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Long memory in stock index futures markets: A value-at-risk approach

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Abstract

In this paper, we investigate the long memory properties for closing prices of three stock index futures markets. The FIGARCH (1, d, 1) and HYGARCH (1, d, 1) models with normal, Student-*t*, and skewed Student-*t* distributions for S&P500, Nasdaq100, and Dow Jones daily prices are estimated first. Then the value-at-risks are calculated by the estimated models. The empirical results show that for the three stock index futures, the HYGARCH (1, d, 1) models with skewed Student-*t* distribution perform better based on the Kupiec LR tests. In particular, for the S&P500 and Nasdag 100 futures prices.

Keywords: FIGARCH; Value-at-risk; Kupiec LR test; HYGARCH

1. Introduction

In this paper, we focus on three stock index futures contracts: S&P500, Nasdaq100, and Dow Jones. Different from most other literatures' analyzing asset returns, we analyze the closing price in order to get more clear profile of long term persistence in the financial time series. Before estimating the models, we implement the de-trended fluctuation analysis (DFA) to detect the long memory property exhibited in the price series of the three futures contracts. The empirical evidences give the conclusion that all the three stock index futures closing prices exhibit long memory characteristics and it is adequate to model the closing price series by long memory models.

The importance of allowing for the fraction orders of integration in modeling long-run phenomena was illustrated by a number of literatures [1–4]. Just as the fractionally integrated ARFIMA models were proven empirically important, a corresponding result may hold true when modeling long-term dependence in conditional variance. Analogous to ARFIMA model, the FIGARCH model proposed by Baillie [1] could successfully describe the high persistence existing in the conditional variance. However, in a more general

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framework, there are good reasons to embed it in a class of models in which unit-amplitude restrictions can be tested, Davidson [5] develops a new model, the "hyperbolic GARCH," or HYGARCH model.

In this study, these two long memory models, FIGARCH (1, d, 1) and HYGARCH (1, d, 1),[1] are estimated to investigate the long-run dependence in the stock index futures price series. The empirical evidences show that for S&P and Nasdaq 100 stock index futures, HYGARCH model with skewed Student-t innovations performs better according to the AIC, log likelihood values, and Liung-Box Q^2 statistics. But FIGARCH model with skewed Student-t innovations is adequate to fit Dow Jones Industrial stock index futures. Our results are similar to those of Sriananthakumar and Silvapulle [6] and Giot and Laurent [7], both of them document that non-normal distributions perform better than the normal one.

To be more specific, Sriananthakumar and Silvapulle [6] estimate the Value-at Risk (VaR) for daily returns of Australian All Ordinaries, S&P500, and Dow Jones Industrial indices using the ARCH class of models based on normal, Student-t, and skewed Student-t distributions and extreme value theory. They have shown that the GARCH (1, 1) model with Student-t errors seemed to capture the typical characteristics of the returns distributions well. The main distinction between their model and the model formulated here is that the long-term dependences for the far away observations in the series are missing in their model. We characterize the long memory characteristics in the model and find that the non-normal error distribution performs much better than the normal one. In addition, the evidences show that the Student parameters (v) are significantly different from zero for the three series both under Student-t and skewed Student-t distributions.

Furthermore, Giot and Laurent's [7] VaR model for the daily returns of three stock indices (the English FTSE, the US NASDAQ, the Japanese NIKKEI stock indices) and three stocks (Alcoa, MacDonald, and Merck) using the parametric models of ARCH class based on normal, Student-t, and skewed Student-t distributions. They show that the models that relied on a symmetric density distribution for the error term performed worse than skewed density models when the left and right tails of distributions of returns must be modeled. Nevertheless, a notable distinction between their papers and ours is that we focus on the closing price rather than the log return of the financial assets.

The in-sample and out-of-sample VaR are calculated by the appropriate long memory models for S&P 500, Nasdaq 100, and Dow Jones Industrial stock index futures prices respectively. The empirical results indicate that FIGARCH or HYGARCH models with skewed Student-t innovations can describe the fat-tail behaviors in these series based on the Kupiec [8] LR tests.

The rest of the paper is organized as follows: In Section 2, the basic definitions and theoretic properties of the FIGARCH (1, d, 1), and HYGARCH (1, d, 1) models are presented. The empirical results of unit root and long-memory tests, and models estimations are summarized in Section 3. Some remarks are concluded in Section 4.

2. Methodology

In this section, we first introduce the DFA and offer the theoretical foundation for the models we use to do the empirical works. And we present the FIGARCH and HYGARCH models with normal, Student-t and skewed Student-t innovations.

2.1. DFA

As the price series in this study are not stationary, we have also gone through the DFA, which has been proposed by Peng et al. [9,10]. It originates from fractal analysis and reveals long-range correlations within data series across different time scales. Advantages of DFA over conventional methods (e.g., spectral analysis and Hurst analysis) are that it permits the detection of intrinsic self-similarity embedded in a seemingly non-stationary time series, and also avoids the spurious detection of apparent self-similarity, which may be an artifact of extrinsic trends. To illustrate the DFA algorithm,[2] first, the price time series (of total length N) is

[1] We have executed FIEGARCH models under three different innovations assumptions, either. But the estimation results are not convergent for most of the orders in the model for these three series. Thus, we do not present the empirical results from that model.

[2] The DFA algorithm presented here follows that in Chen et al. [11].