\alpha + \beta = 1$) clearly indicates that the volatility process does not return to its mean mainly in UK and Texas. The *F* and χ^2 values are 0.01 for UK and 0.06 for Texas respectively. Those are enough to reject the null hypotheses that ($\alpha + \beta = 1$). For Dubai, the coefficient β even is insignificant. The *F* and χ^2 values are quite greater to accept the null hypotheses. This means that the model can be used only to describe short-term volatility especially in UK and Texas in order to predict in the near future.



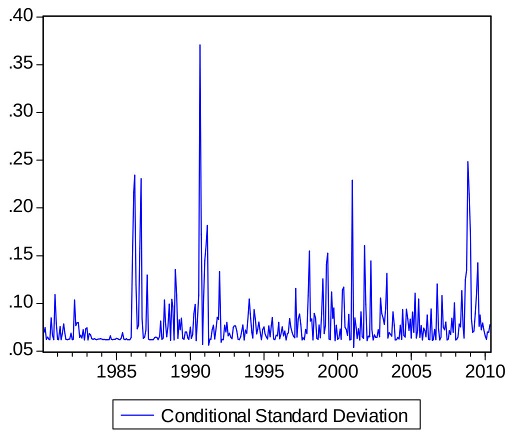
Source: Data processed

Figure 2a: Conditional Standard Deviation of VUK



Source: Data processed.

Figure 2b: Conditional Standard Deviation of VTX



Source: Data processed.

Figure 2c: Conditional Standard Deviation of VDB

Table 7: Asymmetric GARCH Model Estimates

	VUK		*VTX*		*VDB*	
TARCH	Coeff.	*Z*-stat	Coeff.	*Z*-stat	Coeff.	*Z*-stat
Constant	-0.003480	-0.93677	-0.004041	-1.49348	0.004327	1.03028
ω	0.000416	3.11633	9.46E-05	1.54344	0.003915	10.36967
α	0.281078	4.25853	0.282623	3.56680	0.399368	7.35491
β	0.667451	13.51501	0.717981	17.13441	-0.017900	-0.31028
γ	0.102887	0.85241	0.112852	1.06394	0.193605	1.13149
Test: $\gamma = 0$	Value	Prob.	Value	Prob.	Value	Prob.
F	0.726604	0.3946	1.131976	0.2881	1.280276	0.2586
χ^2	0.726604	0.3940	1.131976	0.2874	1.280276	0.2578
EGARCH	Coeff.	*Z*-stat	Coeff.	*Z*-stat	Coeff.	*Z*-stat
Constant	-0.00190	-0.5324	-0.00315	-1.1725	-0.00535	-1.5892
ω	-0.98086	-4.4482	-0.73476	-3.8901	-1.06589	-7.7229
α	0.51025	6.7925	0.49732	6.1763	0.52547	9.1020
β	0.88365	25.1959	0.93344	32.7686	0.86583	42.7314
γ	-0.05553	-0.9699	-0.06908	-1.3464	-0.08179	-1.5509
Test: $\gamma = 0$	Value	Prob.	Value	Prob.	Value	Prob.
F	0.940666	0.3328	1.812796	0.1790	2.405213	0.1218
χ^2	0.940666	0.3321	1.812796	0.1782	2.405213	0.1209

Source : Data estimation.

Volatility is plotted in Figure 2 that shows the conditional standard deviation of the GARCH (1,1) model. Because the volatility process does not return to its mean value, the conditional standard deviation graph contour in UK and Texas rather fluctuates without clear basic pattern. On the contrary, even though also fluctuates, the conditional standard deviation graph contour in UK quite rather flats based on the basic value $\alpha = 0.5015$. Consequently, the standard deviation of oil price in Dubai is relatively more predictable than that in UK and Texas.

As mentioned earlier, in the symmetrical model the conditional variance is a function of the size and not of the sign of lagged residuals. TARCH and EGARCH models take into account the sign of lagged residuals. The results for the TARCH (1,1,1) and EGARCH (1,1) models are presented in Table 9. In general, the results of TARCH and EGARCH models statistically have no different from GARCH models as presented in Table 7.

The individual tests using *Z*, *F*, and χ^2 for γ conclude that all of the leverage effect terms is not significantly positive (even with a one-sided of 5 percent level test) so there does not appear to be an asymmetric effect. In these models, good news ($\varepsilon_t < 0$) and bad news ($\varepsilon_t > 0$) have no different effects on the conditional variance[*)]. The absence of leverage effect that can normally be found on financial markets might be due to that commodity markets are more prone to volatility when the price goes up and when the price goes down as what can be observed in the financial markets.

In term of forecasting, the asymmetric effects imply that the prediction of the oil price in the near future is then relatively easy without considering bad news and bad news. In other words, the conditional variance and standard deviation are controllable so that the prediction value is asymptotically will be more accurate. Furthermore, hedging cost associated with the change in oil prices risk would be minimized. Finally, the optimal position for all

[*)] We do not report results the tests for the TARCH and EGARCH models completely since leverage effects are not significant. They can be available on request to the author.

players in the oil market would be achieved in the frame of market efficiency.

CONCLUSION

In this paper we tried to understand the nature of dependence of the conditional variance on past volatility in oil prices. The volatility is measured by the first log-differenced. The measure of uncertainty we choose is the within-month high-low range of the conditional standard deviations. Time-varying conditional variances are estimated using univariate (G)ARCH models.

GARCH models depend on the frequency of the data, so we also examine monthly time series for the period January, 1980 to May, 2010 representing 365 observations. We focus on volatility of the world crude oil prices in UK, Texas, and Dubai markets. We found that the preferred model is a symmetric GARCH (1,1) model. Asymmetric leverage effects are not found in the three markets. In fact, the positive shocks are more dominant than the negative shocks. However, the volatility process returns to its mean only in Dubai.

Those findings have some important implications for Indonesia. The main policyrecommendation to emerge from this paper is that any effort invested in reducing the oil dependency of the Indonesian economy is more than justified. Moreover, it is worth considering a tightening of the stabilization fund which would lead to a less fragile economic development. Second, the resurgence of energy price crises should redirect energy security policy towards the development and adoption of energy-saving technology, such as gas, coal, solar panels, wind turbines, hydropower, biomass, and other renewable energy.

Third, as a net oil importer country, Indonesia faces a dilemma when the world crude oil price increases. In one hand, the central government revenue increases substantially due to oil and gas taxes. On the other hand, the central government has to spend more subsidies to avoid the increase of domestic fuel prices. In this case, the government could use the dynamics of oil price in Dubai market as a benchmark to set up her state budget in order to realize fiscal sustainability.

The volatility of oil prices is interesting to be explored further. This study used a univariate GARCH model. More advance research could utilize the multivariate GARCH to capture volatility persistence across markets. It is also advisable to use high frequency data i.e. daily data in the longer time horizon to catch uncertainty among oil, commodity, and stock markets. There is no doubt that in the globalization era, oil, commodity, and stock markets are increasingly integrated.

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