Modelling the volatility of crude oil returns : Jumps and volatility forecasts

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Modelling the volatility of crude oil returns: jumps and volatility forecasts

Abstract

We contribute to the scarce literature on the oil market volatility index (OVX) by examining the presence of time-varying jumps in OVX and by assessing the ability of OVX to predict the conditional variance of crude oil returns. Using a GARCH-jump model, we find evidence that OVX is characterized by jump behaviour that tends to vary over time. Further analysis indicates that accounting for the jump behaviour of OVX helps improve the conditional variance forecasts of crude oil returns. Since the studied features of OVX play a crucial role in asset pricing and risk analyses, our findings have policy implications related to refining volatility prediction models and risk measures.

Keywords: OVX; conditional variance; GARCH-jump; time-varying jumps; volatility forecasts

1. Introduction

Crude oil plays a decisive role in economic and financial stability, and its price volatility is crucial to asset pricing, portfolio modelling and risk management (e.g., Bouri et al., 2018). Considering the economic importance of crude oil, academics are constantly engaged in finding appropriate methods of modelling oil price volatility. However, looking for such methods is a challenging task given that oil prices can become highly volatile due to the adverse effects of natural calamities (such as tsunami, drought etc.), and tend to behave differently under diverse market conditions. For example, Choi and Hammoudeh (2010) argue that downturns in global stock markets could lead to a significant drop in oil prices, whereas oil prices usually increase during bullish periods. Moreover, oil price volatility is influenced by the volatilities of other assets such as exchange rates and the gold market.

Released by the Chicago Board Options Exchange (CBOE), the crude oil implied volatility index (OVX) is a reliable gauge for oil price risk. Like the US equity market volatility index (VIX), OVX measures market expectations of 30-day implied volatility. Importantly, OVX conveys useful information for forecasting crude oil price volatility, which makes it an important volatility instrument for investors and policymakers (Corrado and Miller, 2005; Becker et al., 2006; Chatrath et al., 2015). Nevertheless, while the properties of VIX are well-documented in the existing literature[1], the key features of OVX have not received as much attention, especially regarding the presence of jumps, and the forecasting ability of OVX and its jump behaviour. In this study, we extend the scarce related literature by examining the presence of time-varying jumps in OVX and by assessing the ability of OVX to predict the conditional variance of crude oil returns.

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[1] Current studies investigate the impact of including VIX within the volatility forecast model for international equity markets (e.g., Kambouroudis and McMillan, 2015).

The contributions of this empirical research are two-fold. Firstly, we investigate the presence of time-varying jumps in the crude oil volatility index. Such jumps, which are common phenomena in financial and commodity markets, may occur due to terrorist attack, natural disaster, recession or political violence. The importance of analyzing the jump behaviour is illustrated in earlier studies (see Pan and Duffie, 2001; Liu et al., 2003; Ait-Sahalia, 2004; Wright and Zhou, 2009; Bates, 2008; Ait-Sahalia and Hurd, 2015 etc.). Ait-Sahalia (2004) claims that time-varying jumps, which might account for substantial losses, play a crucial role in portfolio risk analysis. Pan and Duffie (2001) argue that large movements in financial data are liable to have thick tails which could exert a significant impact on the value-at-risk (VaR). Since ignoring time-varying jumps could mislead the risk assessment procedure, our current study captures them. We do so via the application of the GARCH-jump model of Chan and Maheu (2002). Such analysis extends the current literature that generally investigates the impact of including VIX within the volatility forecast model for international equity markets (e.g., Kambouroudis and McMillan, 2015). Second, our study examines the role of OVX as a predictor of crude oil price volatility. Specifically, we explore whether the jump behaviour of OVX helps improve the conditional variance forecasts of crude oil returns. To serve this purpose, we incorporate the jump intensity of OVX into symmetric and asymmetric GARCH models and determine their volatility performance. Such analyses add to Haugom et al. (2014), who highlight that the information content of OVX can improve the realized volatility of WTI oil prices. Our analyses have significant implications for investors, researchers and policymakers in regard to refining volatility prediction models and formulating appropriate risk measures.

Our results show that OVX is characterized by jump behaviour that tends to vary over time. We document that the information content of OVX can improve the volatility forecasts of crude oil

returns. Section 2 reviews the related literature. Section 3 describes the data, and Section 4 presents the models. Section 5 presents and discusses the results, and Section 6 concludes.

2. Related studies

Given the aim of this study, we consider two strands of literature: the presence of jumps, and volatility forecasting with implied volatility indexes.

2.1. Jumps

A strand of literature investigates the existence of time-varying jumps in various financial and commodity markets. Beine et al. (2007) show that central bank interventions tend to cause large jumps in the exchange rate volatility. Employing the exponential GARCH-jump approach, Kuttu (2017) examines whether stock market returns for Egypt, Nigeria and South Africa are characterized by jump behaviour. The study reports that time-varying jumps are common events in these countries, except Nigeria. Kuttu et al. (2018) find empirical evidence that time-varying jumps exist in sub-Saharan African foreign exchange markets. Dutta et al. (2017), using the GARCH-jump approach, document that jumps frequently occur in Middle Eastern and African stock markets. The authors demonstrate that OVX acts as a major driving force for these equity markets. Dutta et al. (2018) finds that US ethanol prices are characterized by jump behaviour. Chiou and Lee (2009) check whether time-varying jumps occur in WTI crude oil prices and how such large movements in the oil market affect the S&P 500 returns. Using the GARCH-jump model, the authors document that the impact of oil price on the US equity market is asymmetric. Zhang and Chen (2011) apply the exponential GARCH-jump method to assess the effects of global oil price shocks on the Chinese stock market. They show that the impact of oil price fluctuation is positive and weak and that there exist jumps, which vary over time. Additionally,

Gronwald (2012) uses the GARCH-jump model to analyze the jump behaviour of the WTI oil price index. The author uses daily, weekly and monthly observations and shows that time-varying jumps are present in the daily data only. Fowowe (2013) examines the effect of global oil markets on the Nigerian stock market. One key objective of his work is to investigate the presence of jumps or hikes in the stock market. The study finds that although oil prices do not influence equity prices, Nigerian stocks are characterized by time-varying jumps. Zhang and Qu (2015) explore whether the occurrence of time-varying jumps in crude oil prices have any significant impact on the Chinese commodity markets. The findings reveal an asymmetric linkage between oil and food prices. Zhang and Tu (2016) conduct a similar investigation and find that the impact of oil price jumps on China's metal market is also asymmetric. Zhang et al. (2018) employ the GARCH-jump model to examine the effects of international oil prices on China's precious metal markets. The authors find that jumps exist in the oil market, and such jumps have a significant influence on gold and platinum price series.

Another strand of research investigates whether the equity VIX follows any jump process. Recent contributions include Todorov and Tauchen (2011), Goard and Mazur (2013), Baldeaux and Badran (2014), Ait-Sahalia and Hurd (2015) among others. However, all the published work focuses on stock market volatility indexes and limited papers focus on crude oil implied volatilities. The current study aims to address this void in the literature[2].

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[2] Few studies (Koopman et al. 2005; Zhang and Lan, 2014) examine the presence of jumps in GARCH-RV-type models. Zhang and Lan (2014). for example, show that GARCH-RV type models accounting for jumps have more more power to predict the future volatility of stock prices than other GARCH-RV type approaches.

2.2. Predicting volatility with implied volatility indexes

A strand of literature investigates the role of VIX in predicting the volatility of stock markets. Some recent contributions include Corrado and Miller (2005), Becker et al. (2006), Dennis et al. (2006), Carr and Wu (2006), Giot and Laurent (2007), Yu et al. (2010), Kambauroudis and McMillan (2015), Pati et al. (2018) and others.

Most of these papers suggest that VIX provides additional information beyond the contents of historical equity volatilities. Dennis et al. (2006), for example, show that VIX has predictive power for future index return volatility. Carr and Wu (2006) document that VIX provides better forecasts of realized volatility than GARCH models. Yu et al. (2010) conclude the same. More recently, Kambauroudis and McMillan (2015) find that VIX information should be taken into account when forecasting the realized volatility of international stock markets. Becker et al. (2006), however, show a different picture. Their results suggest that VIX does not provide extra information that could improve the volatility forecasts of equity markets. Similar results are shown by Day and Lewis (1992).

Another line of research considers the information on commodity market volatility indexes, examining their volatility forecasting performances. Haugom et al. (2014) demonstrate that oil implied volatility plays a crucial role in forecasting the variance of oil prices. Luo et al. (2016) show that gold VIX carries important information for predicting the volatility of the Chinese gold futures market. Luo and Ye (2016) document similar results for the Chinese silver futures market.

Unlike most of the above studies, our paper examines the presence of time-varying jumps in OVX and assesses whether the jump intensity of OVX can predict the conditional variance of crude oil prices. It is worth mentioning that while Haugom et al. (2014), Ji and Fan (2016) and

Dutta (2017) use OVX information in predicting oil price volatility, none of these papers consider the jump behaviour of OVX in forecasting oil variance.

3. Data

We use data on the crude oil volatility index (OVX) and WTI oil prices, collected from DataStream[3]. The sample period is 10 May 2007 to 31 December 2017, the starting point of which is based on the data availability of OVX. Notably, we consider both daily and weekly observations of OVX data, in order to examine whether the occurrence of time-varying jumps depends on the data frequency. Fig. 1 shows the daily evolution of OVX and crude oil prices. There seem to be several jumps or hikes in OVX. Earlier studies (see, among others, Liu et al., 2013; Dutta et al., 2017) show that political and economic events are responsible for such spikes. For example, the jumps during the middle of 2008 emerge following the various consequences of the global financial crisis. The hikes that occur at the beginning of 2011 are driven by the Libyan war. It is clear from Fig.1 that jumps are often seen in oil implied volatility and that OVX and WTI oil series are inversely related.

Insert Figure 1 and Table 1 around here

Table 1 shows the descriptive statistics of daily and weekly data. The findings from Panels A and B suggest that the distribution of logarithmic returns do not follow the normality assumption. Applying the Jarque-Bera test of normality, we reach the same conclusion.

Insert Table 2 around here

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[3] A detailed discussion of the construction of the OVX can be found in Liu et al. (2013) and Dutta (2017).

Table 2 shows the results of two unit root tests: the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The null hypothesis for these tests states that the data follow a non-stationary process. We find that OVX is stationary even at levels, while the WTI oil price index becomes stationary considering the logarithmic returns.

4. Methodology

We examine the presence of time-varying jumps in OVX via the GARCH-jump process of Chan and Maheu (2002). We then assess the role of OVX as a predictor of oil return volatility using extended GARCH (1,1) models.

4.1. GARCH-jump model

The GARCH-jump process of Chan and Maheu (2002) is extensively applied in the finance literature. Important properties of this process are highlighted by Fowowe (2013), Dutta et al. (2017) and Zhang et al. (2018). Following Chan and Maheu (2002), the GARCH-jump process assumes the following form:

$$R_t = \pi + \mu R_{t-1} + \epsilon_t \tag{1}$$

where R_t is the logarithmic returns of OVX and ϵ_t is the residual divided into two components:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \tag{2}$$

with ϵ_{1t} having the following form:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1} \tag{3}$$

Additionally, ϵ_{2t} is a jump innovation:

$$\epsilon_{2t} = \sum_{l=1}^{n_t} U_{tl} - \theta \lambda_t \tag{4}$$

where, U_{tl} is the jump size with a mean θ and a variance ϑ^2. $\sum_{l=1}^{n_t} U_{tl}$ is the jump factor, and n_t measures the number of jumps and is assumed to follow a Poisson distribution with an autoregressive conditional jump intensity (ARJI):

$$\lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1} \tag{5}$$

where $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$.

The log-likelihood is given by:

$$L(\Omega) = \sum_{t=1}^{T} \log f(R_t | I_{t-1}; \Omega)$$

where $\Omega = (\pi, \mu, \delta, \omega, \alpha, \beta, \theta, \vartheta, \lambda_0, \rho, \gamma)$.

4.2 Baseline GARCH model

The initial step of specifying our baseline GARCH model includes the specification of the conditional mean as:

$$r_t = \pi + \phi r_{t-1} + \varepsilon_t \tag{6}$$

where, r_t is the daily log return of crude oil price at time t. The error term (ε_t) follows a normal distribution.

For the conditional variance equation, we consider the standard GARCH (1,1) model that takes the following form:

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \qquad (7)$$

In Equation (7), h_t^2 is the conditional variance at time t, and α and β are GARCH parameters. We apply the exponential GARCH (EGARCH) process given by:

$$h_t^2 = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta h_{t-1}^2 \qquad (8)$$

where, γ is the asymmetric term.

4.3. Predictive role of OVX

We assess the role of OVX as a predictor of crude oil price volatility using extended GARCH-models. To this end, we consider in Equation (9) an extended specification of the GARCH model that includes the jump intensity of OVX as an explanatory variable.

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \chi \lambda_{t-1} \qquad (9)$$

where, χ captures the effect of jump intensity on the conditional variance of WTI oil returns. A similar extension is considered for the EGARCH process.

We then investigate whether OVX carries important information that can be useful to better forecast the conditional variance of crude oil prices. Accordingly, we consider the regression:

$$\sigma_{t+1}^2 = a + b\sigma_{f,t}^2 + \xi_t \qquad (10)$$

where σ_{t+1}^2 is the realized volatility of oil returns at time $t + 1$, $\sigma_{f,t}^2$ is the volatility forecast at time t, and ξ_t is the forecast error term. Following Kanas (2013), we use the squared excess

returns as a measure of realized volatility, with $\sigma_{f,t}^2$ characterized by either the conventional or extended GARCH forecast. The forecast performance is assessed by comparing the R^2 values among the base-line and extended GARCH models.

5. Empirical results

5.1. Estimates of the GARCH-jump process

Estimated results of the GARCH-jump process for the full sample period are given in Table 3. The results based on daily data indicate the presence of time-varying jumps in OVX and evidence that the jump intensity is time-varying. The parameter ρ, measuring the persistence in the conditional jump intensity, is 0.9897. The jump intensity parameters (λ_0, ρ, γ) are positive, suggesting that the GARCH-jump model is correctly specified. Practically, the fact that the jump intensity parameters are positive indicates that both current jump intensity (λ_{t-1}) and intensity residuals (ξ_{t-1}) significantly influence tomorrow's jump intensity (λ_t).

Insert Table 3 around here

It is evident from Table 3 that time-varying jumps are non-existent in the weekly observations, as the jump intensity coefficients are all insignificant. However, there is evidence of time-varying jumps in the daily data. These findings are not surprising given prior evidence of the presence of jumps in daily data (Gronwald, 2012).

Our findings are consistent with Wright and Zhou (2009), Bates (2008), Ait-Sahalia and Hurd (2015) and others. These studies show that jumps are common phenomena in implied volatility indexes. As mentioned, our work differs from these papers in that we consider oil market volatility index, while their focus is on the equity market VIX.

We conduct several subsample analyses to verify whether time-varying jumps occur in crisis periods. To this end, we consider the period January 2008 to June 2009 to cover the global financial crisis, and the period July 2014 to December 2015 to include the oil market downturn. The analyses are performed only for daily observations. These findings, presented in Table 4, confirm that time-varying jumps are observed in OVX data.

Insert Table 4 around here

Our overall findings show that oil implied volatility experiences significant jumps and such jumps do vary over time. Given that time-varying jumps, accounting for substantial losses, play a vital role in portfolio risk analysis, ignoring time-varying jumps could mislead the formulation of proper hedging strategies.

5.2. Results of the baseline GARCH model

We present and discuss the findings of the baseline GARCH processes, i.e. without incorporating the jump intensity of OVX as an exogenous variable. The results in Table 5 show that the GARCH parameters in both GARCH and EGARCH models are statistically significant. The sum of ARCH and GARCH parameters in the symmetric specification indicates a high degree of persistence in oil volatility. Therefore, predicting future volatility of the US crude oil market depends on current levels of oil implied volatility, which points to the importance of the degree of volatility persistence in predicting current volatility (Charles and Darné, 2014).

Insert Table 5 around here

5.3. Results of the predictive role of OVX

We now present and discuss the results of the extended GARCH models, where the jump intensity of OVX is added as an exogenous variable in the variance equations. The results of the estimation of Equation (9) are presented in Table 5. They show that the impact of jump intensity on the volatility of oil returns is highly significant, given that the null hypothesis is rejected for $H_0: \chi = 0$ at 1% level. Our findings indicate a reduction in the degree of volatility persistence. For the symmetric GARCH specification, the volatility persistence is high, as reflected in the sum of α and β being very close to 1, whereas the volatility is less persistent in the extended GARCH model. This might be due to the fact that OVX captures more persistence than the GARCH parameters. In fact, the information conveyed by oil implied volatilities may reduce the effects of the conditional variance at $(t - 1)$ on the conditional variance at (t), thus reducing persistence (Kanas, 2013). Quite similar results are reported in Table 5 for the EGARCH process.

Moreover, based on the Akaike Information Criterion (AIC) and Bayesian information Criterion (BIC), we can conclude that the extended GARCH models appear to be best fitted models. Additionally, we observe that the maximum likelihood values for the extended models are lower than that for the baseline specifications. This finding further confirms that the extended GARCH approaches are superior compared to the baseline models. We further note that of the two extended models, the asymmetric model outperforms the symmetric approach as suggested by the AIC, BIC and maximum likelihood values.

Insert Table 6 around here

Coefficient estimates from Equation (10) are given in Table 6. They indicate that the inclusion of the jump intensity of OVX in the GARCH model tends to increase the values of the R^2 statistic. For the symmetric specification, the R^2 statistics of the extended GARCH model (GARCH with jump intensity) increases to 0.24 from the 0.18 level reported in the baseline GARCH model (i.e. GARCH without jump intensity). For the EGARCH specification, the improvement in the R^2 statistic is more important. In fact, the R^2 statistic of the extended EGARCH model (EGARCH with jump intensity) is 0.17, as compared to just 0.09 for the EGARCH without jump intensity. These findings imply that the inclusion of the jump intensity of OVX improves the volatility forecasts of the WTI oil price returns.

Overall, we document that including OVX information is important for correctly specifying the conditional variance of oil market returns. Specifically, the information content of oil implied volatility and its jump behaviour are important to the modelling of crude oil volatility. The results are in line with previous studies that argue that the predictive ability of a model is shaped by the frequency of the data (Poon and Granger, 2003).

6. Conclusion

Unlike the US stock market implied volatility index, which has been broadly studied over the past decades (e.g., Yu et al., 2010), the implied volatility of crude oil returns does not receive as much attention among researchers. In this paper, we contribute to the existing literature in two ways. Firstly, we examine the presence of time-varying jumps in OVX. Secondly, we explore the role of jumps occurring in OVX as a predictor of crude oil price volatility. Our main findings reveal that OVX is characterized by a jump behaviour that varies over time. However, jumps occur in daily data but not in weekly data, suggesting that the frequency of data matters to the

presence of jumps in oil implied volatility. The results of the subsample analyses indicate the appearance of time-varying jumps during stress periods such as the global financial crisis and oil market downturn of July 2014 to December 2015. We also find that accounting for the jump intensity of OVX can improve the volatility forecasts of crude oil prices.

The findings of our empirical analyses have implications for investors, policymakers and academics. Since oil is often used to hedge portfolio risk, investors can use our results in designing appropriate hedging strategies and risk measures. They can use our results to refine the forecasting of oil volatility based on the information content of oil implied volatility. Specifically, they are advised to account for the presence of jumps in the crude oil implied volatility index at the daily frequency only, especially during stress periods. Given that crude oil has a crucial role in economic and financial stability, policymakers can build on our empirical findings to gain a better understanding of the dynamics of oil price volatility and formulate effective policies involving oil market uncertainty. For academics, our findings could be used to develop more precise asset-pricing models and volatility prediction methods.

One of the limitations of our analysis is that we have not checked for potential outliers in the crude oil volatility index. Therefore, future studies could investigate whether outliers are present in OVX. Detection of outliers in financial variables is crucial, as the existence of such outliers can lead to serious distortion of model specifications, parameter estimation, and risk prediction (Grané and Veiga, 2010; Carnero et al., 2012). It is also noteworthy that OVX might be characterized by structural breaks which are often observed due to different economic and political events such as recessions, wars etc. Ignoring such breaks, when modelling crude oil volatility, might mislead the risk assessment procedure, since the dynamics of the association amongst the variables under study might change as a consequence of these breaks (Ewing and

Malik, 2017). To sum up, this research can be extended to study the effects of both outliers and structural breaks in oil volatility on the risk-return nexus.

Data Sharing: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1. Descriptive Statistics for daily data (10 May 2007 - 31 December 2017)

	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera test
Panel A: Daily data					
OVX levels	36.8223	13.8723	1.3995	5.81	1818.53 (0.00)***
WTI levels	76.5462	24.2061	-0.0216	2.07	99.29 (0.00)***
OVX logarithmic returns	-0.0086	4.7373	0.6749	13.19	12226.87 (0.00)***
WTI logarithmic returns	-0.0008	2.4157	0.1039	7.98	2869.21 (0.00)***
Panel B: Weekly data					
OVX levels	36.7761	13.8808	1.4357	6.01	400.51 (0.00)***
OVX logarithmic returns	-0.0483	9.3130	0.5826	4.23	66.44 (0.00)***

Notes: *p*-values are given in parentheses, *** denotes statistical significance at 1% level.

Table 2. Results of stationarity tests for daily data (10 May 2007 - 31 December 2017)

	ADF Tests		PP Tests	
	Levels	Logarithmic returns	Levels	Logarithmic returns
OVX	-3.04 (.03)**	-33.55 (.00)***	-3.12 (.02)**	-60.89 (.00)***
WTI	-1.83 (.37)	-54.35 (.00)***	-1.82 (.37)	-54.37 (.00)***

Notes: *p*-values are given in parentheses, *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Table 3. Results of GARCH-jump process - full sample (10 May 2007 - 31 December 2017)

	Daily		Weekly	
	Estimates	Standard errors	Estimates	Standard errors
π	-0.0964***	0.0204	-0.5300***	0.1147
μ	-0.0413**	0.0190	-0.2179***	0.0500
ω	0.0792***	0.0202	0.1069	0.1043
α	0.1067***	0.0121	0.1259***	0.0355
β	0.7702***	0.0275	0.7886***	0.0472
θ	1.0613	0.2605	3.5673***	1.3908
d^2	2.9893***	0.2913	-3.2625***	0.6092
λ_0	0.0017**	0.0008	0.1615	0.1163
ρ	0.9897***	0.0044	0.1746	0.4265
γ	0.0672***	0.0218	0.2327	0.2164
Log-likelihood	-4982.29		-1405.41	

Note: ** and *** indicate statistical significance at 5% and 1% levels respectively.

Table 4. Results of GARCH-jump model - subsamples analysis with daily data

	2008 Crisis (January 2008 - June 2009)		Oil market downturn (July 2014 - December 2015)	
	Estimates	Standard errors	Estimates	Standard errors
π	-0.2389***	0.0004	-0.0927***	0.0055
μ	0.0239***	0.0004	-0.1091***	0.0043
ω	0.0729***	0.0013	0.1432***	0.0190
α	0.0689***	0.0012	0.1443***	0.0113
β	0.8745***	0.00001	0.6951***	0.0142
θ	0.2900	0.2104	2.1972***	0.4726
d^2	1.7461***	0.0307	4.5482***	0.6301
λ_0	0.1648***	0.0253	0.0531***	0.0087
ρ	.7855***	.0067	0.5187***	0.0632
γ	0.5267*	0.3055	0.1032	0.0760
Log-likelihood	-308.2595		-1402.22	

Note: * and *** indicate statistical significance at 10% and 1% levels respectively.

Table 5. Estimates of GARCH models

	GARCH	EGARCH	Extended GARCH (GARCH with jumps)	Extended EGARCH (EGARCH with jumps)
ω	0.0341***	0.0701***	-0.8682***	-4.3866***
α	0.0653***	0.1089**	0.0259***	0.0402*
β	0.9297***	0.9906***	-0.6556***	-0.6329***
γ		-0.0694***		-0.0023
χ			0.1814***	0.2917***
Log-likelihood	-5886.44	-5859.07	-3521.79	-3433.07
AIC	4.2461	4.2270	2.5425	2.4793
BIC	4.2567	4.2398	2.5553	2.4942

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

Table 6. Volatility forecasting performance

	GARCH	EGARCH	Extended GARCH (GARCH with jumps)	Extended EGARCH (EGARCH with jumps)
a	0.0491	-0.0124	-1.0782***	0.5871***
b	0.9432***	0.0960***	2.4084***	0.3941***
R^2	0.18	0.09	0.22	0.17

Note: *** indicates significance at 1% level.