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Value-at-risk estimation with wavelet-based extreme value theory: Evidence from emerging markets

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ABSTRACT

This paper introduces wavelet-based extreme value theory (EVT) for univariate value-at-risk estimation. Wavelets and EVT are combined for volatility forecasting to estimate a hybrid model. In the first stage, wavelets are used as a threshold in generalized Pareto distribution, and in the second stage, EVT is applied with a wavelet-based threshold. This new model is applied to two major emerging stock markets: the Istanbul Stock Exchange (ISE) and the Budapest Stock Exchange (BUX). The relative performance of wavelet-based EVT is benchmarked against the Riskmetrics-EWMA, ARMA–GARCH, generalized Pareto distribution, and conditional generalized Pareto distribution models. The empirical results show that the wavelet-based extreme value theory increases predictive performance of financial forecasting according to number of violations and tail-loss tests. The superior forecasting performance of the wavelet-based EVT model is also consistent with Basel II requirements, and this new model can be used by financial institutions as well.

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1. Introduction

Value-at-risk (VaR) became a common tool for financial forecasting with the Riskmetrics-exponentially weighted moving average (EWMA), made famous by Morgan in the early 1990s. This model is actually a special case of Bollerslev's [1] generalized autoregressive conditional heteroskedasticity (GARCH) model. More than 100 volatility models were developed during the last 28 years [2]. One of the most important features that made the conditional volatility models popular is their ability to capture many of the typical stylized facts of a financial time series, such as time-varying volatility, persistence and volatility clustering. However, conditional volatility models cannot capture extreme movements, as these models are based on past volatility rather than the extreme observations. Extreme value theory models can capture extreme movements, and the forecasting performance of these models is better than that of GARCH type models [3]. There are some important reasons to model the returns with extreme value theory. First, the distribution of returns is heavy-tailed or leptokurtic for most of the financial returns. Second, the right and left tails of returns are not symmetrical, and extreme value theory models can be applied to each tail with different parameters, as opposed to GARCH and other volatility models.

The methodology of forecast combination was introduced by Bates and Granger [4]. They urged that we should combine forecasts as a weighted average of the individual forecasts. Forecast combination can be estimated by a combination of individual forecasts or by a combination of models. Individual forecasts' combination can be estimated with artificial intelligence techniques. Liu [5] and Ozun and Cifter [6] proposed neural networks for a combination of individual forecasts. Liu [5] combined neural networks with historical simulation and GARCH(1, 1) models and found that the combination of historical estimation with GARCH and neural networks significantly improved forecasting performance. Ozun and Cifter [6]

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combined Hill [7] type EVT with historical simulation and GARCH models with neural networks. They found that the combination of EVT and other models improves forecasting performance.

Hybrid models as a combination of EVT with conditional volatility models were proposed by McNeil and Frey [8]. This model uses a two-stage approach. In the first stage, a GARCH type model is applied to residuals. In the second stage, EVT is applied to standardized residuals. McNeil and Frey [8] found that the conditional EVT procedure gives a better one-day-ahead forecast than methods which ignore the heavy tails of the innovations or the stochastic nature of the volatility.

Wavelets can also be used to estimate hybrid financial forecasting models. The combination of wavelet transform and GARCH models was introduced by Chi and Kai-jian [9], Lai et al. [10,11], He et al. [12,13], and Tan et al. [14]. Chi and Kai-jian, Lai et al., and He et al. [12] proposed wavelet-decomposed value-at-risk, and He et al. [13] proposed wavelet denoising ARMA–GARCH models. This paper typically used Kupiec [15]'s test for backtesting, and although their model is superior to conventional ARMA–GARCH models, the number of violations is greater than that of ARMA–GARCH models. Tan et al. [14] combined wavelet transform with ARIMA and GARCH models and applied this model to one-day-ahead electricity price forecasting. They found that their model is far more accurate than other forecasting models.

Yamada and Honda [16] used wavelet analysis to predict business turning points of the Nikkei 225 index and found that wavelet analysis can capture business peaks and troughs (minimum points) as an alternative structural break analysis. Bowden and Zhu [17] combined wavelet analysis with structural breaks and applied this combined model to the agribusiness cycle. By using wavelets, they added the business cycle feature to structural break analysis.

In this paper, wavelet-based extreme value theory (EVT) is introduced for univariate value-at-risk estimation. A wavelet-based EVT model is proposed as a combination of wavelets and the EVT model following the approach of McNeil and Frey [8]. In the first stage, wavelets are used as a threshold in generalized Pareto distribution, and in the second stage, EVT is applied with wavelet-based thresholds. The relative performance of this new hybrid model is compared with conventional volatility models for one-day-ahead forecasts, and wavelet-based EVT is benchmarked against the Riskmetrics-EWMA, ARMA–GARCH, generalized Pareto distribution, and conditional generalized Pareto distribution models. This new model is applied to two major emerging stock markets: the Istanbul Stock Exchange (ISE) and the Budapest Stock Exchange (BUX). It is found that the wavelet-based EVT model increases predictive performance of financial forecasting according to the number of violations and tail-loss tests for emerging markets.

The remainder of the paper is organized as follows. Section 2 provides value-at-risk methodologies. Section 3 describes the data on daily index returns. Section 4 presents empirical results for the forecasting performance of the models. Section 5 concludes the study.

2. Value-at-risk models

Value-at-risk (VaR) became the standard benchmark for measuring risks in modern risk management. Financial institutions are required to report VaR according to Basel requirements and regulatory authorities, and most non-financial institutions also prefer to report VaR for trading and management purposes. VaR become popular in the 1990s, following well-known disasters such as Orange Country, Barings, Metallgesellschaft, Dawia, and many others, but are now used to measure credit, operational and liquidity risks. VaR measures the worst expected loss over a given horizon under normal market conditions at a given confidence level [18]. For a single asset, VaR is estimated as

$$\mathrm{VaR}^{p}_{t+1,q} = \mu_{t+1} + \sigma_{t+1}F^{-1}(p)\sigma_{t+1} \tag{1}$$

where μ_{t+1} is the forecast of the conditional mean, σ_{t+1} is the forecast of the conditional standard deviation, and $F^{-1}(p)$ is the corresponding quantile of the assumed distribution [19].

In the following section, wavelet-based EVT and benchmarked VaR models are introduced. Riskmetrics-EWMA and ARMA–GARCH models are selected as conditional volatility models, where generalized Pareto distribution is selected as the EVT model, and conditional generalized Pareto distribution is selected as the hybrid GARCH-EVT model for benchmarking.

2.1. Riskmetrics-EWMA model

The simplest and well-known volatility forecasting model, called Riskmetrics-exponentially weighted moving average (EWMA), was developed by Morgan for computing market risks. This model may be defined as a special case of the GARCH model, where $\alpha = 1 - \lambda$ and $\beta = \lambda$ and $\omega = 0$. Riskmetrics-EWMA variance model can be written as [20]:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2 \tag{2}$$

where λ is the decay factor that determines relative weights, r_{t-1} is the previous squared returns and σ_{t-1}^2 is the previous variance of return. Optimal λ can be determined by the in-sample optimization algorithm. λ is usually set to 0.94 for daily data and 0.97 for monthly data [21]. The higher the decay factor, the longer the previous returns. If λ equals 1, volatility is explained by solely previous volatility. Therefore, the mean reverting can be transformed into unconditional variance.

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