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Why does skewness and the fat-tail effect influence value-at-risk estimates? Evidence from alternative capital markets

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ABSTRACT

In this study, the generalized autoregressive conditional heteroskedasticity (GARCH) model involving skewed generalized error distribution (SGED) was used to estimate the corresponding volatility and value-at-risk (VaR) measures for various commodities distributed across four types of commodity markets. The empirical results indicated that the return (volatility) of most of the assets distributed in alternative markets significantly decreased (increased) as a result of the global financial crisis. Conversely, the oil crisis yielded inconsistent results. Regarding the influences of both crises on return and volatility, the global financial crisis was more influential than the oil crisis was. Moreover, regarding confidence levels, the skewness effect existed among VaR estimations for only the long position, whereas the fat-tail effect existed among the VaR estimations for only high confidence levels, irrespective of whether a long or short position was traded. Finally, regarding the popular confidence levels in risk management, the SGED (GED) was the optimal return distribution setting for a long (short) position.

1. Introduction

Since 2000, the world experienced two crucial crises. First was the oil crisis that began on September 1, 2003 and ended July 1, 2008. Before September 1, 2003, the inflation-adjusted price of a barrel of crude oil on NYMEX was typically below $25/barrel. During 2003, the price rose to above $30, reached $60 by August 11, 2005, and peaked at $147.30 in July 2008. Commentators attributed the price increases to several factors, including the decreasing value of the U.S. dollar and oil price speculation. High oil prices increase the production costs of industries, indirectly affect national economic development, and may influence the prices of commodities in a capital market. Second was the global financial crisis that began on January 2, 2007 and ended December 31, 2008. This crisis arose from the U.S. subprime mortgage crisis that began in late 2006; it produced far-reaching, worldwide consequences causing numerous enterprises to enter liquidation and several countries to experience depressed economies. These crises directly and indirectly affected the lives of people throughout the world. Consequently, accurately controlling and forecasting market risk is a critical topic, particularly during crisis periods. Moreover, because value-at-risk (VaR) attempts to provide a single number summarizing the total risk in a portfolio of financial assets for senior management, it can be simply used to measure market risk in this study. VaR is also widely used for managing financial risk by institutions, including banks, regulators, and portfolio managers.

The features of a financial data return series and trade positions of investors can influence the forecasting performance of a model. Thus, we must describe and explore the aforementioned problems to precisely estimate the VaR. First, regarding the features of the

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financial data return series, the logarithmic returns for most financial assets yield empirical distributions that are leptokurticly relative to normal distribution and are often skewed (Fama, 1965; Mandelbrot, 1963; Theodossiou, 1998). For example, French, Schwert, and Stambaugh (1987) reported skewness in daily Standard and Poor (S&P) 500 returns, and Bollerslev (1987) observed leptokurtosis in monthly S&P 500 returns. Moreover, Engle and Gonzalez-Rivera (1991) observed skewness and excess kurtosis in small stocks and exchange rates. Second, regarding trade position, most investors performed well in the long position, but hedgers, speculators, and arbitragers exist in the financial market, causing short sales to gradually increase. Investors holding long (or short) positions are concerned with only the downside (or upside) of the returns distribution, specifically, the tailed distribution on the left (or right) side of the returns distribution. However, the degree of fat-tail and skewness influences the tail of the returns distribution. Estimations of VaR frequently assume that log returns are normally distributed (Angelidis, Benos, & Degiannakis, 2004; Bellini & Figá-Talamanca, 2007; Chen & Liao, 2009; So & Yu, 2006). This assumption has been rejected for most financial time series such as individual stocks, stock indices, exchange rates, and precious metals. Therefore, VaR estimators based on a normal distribution cause either an underestimation or overestimation of the true risk.

Consequently, researchers have successively used the fat-tailed and asymmetric types of return distribution settings to estimate the VaR. For example, because a student's *t* random variable appears to capture the non-normal aspects of innovations better (Baillie & Bollerslev, 1992; Beine, Laurent, & Lecourt, 2002; Bollerslev, 1987) numerous studies have proposed using a student's *t* distribution (Ané, 2006; Angelidis et al., 2004; Huang & Lin, 2004; So & Yu, 2006) and fat-tailed generalized error distribution (GED) (Angelidis et al., 2004; Su & Knowles, 2006) to capture extreme events when modeling VaR. However, neither the GED nor student's *t* distribution can consider the skewness of return innovations. Moreover, Giot and Laurent (2003) argued that the asymmetric power ARCH (APARCH) model with symmetric normal innovation delivered poor VaR forecasts. Furthermore, Brooks and Persand (2003) provided evidence that models that do not allow for asymmetries in the unconditional return distribution underestimate the true VaR. According to the aforementioned literature review, it is pivotal to simultaneously consider the kurtosis and skewness features of return distributions when estimating the VaR. Thus, we used the skewed generalized error distribution (SGED) of Theodossiou (2001) as the return distribution setting in this study, because the SGED can simultaneously capture the kurtosis and skewness features among a financial return series.

The foregoing focuses on the type of return innovation processes involved in estimating the VaR. Regarding the mean and variance specifications of log returns, the generalized autoregressive conditional heteroskedasticity (GARCH) type of volatility specification can capture the stylized facts existing in the volatility of financial market returns. These stylized facts include the volatility clustering, mean reversion, and comovements of volatilities across assets and financial markets (Engle & Patton, 2001; Jondeau & Rockinger, 2003; Poon & Granger, 2003). Thus, the GARCH family of models has been widely used for various financial purposes, such as estimating volatility, VaR, and option pricing, and are employed in this study. For example, Leeves (2007) applied three GARCH-type models to investigate the conditional volatility of stock returns in Indonesia during 1990–1999 which covered the Asian financial crisis. Ewing and Malik (2013) employed univariate and bivariate GARCH models to examine the volatility dynamics of gold and oil futures from 1993 to 2010. Liu, Chiang, and Cheng (2012) used four GARCH-type models with the skewed generalized *t* (SGT) return distribution setting to forecast both volatility and VaR for Standard & Poor's Depositary Receipts (SPDRs) from 2002 to 2008. McAleer, Jimenez-Martin, and Perez-Amaral (2013) used four GARCH-type models with normal, student's *t*, and generalized normal return distribution settings to forecast the VaR for Standard and Poor's Composite 500 index (S&P500) from January 3, 2000 to March 16, 2010, establishing three subperiods: before, during, and after the 2008–2009 global financial crisis. According to the aforementioned literature, first, the GARCH model is widely used as an empirical model irrespective of whether the volatility or the VaR is estimated. Second, although the study data covered the oil and global financial crises, they focused only on performance comparisons among various VaR models (Liu et al., 2012; McAleer et al., 2013) and did not consider how these crises influenced return and volatility estimates. Excluding McAleer et al. (2013), the study period was divided into three subperiods to estimate the VaR according to the time that the global financial crisis occurred. Finally, the study data were limited to a few assets, such as the stock returns in Indonesia (Leeves, 2007), the gold and oil (Ewing & Malik, 2013), SPDRs (Liu et al., 2012), and the S&P500 index (McAleer et al., 2013).

In contrast to previous studies, in the current study, three time dummy variables were set in the mean and variance equations of the GARCH volatility specification, because the study period covered two major crises: the oil crisis (September 1, 2003 to July 1, 2008) and the global financial crisis (January 2, 2007 to December 31, 2008); the crisis periods overlapped from January 2, 2007 to July 1, 2008. The three time dummy variables, which were set according to the times of the global financial and oil crises, were used to explore how the two crises influenced the mean and variance estimates of asset return and evaluate which crisis was more influential. The aforementioned topics are innovations in the field of VaR. Second, we extensively applied the study data to stock markets and three commodity markets (agriculture, energy, and metal), totaling 21 assets, to evaluate the consistency of the obtained results (i.e., how the crises influenced mean and volatility estimates and the skewness and fat-tail effects existing in the VaR estimates).

Thus, this study considered the applicability of the GARCH (1,1) model by using the SGED of Theodossiou (2001) and its degenerative distributions, namely the normal and skewed normal (SN) distributions used by Theodossiou and Trigeorgis (2003) and the GED described by Box and Tiao (1973), estimating volatility and VaR measures based on various assets distributed across four types of markets (agriculture, energy, metal, and stock markets) for both long and short positions. Moreover, we set three time dummy variables in the mean and variance equations of the surveyed model according based on the times of the global financial and oil crises, to investigate how these crises influenced the return and volatility estimates and determine which crisis was more influential. Subsequently, several issues were investigated in this study. First, how did the crises affect the return estimates of these four types of commodity markets? Second, was the volatility among these commodity markets influenced by