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Forecasting daily conditional volatility and *h*-step-ahead short and long Value-at-Risk accuracy: Evidence from financial data

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Abstract

In this article we evaluate the daily conditional volatility and h-step-ahead Value at Risk (VaR) forecasting power of three long memory GARCH-type models (FIGARCH, HYGARCH & FIAPARCH). The forecasting exercise is done for financial assets including seven stock indices (Dow Jones, Nasdaq100, S&P 500, DAX30, CAC40, FTSE100 and Nikkei 225) and three exchange rates vis-a-vis the US dollar (the GBP- USD, YEN-USD and Euro-USD). Because all return series are skewed and fat tailed, each conditional volatility model is estimated under a skewed Student distribution. Consistent with the idea that the accuracy of VaR estimates are sensitive to the adequacy of the volatility model used, h-step-ahead VaR forecasts are based on the skewed Student-t AR(1)-FIAPARCH (1,d,1). This model can jointly accounts for the salient features of financial time series. Our findings reveal that the skewed Student AR (1) FIAPARCH (1.d.1) relatively outperforms the other models in out-of-sample forecasts for one, five and fifteen day forecast horizons. However, there is no difference for the AR (1) FIGARCH (1.d.1) and AR (1) HYGARCH (1.d.1) models since they have the same forecasting ability. Results indicate also that skewed Student-t FIAPARCH (1,d,1) model provides more accurate one-day-ahead VaR forecasts for both long and short trading positions than those generated using alternative horizons (5-day and 15-day-ahead). This result holds for each of the financial time series.

JEL classification: G11; L94; E39; G15

Keywords: Value-at-Risk; Forecasting volatility; Skewed student distribution; Long-range memory

1. Introduction

ARCH model was born in the literature with the publication paper of,[1] soon the model was generalized (GARCH) by Bollerslev (1986). While ARCH was developed to model the changing volatility of inflation series, the model and its later extensions were quickly adopted for modeling conditional volatility of financial returns,[2] The main advantage of GARCH models is that they captured jointly heavy tails and volatility clustering: “large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes”.[3] To account for some financial time series stylist facts, many variants of GARCH class models were proposed such as EGARCH, GJR-

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GARCH, APARCH, FIGARCH, HYGARCH … etc. The models and their later extensions were quickly found to be relevant for the conditional volatility of financial returns. More precisely, those models are usually used for both volatility modeling and forecasts of financial time series. See Bollerslev, Chou and Kroner,[4] Bollerslev, Engle and Nelson,[5] Bera and Higgins (1995) and Diebold and Lopez.[6] Ghysels, Harvey and Renault,[7] Allen et al (2005), Angelidis et al,[8] Assaf (2009), Chiu et al (2006), Cheong (2008), Shieh and Wu (2007), Lee and Saltoglu (2002), Awartani Corradi (2005), Gençay Selçukc (2004), Fan et al (2004), Tse[9] Giot and Laurent,[10] Bollerslev,[11] Wright, (2008), Bali Bali,[12] Engle,[13] Hamilton and Susmel (1999), Gallo and Pacini (1998). In general, models that allow for volatility asymmetry come out well in the forecasting contest because of the strong negative relationship between volatility and shock. Cao and Tsay,[14] Heynen and Kat,[15] Lee[16] and Pagan and Schwert[17] favor the EGARCH model for volatility of stock indices and exchange rates, whereas Brailsford and Faff (1996) and Taylor Taylor, J.[18] find GJR-GARCH outperforms GARCH in stock indices. During the last decades long-memory processes (the presence of statistically significant correlations between observations that are a large distance apart.) have evolved into a vital and important part of the time series analysis. A long memory series has autocorrelation coefficients that decline slowly at a hyperbolic rate. These features change dramatically the statistical behavior of estimates and predictions. An important property of fractionally integrated GARCH models is their ability to capture both volatility clustering and long memory in financial time series. During recent years, several researches have been concerned with the long-range memory on both price variations and price volatilities. More precisely, the empirical literature is focused on volatility modeling when studied time series are governed by a long memory process. See Tang and Shieh (2007), Yu So (2010), Assaf (2009), Chiu et al (2006), Cheong (2008), Shieh and Wu (2007), Lee and Saltoglu (2002), Kang and Yoon,[19] Mabrouk and Aloui,[20] Mabrouk and Saadi (2012) … etc. These studies showed that stock market and exchange market volatility are governed by a long memory process. They concluded that the long memory GARCH class models outperform the other models. The long memory characteristic of financial market volatility has important implications for volatility forecasting and option pricing. Comparing forecasting performance of studied models is crucial for any forecasting exercise. In contrast to the efforts made in the construction of volatility models and forecasts, little attention has been paid to forecast evaluation in the volatility forecasting literature. Figlewski[21] finds GARCH superiority confined to the stock market and for forecasting volatility over a short horizon only. Vilasuso (2002) tested FIGARCH against GARCH and IGARCH for volatility prediction for five major currencies. Vilasuso (2002) finds FIGARCH produces significantly better 1- and 10-day-ahead volatility forecasts for five major exchange rates than GARCH and IGARCH. Zumbach[22] produces only one-day-ahead forecasts and find no difference among model performance. In most applications, the excess kurtosis implied by the GARCH class model under a normal density is not enough to mimic what we observe on real data. Other distributions are possible. Bollerslev[2] proposed to use the Student-t distribution, since it implies conditional leptokurtosis and, therefore, stronger unconditional leptokurtosis. To account for excess kurtosis, the generalized error (GE) distribution was proposed by Nelson.[23] As reported by Pagan,[24] the use of symmetric heavy-tailed distributions (such as Student-t distribution and the generalized error distribution) is common in the finance literature. In particular, Bollerslev,[2] Hsieh (1989), Baillie and Bollerslev[25] and Palm and Vlaar (1997) among others show that these distributions perform better in order to capture the excess kurtosis. However, many financial times series returns are fat tailed and skewed. To account for both asymmetric and fat tail in the empirical density, Fernandez and Steel (1998) proposed skewed-Student density which has been extended by Lambert and Laurent (2000), Lambert and Laurent.[27] The last decade has seen a spectacular development in market risk management techniques. VaR has become a popular method of risk quantification. Indeed, the VaR is adopted by several financial institutions and risk managers as being an effective tool to measure the market risk. Thanks to its conceptual simplicity, VaR has also become a standard risk measure used in financial risk management. Therefore, VaR is widely used to assess exposure to investment risk. VaR can be defined as the maximum potential loss for a given period and at a fixed confidence level. At first the determination of VaR is based on the normal distribution of returns. However, the series returns are leptokurtic (see 3,4,28–32. Therefore, the normal distribution fails to provide good results. To improve the VaR results, empirical studies suggest other distributions such as the Student distribution,[33–36,8] Cheong, 2008), and distribution (GED).[8] The goal is to capture the fat tails of returns. However, the financial asset time series returns are usually both asymmetric and fat tailed. The skewed distribution Student is recommended for estimating VaR since it takes into accounts both asymmetry and fat tail of the return distribution. Therefore, have accurate VaR requires that the volatility model jointly accounts for the salient features of financial time series: fat tails, asymmetry, volatility clustering and long memory. The aim of this paper is to contribute to the finance literature on volatility forecasting and VaR accuracy of financial time series. Thus, our goal is to

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