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# How do financial features affect volatility forecasts? Evidence from the oil market and other markets

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This study uses six types of generalized autoregressive conditional heteroscedasticity (GARCH) models to estimate the volatility of 28 assets dispersed in the oil, metal, stock, and exchange rate markets, and it explores whether the three financial features of price level, distribution, and leverage effects exist in these four markets. Through an accuracy evaluation, this study also investigates how the financial features affect volatility forecasts and *which feature plays the most substantial role in volatility forecasts in each market.* Empirical results show that the assets in the oil (resp. exchange rate) market have the greatest (resp. smallest) risk. **Moreover**, the fat-tailed effect most significantly exists in these four markets, followed by the price level, skewness, and leverage effects. **Notably**, a negative (resp. positive) volatility elasticity exists in the oil, exchange rate, and stock (resp. metal) markets. **Furthermore**, both the price level and distribution effects significantly affect the volatility forecasts in the oil market, whereas only the leverage effect slightly affects the volatility forecasts in the metal market. Conversely, the price level, distribution, and leverage effects slightly affect the volatility forecasts in the stock market, whereas no effect can affect the volatility forecasts in the exchange rate market. The price level effect is the most crucial in volatility forecasts in the oil market, whereas the leverage effect is the most crucial in volatility forecasts in the metal and stock markets. Additionally, the GJR-GARCH-N has the best performance in volatility forecasts among the three asymmetric GARCH models.



## 1. Introduction

According to the literature (see Jiménez-Rodríguez & Sánchez, 2005; Sadorsky, 1999), changes in energy prices affect economic activities. Hence, sudden and large hikes in energy price through actual or envisioned supply interruptions have far-reaching implications on all economies. For example, the US underwent extremely high inflation and unemployment rates during the periods of the first and second energy shocks (1973–74 and 1979, respectively). As reported by Kim and Loungani (1992), these two energy shocks were a major contributor to economic fluctuations over the past three decades. The volatility can be used to represent the risk, and it can also be used to price the option or to estimate the value-at-risk and hedge ratio. Subsequently, the investor can construct the more efficient portfolio in accordance with the return and risk information of each component asset. Moreover, under the 1996 Market Risk Amendment (MRA) to the Basel Capital Accord, commercial banks can appropriately provide the regulatory capital for their trading positions according to the banks' own internal VaR estimates. Furthermore, an appropriate position of futures must be short (resp. long) for the factory owner that will need to sell (resp. buy) a quantity of commodity in a specific period in the future. Hence, if the volatility is not predicted precisely, then the above more efficient portfolio, the suitable regulatory capital, and the appropriate position of futures cannot be attained. Therefore, it is important to precisely forecast the volatility of an asset.

Through evaluation of accuracy, recent studies on volatility forecasts almost always focus on how to enhance the forecast performance of existing approaches.[1] In the literature, one competing model is compared with one selected benchmark model based on the criteria of accuracy evaluation, such as the loss functions root mean square error (RMSE), mean absolute error

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[1] Due to limited space, most of the relative studies are not reviewed here.

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(MAE), and Diebold–Mariano (DM) test. Simpler models, such as the generalized autoregressive conditional heteroskedasticity (GARCH) model[2] with normal distribution, are always chosen as the benchmark model, whereas competing models may be the varieties of GARCH models with non-normal distribution settings (see Agnolucci, 2009; Arouri, Lahiani, Lévy, & Nguyen, 2012; Byun & Cho, 2013; Charles & Darné, 2014; Chortareas, Jiang, & Nankervis, 2011; Cifter, 2013; Hou & Suardi, 2012; Lee & Pai, 2010; Wei, 2012; Wei, Wang, & Huang, 2010). The varieties of GARCH models include Engle and Lee's (1993) component GARCH (CGARCH), the GJR-GARCH model of Glosten, Jagannathan, and Runkle (1993), the exponential GARCH (EGARCH) model of Nelson (1991), the threshold GARCH (TGARCH) model of Zakoian (1994), the integrated GARCH (IGARCH) model of Bollerslev (1986), the fractionally integrated GARCH (FIGARCH) of Baille, Bollerslev, and Mikkelsen (1996), and the asymmetric power ARCH (APARCH) model of Ding, Granger, and Engle (1993). The above-mentioned varieties of GARCH model are used to accurately capture the features of actual return variance. These features of the return variance contain the volatility clustering,[3] leverage effect,[4] long memory, and mean reversion in each asset or financial market. As for non-normal distribution settings, the student's *t*, the generalized error distribution (GED) described by Box and Tiao (1973), the skewed student's *t* (ST) of Hansen (1994), and the skewed generalized student's *t* (SGT) of Theodossiou (1998) return distributions are used to determine the features of true return distribution, such as fat tails, leptokurtosis, and a moderate amount of skewness, the so-called distribution effect (see Mandelbrot, 1963). For instance, Agnolucci (2009) found that when forecasting the volatility of the West Texas Intermediate (WTI) future contract, the GARCH-type models (i.e. GARCH and CGARCH models with normal, student's *t*, and GED distribution settings) seem to perform better than the implied volatility models. He also found that, among the above-mentioned GARCH-type models, the models with GED distribution perform best compared with those with the others distributions, whereas the CGARCH model does not perform as well as the GARCH model based on the same return distribution. Wei et al. (2010) discovered that, regarding the volatility forecasts of Brent and WTI crude oil, the nonlinear GARCH-type models (i.e. IGARCH, GJR-GARCH, EGARCH, APARCH, FIGARCH, FIAPARCH, and HYGARCH), which are capable of capturing long memory and/or asymmetric volatility, exhibit greater forecasting accuracy than the linear ones (i.e. RiskMetrics and GARCH). Arouri et al. (2012) applied a variety of GARCH-type models, such as GARCH, IGARCH, GJR-GARCH, FIGARCH and RiskMetrics, and GARCH with structural breaks, to predict the conditional volatility of energy spot and futures prices like WTI crude oil, gasoline, and heating oil, and they found that the volatility models with structural breaks and long memory provide the best volatility forecasts in most cases. Byun and Cho (2013) discovered that, regarding the volatility forecasting of carbon futures contracts at the European Climate Exchange, GARCH-type models (i.e. GARCH, EGARCH, TGARCH, and GJR-GARCH models with normal and student's *t* distribution settings) perform better than the implied volatility model. In addition, the GJR-GARCH model with a normal distribution shows the best forecast performance among the above-mentioned GARCH-type models.

As shown in the literature review, the asymmetric or more generally nonlinear GARCH-type models seem to perform better than symmetric GARCH models (see Byun & Cho, 2013; Wei et al., 2010), and the models with non-normal distributions perform better than those with normal distribution (see Agnolucci, 2009), since the asymmetric GARCH-type models and non-normal distribution can capture the three features (i.e. the volatility clustering, leverage, and distribution effects) of data well. In contrast to prior studies, the model used in this study not only considers the above-mentioned effects but also embeds with the price level effect of Brenner, Harjes, and Kroner (1996) (hereafter, BHK). The variance specification of this BHK model is a function of both the price level and its unexpected shocks. This study is the first to use the price level effect to forecast the volatility of the assets in the oil, metal, stock, and exchange rate markets[5] rather than that of the interest rate market, as used by Brenner et al. (1996). Consequently, the empirical models of this study are composed of five GARCH-based variance specifications and two return distribution settings. The five GARCH-based variance specifications are the GARCH model of Bollerslev (1986), the asymmetric GARCH (AGARCH) model of Engle (1990), the quadratic GARCH (QGARCH) model of Sentana (1995), the threshold GARCH model of Glosten et al. (1993) (GJR-GARCH), and the price level GARCH model of BHK (BHK-GARCH). The two return distribution settings are the normal and Hansen's (1994) skewed student's *t* (ST) distributions. Hence, the six models (i.e. the BHK-GARCH, AGARCH, QGARCH, GJR-GARCH, standard GARCH models with normal distribution, and the GARCH model with ST distribution) are used to seize some common stylized facts mentioned above and to estimate the volatility of seven commodities in the US oil market, seven metal commodities in the London metal exchange (LME), and seven countries' exchange rates and stock indices. They are further used to explore (1) whether the price level, distribution, and leverage effects exist in the assets dispersed in the four markets (i.e. oil, metal, stock, and exchange rate markets); (2) how each of the three financial features affects the volatility forecasts in each market; (3) which feature plays the most substantial role in the volatility forecast in each market; and (4) which of the three asymmetric GARCH models (AGARCH-N, QGARCH-N, and GJR-GARCH-N) has the best forecast performance.

Our results show that the assets in the oil (resp. exchange rate) market have the greatest (resp. smallest) risk. **Moreover**, the fat-tailed effect most significantly exists in these four markets, followed by the price level, skewness, and leverage effects. **Notably**, a negative (resp. positive) volatility elasticity exists in the oil, exchange rate, and stock (resp. metal) markets. **Furthermore**, both the price level and distributions effects significantly affect the volatility forecasts in the oil market, whereas only the leverage effect slightly affects the volatility forecasts in the metal market. Conversely, the price level, distribution, and leverage effects slightly affect the volatility forecasts in the stock market, whereas no effect can affect the volatility forecasts in the exchange rate market. Notably, the price level effect is the most crucial in volatility forecasts in the oil market, whereas the leverage effect is the most crucial in volatility forecasts in the metal and stock markets. Additionally, the GJR-GARCH-N has the best performance of

[2] Because many time series data of financial assets appear to exhibit autocorrelated, volatility clustering, and leverage effects, and the GARCH-type of variance specification can capture the above stylized facts, GARCH family models are widely used in financial issues such as return transmission and volatility spillover (see Huang & Kuo, 2015; Su, 2014b), volatility forecasts (see Chuang, Huang, & Lin, 2013; Su, 2015), and VaR estimates (see Haas, Krause, Paolella, & Steude, 2013; Su, 2014a, and so on).

[3] Volatility clustering is the tendency of volatility appearing in bunches in financial markets. Thus, large returns are expected to follow large returns, and small returns to follow small returns.

[4] The leverage effect is the tendency for volatility to increase following a large price fall rather than following a price rise of the same magnitude.

[5] Besides the assets in the oil market, the assets in the metal, stock, and exchange rate markets are used to explore the issues of this study in order to obtain more robust results.

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