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Testing and comparing the performance of dynamic variance and correlation models in value-at-risk estimation

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ABSTRACT

This study addresses and examines certain advanced approaches for value-at-risk (VaR) estimation. In particular, we employ a multivariate generalized autoregressive conditionally heteroskedastic (MVGARCH) model involving time-varying settings and multivariate Markov switching autoregressive conditionally heteroskedastic (MVSWARCH) model with regime-switching techniques and compare them with a conventional linear regression-based (LRB) model. Our empirical findings are as follows: First, while the LRB VaR model behaves reasonably well in tranquil periods, it significantly underestimates actual risk during unstable periods. Second, in comparison with the LRB VaR model, MVGARCH- and MVSWARCH-based VaR models do better under unusual conditions, whereas better models are needed to estimate VaR. Third, dynamic variance settings improve the accuracy of VaR estimates. However, the effect of dynamic correlation designs on VaR is marginal.

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1. Introduction

Practitioners have turned their attention to value at risk (VaR), particularly after the Basel Committee endorsed its use to measure banks' capital adequacy ratios in 1996.[1] In addition, there has been growing interest in forecasting VaR in the financial econometrics literature (Nieto & Ruiz, 2016). One can use VaR to measure the level of market risk and, thus, capital adequacy ratios.[2] Three

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[1] Apart from VaR, the recent Basel Accord also suggested the expected shortfall as an alternative measure of risk (Acerbi & Tasche, 2002). There has also been growing interest in forecasting the expected shortfall in recent literature (e.g., Chen, 2008; Chen, Gerlach, & Lu, 2012; Brandtner, 2013; Lönnbark, 2013; Stoyanov, Rachev, & Fabozzi, 2013).

[2] Duffie and Pan (1997) suggested that one can measure default risk, credit risk, operation risk, and liquidity risk via a VaR algorithm.

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methods are used to calculate VaR: (1) the parametric VaR method, (2) historical simulation, and (3) Monte Carlo simulation. Each VaR approach has its strengths and weakness, but this study focuses on parametric VaR.

The approach is parametric in that it assumes that the probability distribution is normal and then requires the calculation of variance and correlation parameters. Thus, it is also known as the variance–covariance VaR method. One key advantage of the parametric VaR method in comparison with historical and Monte Carlo simulation is that it allows for the calculation of the contribution of VaR.[3] However, the conventional parametric VaR implicitly assumes that variances and correlations are stable and constant over time.

The observed non-constant variances in financial returns have led to the development of different dynamic variance models. In particular, Engle (1982) proposed the autoregressive conditionally heteroskedastic (ARCH) model and Bollerslev (1986) developed the generalized ARCH (GARCH) model. Hamilton and Susmel (1994) set up a Markov switching ARCH (SWARCH) model that incorporates regime switches with an ARCH process to estimate volatility. Gray (1996) also developed a model that incorporated both regime switches and GARCH effects.

Numerous studies have applied these dynamic variance settings to estimate VaR. In particular, Angelidis, Benos, and Degiannakis (2004) examined the performances of different ARCH models in modeling daily VaR. Christoffersen, Hahn, and Inoue (2001) compared the performances of VaR models based on GARCH, RiskMetrics methodology, and stochastic volatility. Thupayagale (2010) and Chen (2011) examined the performance of GARCH-based models in VaR estimation. Andersen, Bollerslev, Christoffersen, and Diebold (2005) considered portfolio VaR measurement using multivariate smoothing and multivariate GARCH (MVGARCH). Berkowitz and O'Brien (2002) demonstrated how a simple reduced-form GARCH model can outperform banks' in-house VaR models. Billio and Pelizzon (2000) and Haas, Mittnik, and Paolella (2004) used switching volatility models to estimate VaR. Guidolina and Timmermann (2006) and Haas (2009) compared various single-regime and regime-switching models using monthly and daily data, respectively.

Following the above studies, this study considers the MVGARCH models involving time-varying settings and a multivariate SWARCH (MVSWARCH) model with regime-switching techniques and compares their performance with a conventional linear regression-based (LRB) model in VaR forecasts. This study departs from earlier studies by examining the effects of dynamic correlations on VaR and conducting a comparative analysis across various market conditions. In particular, although prior studies have shown that dynamic variance settings significantly enhance the accuracy of VaR estimates, could dynamic correlation designs help VaR estimation further? And are dynamic variance and correlation models more or less valid in VaR forecasts under highly unstable conditions? To our knowledge, few studies have addressed these two significant issues regarding VaR estimation.

Our study contributes to the literature in several ways. First, we develop a methodology that considers dynamic volatilities and correlations in stock markets, thus producing results that cannot be captured by traditional linear approaches. Second, we estimate the models via a one-step procedure where dynamic market volatilities and correlations are jointly determined, thereby relaxing the assumption involved in the two-step procedure used by Engle (2002) and Pelletier (2006). Third, we consider various VaR backtesting methods and differentiate between stable and unstable periods. Taking advantage of the less restrictive empirical model and research design, our study provides evidence that helps to systematically examine the performance of dynamic variance and correlation models in VaR estimation.

The remainder of this study is organized as follows. Section 2 outlines the VaR models we use in this study: (1) the linear model with constant variance and correlation, (2) the MVGARCH model for the development of time-varying variances and correlations, and (3) the MVSWARCH with regime-switching techniques. Section 3 presents the non-normality issue and VaR estimation under a regime-switching framework. Section 4 describes alternative backtesting methods for VaR estimation. Empirical checks of the accuracy of VaR measurements across various models are conducted in Section 5. Finally, Section 6 draws the conclusions of this investigation and suggests directions for future research.

2. Model specification

2.1. Linear model with constant variance and correlation

The usual approach to constructing variance and correlation is to calculate variance and correlation of the risk factors over the last few months and to assume that tomorrow's changes in the risk factors will come from a distribution that has the same variance and correlation as that experienced historically. The traditional linear model with constant variance and correlation is presented below:

$$R_{x,t} = u_x + e_{x,t}, \tag{1}$$

$$R_{y,t} = u_y + e_{y,t}, \tag{2}$$

[3] By contrast, it is difficult to apply historical and Monte Carlo simulation methods to calculate the VaR contribution. The VaR contribution technique is useful because it measures the risk of each individual subportfolio that includes interportfolio correlation effects. The VaR contribution is also useful in allocating a bank's capital to those units causing the risk and for setting limits on the amount of risk that individual traders can take on.