

Long Memory Conditional Volatility and Dynamic Asset Allocation

Submitted by Anh Thi Hoang Nguyen to the University of Exeter as a thesis for the degree of Doctor of Philosophy in Finance in September 2011.

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Abstract

The thesis first evaluates the forecast performance of multivariate long memory conditional volatility models among themselves and against that of short memory conditional volatility models, using the asset allocation framework of Engle and Colacito (2006). While many alternative conditional volatility models have been developed in the literature, my choice reflects the need for parsimonious models that can be used to forecast high dimensional covariance matrices. In particular, I compare the statistical and economic performance of four multivariate long memory volatility models (the long memory EWMA, long memory EWMA-DCC, FIGARCH-DCC and Component GARCH-DCC models) with that of two multivariate short memory volatility models (the short memory EWMA and GARCH-DCC models). The research reports two main findings. First, for longer horizon forecasts, long memory volatility models generally produce forecasts of the covariance matrix that are statistically more accurate and informative, and economically more useful than those produced by short memory volatility models. Second, the two parsimonious long memory EWMA models outperform the other models – both short memory and long memory – in a majority of cases across all forecast horizons. These results apply to both low and high dimensional covariance matrices with both low and high correlation assets, and are robust to the choice of estimation window.

The multivariate conditional volatility models are then analysed further to shed light on the benefits of allowing for long memory volatility dynamics in forecasts of the covariance matrix for dynamic asset allocation. Specifically, the research evaluates the economic gains accruing to long memory volatility timing strategies, using the procedure of Fleming et al. (2001). The research consistently identifies the gains from incorporating long memory volatility dynamics in investment decisions. Investors are willing to pay to switch from the static to the dynamic strategies, and especially from the short memory volatility timing to the long memory volatility timing strategies across both short and long investment horizons. Among the long memory conditional volatility models, the two parsimonious long memory EWMA models, again, generally produce the most superior portfolios. When transaction costs are taken into account, the gains from the daily rebalanced dynamic portfolios deteriorate; however, it is still worth implementing the dynamic strategies at lower rebalancing frequencies. The results are robust to estimation error in expected returns, the choice of risk aversion coefficients and the use of a long-only constraint.

The long memory conditional covariance matrix is inevitably subject to estimation error. The research then employs a factor structure to control for estimation error in forecasts of the high dimensional covariance matrix. Specifically, the research develops a dynamic long memory factor (the Orthogonal Factor Long Memory, or OFLM) model by embedding the univariate long memory EWMA model of Zumbach (2006) into an orthogonal factor structure. The new factor model follows richer processes than normally assumed, in which both the factors and idiosyncratic shocks are modelled with long memory behaviour in their volatilities. The factor-structured OFLM model is evaluated against the six above multivariate conditional volatility models, especially the fully estimated multivariate long memory EWMA model of Zumbach (2009b), in terms of forecast performance and economic benefits. The results suggest that the OFLM model generally produces impressive forecasts over both short and long forecast horizons. In the volatility timing framework, portfolios constructed with the OFLM model consistently dominate the static and other dynamic volatility timing portfolios in all rebalancing frequencies. Particularly, the outperformance of the factor-structured OFLM model to the fully estimated LM-EWMA model confirms the advantage of the factor structure in reducing estimation error. The factor structure also significantly reduces transaction costs, making the dynamic strategies more feasible in practice. The dynamic factor long memory volatility model also consistently produces more superior portfolios than those produced by the traditional unconditional factor and the dynamic factor short memory volatility models.

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List of Abbreviations

APT	Arbitrage Pricing Theory
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BEKK	Baba, Engle, Kraft and Kroner
BIRR	Burmeister, Ibbotson, Roll and Ross
CAPM	Capital Asset Pricing Model
CCC	Constant Conditional Correlation
CGARCH	Component Generalised Autoregressive Conditional Heteroskedasticity
CML	Capital Market Line
CRR	Chen, Roll and Ross
DCC	Dynamic Conditional Correlation
DJIA	Dow Jones Industrial Averages
EGARCH	Exponential Generalised Autoregressive Conditional Heteroskedasticity
EWMA	Exponentially Weighted Moving Average
FIGARCH	Fractionally Integrated Generalised Autoregressive Conditional Heteroskedasticity
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GJR-GARCH	Glosten-Jagannathan-Runkle Generalised Autoregressive Conditional Heteroskedasticity
GMM	Generalised Method of Moments
GMV	Global Minimum Variance
GPH	Geweke-Porter-Hudak log periodgram estimator
HAC	Heteroscedasticity and Autocorrelation Consistent
HML	High Minus Low
HMSE	Heteroscedasticity-adjusted Mean Squared Error
HYGARCH	Hyperbolic Generalised Autoregressive Conditional Heteroskedasticity
i.i.d	independently identically distributed

IC	Information Criterion
IGARCH	Integrated Generalised Autoregressive Conditional Heteroskedasticity
LM-EWMA	Long Memory Exponentially Weighted Moving Average
MAE	Mean Absolute Error
MS	Moulines-Soulier log periodgram estimator
MSE	Mean Squared Error
OFLM	Orthogonal Factor Long Memory
PCA	Principal Components Analysis
RMSE	Root Mean Squared Error
S&P500	Standard & Poor's 500 Index
SMB	Small Minus Big
TGARCH	Threshold Generalised Autoregressive Conditional Heteroskedasticity

Author's Declaration

I hereby declare that this thesis incorporates materials that are results of joint research, as follows:

Chapter 5 is based on a paper submitted to the International Journal of Forecasting co-authored with Professor Richard Harris. Professor Richard Harris provided editorial advice and guidance throughout the development of the analysis and the paper. Anh Nguyen carried out the analysis and wrote most of the paper.

Parts of Chapters 6 and 7 are based on a working paper co-authored with Professor Richard Harris. Professor Richard Harris provided editorial advice and guidance throughout the development of the model and the paper. Anh Nguyen developed the model, carried out the analysis and wrote most of the paper.

I am aware of the University of Exeter's regulation and I certify that I have properly acknowledged the contribution of other researchers to my thesis, and have obtained permission from them to include the above materials in my thesis.

I certify that, with the above qualification, this thesis, and the research to which it refers, is the product of my own work.