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Communication

Modelling oil price volatility

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Abstract

In this paper, we examine the volatility of crude oil price using daily data for the period 1991–2006. Our main innovation is that we examine volatility in various sub-samples in order to judge the robustness of our results. Our main findings can be summarised as follows: (1) across the various sub-samples, there is inconsistent evidence of asymmetry and persistence of shocks; and (2) over the full sample period, evidence suggests that shocks have permanent effects, and asymmetric effects, on volatility. These findings imply that the behaviour of oil prices tends to change over short periods of time.

Keywords: Volatility; Asymmetry; Shock persistence

1. Introduction

Understanding the volatility of oil price is crucial because persistent changes in volatility can expose producers and industrial consumers to risk, thus affecting investments in oil inventories and facilities for production and transportation (Pindyck, 2004a). Volatility also determines the value of commodity-based contingent claims; thus, the behaviour of volatility is important for derivative valuation, hedging decisions, and decisions to invest in physical capital tied to production or consumption of natural gas and oil (Pindyck, 2004a). Furthermore, Pindyck (2004b) argues that volatility can affect the total marginal cost of production, thus affecting the value of the firms' operating options and thus the opportunity cost of current production.

The more volatile crude oil prices become the more uncertainty it creates, leading to economic instability for both oil-exporting and oil-importing countries. Higher crude oil prices contribute to inflation; the result is recession in oil-dependent countries. One branch of this literature demonstrates that oil prices have a negative impact on economic growth (see, *inter alia*, Ferderer, 1996; Jimenez-Rodriguez and Sanchez, 2005).

There is lack of research on understanding the volatility of oil prices. The related literature has attempted to forecast volatility (Sadorsky, 2006), examined the relationship between oil price volatility and the macroeconomy (Ferderer, 1996; Lee et al., 1995; Yang et al., 2002; Chen and Chen, 2007), examined the relationship between oil price volatility and stock prices (Huang et al., 1996; Sadorsky, 1999, 2003), comparatively examined volatility of crude oil, refined petroleum and natural gas prices (Regnier, 2006; Plourde and Watkins, 1998; Pindyck, 1999), and examined the asymmetry of the impact of oil price shocks on economic activities (Huang et al., 2005).

The goal of this paper is to add to the scarce literature on crude oil price volatility. We, thus, model crude oil price volatility using daily data for the period 9/13/1991–9/15/2006. To the best of our knowledge, there is no study that models crude oil prices using daily data. To model volatility, we use the exponential generalised conditional heteroskedasticity (EGARCH) model. In using the EGARCH model, our intention is to gauge two features of crude oil price volatility, namely asymmetry and persistence of shocks.

Foreshadowing our main results, we find evidence that shocks have both permanent and asymmetric effects on volatility. That shocks have asymmetric effects on oil price

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volatility suggests that negative and positive shocks have different effects on oil price volatility. We organise the remaining of the paper as follows. In Section 2, we discuss the estimable model and the econometric methodology. In Section 3, we discuss the results. In Section 4, we provide some concluding comments.

2. Model and statistical properties of data

We begin with the following representation of the return on the price of crude oil, R_t:

$$R_t = \frac{(P_t - P_{t-1})}{P_{t-1}}, \tag{1}$$

where P_t is the price of crude oil. The logarithm of crude oil price is plotted in Fig. 1. These data are obtained from Datastream. There is evidence of unsteady behaviour of oil prices. The mean oil price over the period 1991–2006 has been around US$24.08, with a maximum price of US$72.49. The standard deviation is around US$12.91.

On a continuous compounding basis, one can compute the price return as the logarithm of price at the end of the period less the logarithm of price at the beginning of the period, as follows:

$$r_t = \ln(1 + R_t) = \ln\left(\frac{P_t}{P_{t-1}}\right). \tag{2}$$

We take the logarithm of price as a random walk process:

$$p_t = \alpha + p_{t-1} + \varepsilon_t. \tag{3}$$

This is the same as

$$r_t = p_t - p_{t-1} = \mu + \varepsilon_t, \tag{4}$$

where $\varepsilon_t = \sigma\omega_t$ and $\omega_t \sim IID\ N(0,1)$.

This implies that the returns are normally distributed. However, when we analyse the actual data on crude oil prices, there is lack of evidence supporting a normally distributed series. Consider, first, the plot of crude oil price returns depicted in Fig. 2. There is evidence of volatility clustering; that is, periods of high volatility followed by periods of tranquillity. There is also evidence of structural breaks in volatility. Second, the test statistic, such as the Jarque–Bera test, suggests that neither the oil price nor the oil price return series are normally distributed. The kurtosis test statistic of greater than three suggests that the series has a fat tail. The returns series has a small and negative skewness statistic, suggesting the presence of a left tail. Moreover, in Figs. 3 and 4, we plot the QQ graphs for the log of oil price and oil returns, respectively. These graphs reveal that both large positive and large negative shocks are responsible for the non-normality of the series.

To test for conditional heteroskedasticity, we use the Ljung–Box (LB) statistics of squared residuals (McLeod and Li, 1983) and the ARCH test suggested by Engle (1982), which examines the null of 'no ARCH' effects. Based on an $ARMA$(12,12) model, we find evidence of high statistics on squared residuals and we reject the null hypothesis of 'no ARCH' effects. This suggests that the returns on price suffer from heteroskedasticity. To remedy the presence of heteroskedasticity, we follow the work of Engle (1982) and Bollerslev (1986) and model oil price return within an ARCH/GARCH framework. We use an extension of the ARCH/GARCH model suggested by Nelson (1991), who proposed an exponential GARCH (EGARCH) model. The EGARCH model has several attractive features that motivate our work. We assume a

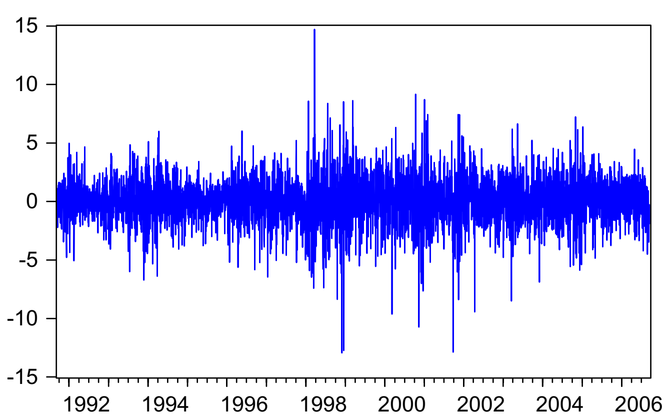

Fig. 2. Oil price returns, 9/13/1991–9/15/2006.

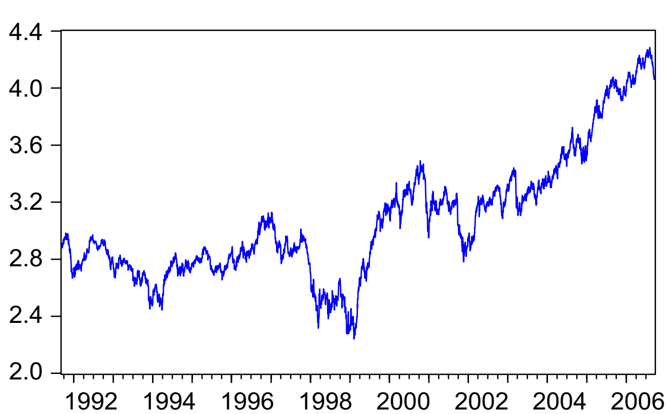

Fig. 1. Logarithm of daily oil prices, 9/13/1991–9/15/2006.

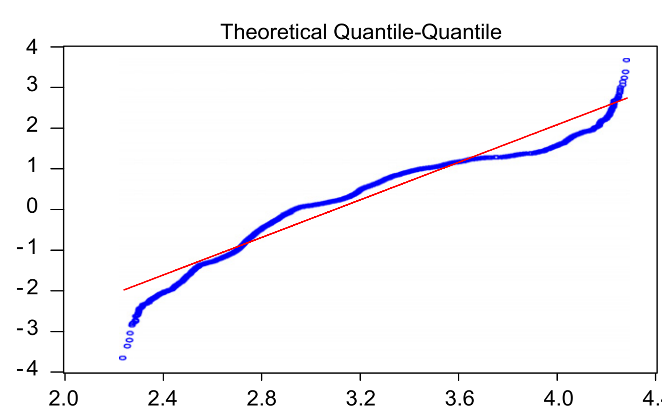

Fig. 3. QQ plot for the oil price series.

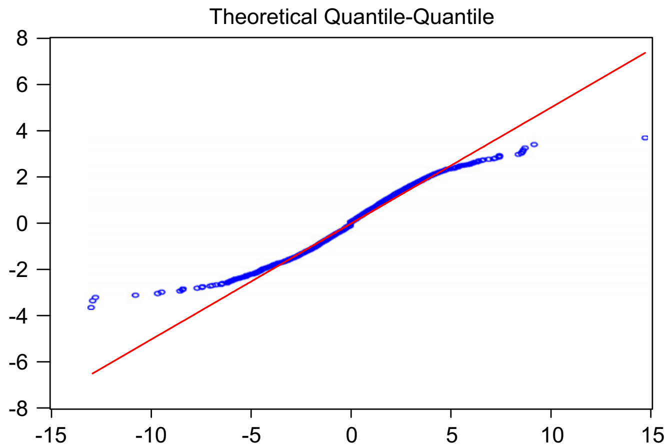

Fig. 4. QQ plot for the oil price returns series.

conditional normal distribution and specify an $ARMA(p,q) - EGARCH(1,1)$ in the mean model with the following mean and variance structures:

Mean equation:

$$r_t = c + \sum_{i=1}^{p} \delta_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \vartheta \varepsilon_{t-j} + \lambda \sigma^2. \tag{5}$$

Variance equation:

$$\log(\sigma_t^2) = \omega + \alpha \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\delta}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-1}^2). \tag{6}$$

We favour the use of the EGARCH model for the following reasons. First, unlike the GARCH model, it does not impose any restrictions on α, γ, and β. Second, unlike the GARCH model, there is provision for oscillatory behaviour in the conditional variance since the β coefficient can be either negative or positive. The estimate of β allows one to evaluate whether shocks to the variance are persistent or not. Nelson (1991) shows that $|\beta|<1$ ensures stationarity and ergodicity for the $EGARCH$(1,1). Third, EGARCH model allows one to judge asymmetric volatility, which is captured by the parameter γ. If $\gamma>0$, the implication is that positive shocks give rise to higher volatility than negative shocks, and vice versa. Fourth, the parameter α represents the magnitude of the conditional shock on the conditional variance.

To obtain robust inference about the estimated models, we compute the robust standard errors as suggested by Bollerslev and Wooldridge (1992) . We estimate the $ARMA(p,q) - EGARCH(1,1)$ using the maximum likelihood estimation technique, assuming normally distributed errors, and the optimal lag lengths are selected using the Schwarz Bayesian criterion (Schwartz, 1978).

3. Empirical results

We begin the discussion of results by first considering the full sample period (Table 1, column 2). We notice that the coefficient on γ, that measures asymmetry of shocks, is negative and statistically significant at the 1 per cent level. The sign is negative, suggesting that negative shocks reduce volatility more than positive shocks. This suggests that shocks have asymmetric effects on the volatility of crude oil prices. β, the sign that captures persistence of shocks, is positive and statistically significant at the 1 per cent level. The coefficient is very close to 1, suggesting that shocks to crude oil price volatility do not die out rapidly; rather, shocks tend to persist. This implies that shocks have permanent effects on crude oil price volatility.

Next, we consider results obtained from sub-samples, beginning with column 3 of Table 1. For the sub-samples 9/13/1991–2/19/1992 and 2/20/1992–11/05/1992, the coefficient on γ is negative and statistically significant. The coefficient is -0.52 over the 9/13/1991–2/19/1992 period and decreases to -0.75 over the 2/20/1992–11/05/1992 period. This implies that the role of positive shocks in reducing crude oil price volatility was higher over the 1991 period than over the 1992 period. When we examine the results for shock persistence, we find that the coefficient on β increases from 0.19 over the 9/13/1991–2/19/1992 period to 0.61 over the 2/20/1992–11/05/1992 period. Moreover, the significance level increases from 5 to 1 per cent. This result suggests that the persistence of shocks increased dramatically from the 9/13/1991–2/19/1992 period to the 2/20/1992–11/05/1992 period. However, the coefficient of 0.61 suggests that shocks to crude oil price volatility die out overtime and thus are not permanent.

Over the next two sub-sample periods, namely the 11/06/1992–6/29/1993 and 6/30/1993–5/06/1994 periods, results on symmetry and persistence of shocks are fairly similar. For instance, across all two sub-samples, the coefficient on γ is statistically insignificant, suggesting that shocks have symmetric effects on crude oil price volatility. This finding implies that over the 1992–1994 period positive and negative shocks have similar effects, in terms of magnitude, on oil price volatility. We notice that the coefficient on β is fairly high—close to 1—and statistically significant at the 1 per cent level, implying that shocks have persistent effects on oil price volatility.

Over the period 5/09/1994–1/08/1996, we notice that shocks have asymmetric effects on crude oil price volatility, but there is evidence that shocks to volatility die out; thus, shocks are transitory. However, sub-samples in the post-2001 period reveal that shocks have symmetric effects on oil price volatility and transitory effect on volatility.

In sum, our attempt to analyse symmetry and persistence of shocks over several sub-periods reveals mixed evidence of asymmetry and persistence. Broadly speaking, there appears to be a pattern: over the 1991–1992 period, evidence suggests that shocks have asymmetric effects on volatility, while evidence on persistence is mixed. On the other hand, over the 1993–1994 and the 2001–2006 periods, evidence points to the symmetric effect of shocks on volatility, while again evidence on persistence is mixed. It follows that our analysis of the pattern of crude oil price

Table 1
Parameters of mean and variance equations

	Full sample period	9/13/1991–2/19/1992	2/20/1992–11/05/1992	11/06/1992–6/29/1993	6/30/1993–5/06/1994
λ	0.0463**	0.1595***	0.1902***	2.0823	−0.6598**
	(0.0187)	(0.0547)	(0.0868)	(1.4295)	(0.2734)
c	−0.1699**	−0.6808***	−0.5268***	−4.0282	2.8198***
	(0.0685)	(0.1388)	(0.0679)	(2.7752)	(0.9807)
δ	−0.8392***	−0.8012***	0.2523***	0.5854***	0.7484***
	(0.0479)	(0.0300)	(0.0758)	(0.0710)	(0.1243)
ϑ	0.8544***	0.8949***	−0.1304***	−0.8741***	0.7689***
	(0.0461)	(0.0089)	(0.0971)	(0.0350)	(0.1219)
ω	−0.0341***	1.6757***	2.9743***	0.0571	0.1296
	(0.0076)	(0.2008)	(1.0373)	(0.0498)	(0.0985)
α	0.0582***	−1.1572***	−1.1626**	0.0384	−0.0347
	(0.0098)	(0.1953)	(0.5647)	(0.0329)	(0.0254)
γ	−0.0357***	−0.5223***	−0.7521**	−0.0407	0.0071
	(0.0093)	(0.1191)	(0.3441)	(0.0275)	(0.0162)
β	0.9928***	0.1874**	0.6069***	0.8519***	0.9269***
	(0.0025)	(0.0885)	(0.1673)	(0.0685)	(0.0602)
Diagnostic test: ARCH					
6	8.6914	3.8511	12.1512	2.1512	10.6576
	[0.1917]	[0.6968]	[0.0587]	[0. 8722]	[0.0995]
12	13.7313	10.5288	12.6825	11.0089	14.8445
	[0.3182]	[0.5697]	[0.3925]	[0.2987]	[0.2500]
18	22.8457	11.8950	18.4707	22.0991	26.9362
	[0.1965]	[0.8526]	[0.4251]	[0.1899]	[0.0802]

	5/09/1994–1/08/1996	1/09/1996–12/26/1997	12/29/1997–3/17/1999	3/18/1999–6/29/2000	9/08/2000–12/14/2001	12/17/2001–8/19/2004	8/20/2004–9/15/2006
λ	0.0581	−0.9912**	−0.1774*	−0.2998	0.0301	−5.1572	−6.2857
	(0.1482)	(0.4105)	(0.1005)	(0.2594)	(0.0574)	(3.4014)	(4.7861)
c	−0.0535	3.1744**	1.6956**	1.4688	−0.2962	19.9451	20.6477
	(0.2390)	(1.2902)	(0.8607)	(1.1399)	(0.3550)	(12.6996)	(16.0153)
δ	−0.6202***	−0.9384***	0.7938***	0.8864***	−0.7224***	−0.0145	0.0627
	(0.1132)	(0.1573)	(0.0497)	(0.0303)	(0.1573)	(0.0303)	(0.0486)
ϑ	0.6570***	0.9616**	−0.8836***	−0.9488***	0.7638***	−0.0093	−0.0302
	(0.1121)	(0.0101)	(0.0437)	(0.0128)	(0.1545)	(0.0313)	(0.0448)
ω	0.2010*	0.2168*	1.2574**	1.7633***	0.0436	1.1750***	1.3445***
	(0.1143)	(0.1164)	(0.5479)	(0.6200)	(0.0414)	(0.3701)	(0.2353)
α	−0.0222	0.0072	0.0010	0.1924	−0.0290	0.0131	0.0104
	(0.0791)	(0.0205)	(0.1130)	(0.1763)	(0.0551)	(0.0108)	(0.0014)
γ	−0.1818***	0.0293*	0.2324**	−0.0172	−0.0946**	0.0083	0.0093
	(0.0586)	(0.0167)	(0.1039)	(0.0645)	(0.0308)	(0.0065)	(0.0079)
β	0.6288***	0.8087***	0.4189*	−0.2994	0.9857***	0.1214	−0.1397
	(0.1549)	(0.1015)	(0.2391)	(0.3707)	(0.0232)	(0.2613)	(0.1855)
Diagnostic test: ARCH							
6	5.4302	8.9129	1.8752	7.9849	2.7397	16.7118	4.5511
	[0.4899]	[0.1785]	[0.9308]	[0.2392]	[0.8407]	[0.0104]	[0.6025]
12	13.1209	11.2052	10.4374	10.8705	4.3114	28.1597	18.6695
	[0.3603]	[0.5114]	[0.5776]	[0.5400]	[0.9772]	[0.0052]	[0.0968]
18	25.1963	15.0529	11.9194	12.1307	6.1715	33.5284	34.7865
	[0.1196]	[0.6583]	[0.8514]	[0.8404]	[0.9955]	[0.0144]	[0.0101]

Note: *, **, and *** denote statistical significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.

volatility does not reveal any consistent evidence of symmetry and persistence of shocks. However, when we consider a longer time period (full sample period), there is clear evidence that shocks to crude oil price volatility have asymmetric and persistent effects.

4. Concluding remarks

The goal of this paper was to examine crude oil price volatility using daily data for the period 9/13/1991–9/15/2006. To model volatility, we used the EGARCH model, with the aim of examining whether or not shocks have asymmetric and persistent effects on oil price volatility. Our main innovation was that we examined several sub-samples and tested for asymmetry and persistence of shocks not only over the full sample period but also over the various sub-samples in order to gauge the robustness of our results. Our main findings were as follows. We found that across the sub-samples there was inconsistent evidence of asymmetry and persistence of shocks. Over the full sample period, evidence suggested that shocks have permanent effects on volatility and asymmetric effects on volatility. There are three direct implications from our findings. First, these findings imply that the behaviour of oil prices tends to change over short periods of time. It follows that investment decisions need to consider this nature of oil price behaviour. Second, when we consider our results over the full sample period, evidence suggests that shocks have asymmetric effects on oil price volatility. This implies two things. One, that positive shocks have a different effect on volatility than negative shocks. This finding relates directly to those studies that have demonstrated rising oil prices having a negative effect on economic growth. Our finding confirms that a negative shock that raises oil prices is not fully compensated for by a positive shock that reduces the oil price. Two, asymmetry implies that oil prices may have experienced regime shifts. This suggests that, in modelling oil prices, the issue of regime shifts need to be taken into account through using models that do accommodate for regime changes. Third, it is clear from the plot of oil prices that prices have not been stable; there is evidence of high volatility. This implies that shocks, whether political or economical in nature, will lead to a gradual rise or decline in crude oil prices depending on whether shocks are positive or negative.

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