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Multivariate models with long memory dependence in conditional correlation and volatility

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ABSTRACT

Multivariate models with long memory (LM) in conditional correlation and volatility are proposed. The models employ a fractionally integrated version of the dynamic conditional correlation GARCH (DCC-GARCH) process (Engle, 2002), and can be used to forecast conditional covariance matrices of high dimension. The models are applied to a data set consisting of ten US stocks and out of sample forecasts over 1–80 days evaluated using statistical and economic loss functions. If intraday data is unavailable, the statistical loss function reveals that LM correlation models provide superior return covariance matrix forecasts over 20–80 days. When intraday data is available, LM correlation models provide superior forecasts of the realised covariance matrix over the same horizons, however the gains when forecasting the return covariance matrix are small. Finally, when forecasting minimum variance portfolio weights, even though the benefits from LM correlation models diminish completely, they are not consistently outperformed by any of the benchmarks.

1. Introduction

Long memory models for the first and second moments have been well studied over the last two to three decades (Baillie, 1996; Robinson, 2003; Kirman and Teyssiere, 2007), with more recent attention focused on the realised covariance matrix (Bauer and Vorkink, 2011; Chiriac and Voev, 2011). Long memory in conditional correlations has been documented as far back as Andersen et al. (2003), yet no multivariate long memory conditional correlation models have been developed. This paper seeks to fill this gap by proposing fractionally integrated versions of the dynamic conditional correlation (DCC) process (Engle, 2002). Analytical conditions for positive definiteness (PD) are derived, and out of sample forecast performance is evaluated against a number of benchmarks.

Long memory is commonly used to describe persistent dependence between time series observations as the lag increases. This is typically characterised by hyperbolic decay of the autocovariance function which is not absolutely summable. In contrast, weakly dependent or short memory (SM) processes like DCC-GARCH have exponential decay of the auto-covariance function which is absolutely summable.

A voluminous literature has documented long memory in the volatility of equities, currencies and commodities. Long memory in volatility may arise from aggregation of multiple volatility components caused by heterogeneous information flows (Andersen and Bollerslev, 1997) or heterogeneous traders (Müller et al., 1997), it may also arise from a heavy tailed regime switching process (Liu, 2000). Multivariate extensions have examined spectral density estimators of the fractional differencing parameter d (Lobato, 1999; Lobato and Velasco, 2000), common long memory factors in large systems (Morana, 2007), fractional cointegration (Brunetti and

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Gilbert, 2000), long memory stochastic volatility models (So and Kwok, 2006) and vector fractionally integrated ARMA (VARFIMA) models on Cholesky factors from realised covariance matrices (Chiriac and Voev, 2011).

This paper proposes two long memory correlation models. Both employ fractionally integrated versions of the DCC process, with the key difference being the assumed information set. The first model extends the multivariate HEAVY (M-HEAVY) specification of Noureldin et al. (2012), which conditions on intraday data and uses realised covariance matrices as innovations. Noureldin et al. (2012) use a SM model via a BEKK GARCH structure, to model conditional covariance matrix dynamics. Instead the proposed Long Memory Multivariate HEAVY (LM-M-HEAVY) model allows for LM in the conditional correlations and volatilities via fractional integration. The second model has similar correlation dynamics to the first, but conditions on a lower frequency data set, employing innovations that are a function of daily returns. The proposed LM-DCC model therefore represents a fractionally integrated version of the more conventional DCC process (Engle, 2002). This model is considered given its popularity in the literature, and that high frequency intraday data may not always be available.

The proposed long memory correlation models are motivated by the following. First, the HEAVY specification jointly models the dynamics of the realised covariance matrix as well as the daily return covariance matrix. The vast majority of the literature that employs realised volatility or covariance matrices assumes that investors open their position at the commencement of trade and close out at the end of the day (Corsi, 2009; Chiriac and Voev, 2011; Bauer and Vorkink, 2011; Golosnoy et al., 2012). This is inadequate for the majority of investors who hold positions over night, because they require close to close forecasts. The HEAVY model meets this need as it can be fit to close to close or open to close returns. HEAVY model forecasts may also exhibit short-run momentum and respond rapidly to sudden changes in volatility or correlation, outperforming univariate (Shephard and Sheppard, 2010) and multivariate (Noureldin et al., 2012) GARCH forecasts over short term horizons.

Second, dynamic correlation models fit to daily returns and realised correlation proxies support the presence of long memory. Short memory dynamic conditional correlation (SM-DCC) models often imply near unit root behaviour (Engle, 2002; Tse and Tsui, 2002; Janus et al., 2014; Hafner and Manner, 2010). It is now well understood that near unit roots may occur if the data generating process (DGP) has long memory or is weakly dependent with occasional breaks. These two processes may be easily confused: in the presence of long memory, a weakly dependent model will spuriously identify occasional breaks; while long memory will be spuriously identified if the DGP is weakly dependent with occasional breaks. See Banerjee and Urga (2005) and Perron and Qu (2010) for comprehensive reviews.

Both approaches have been adopted when examining dynamic correlations. SM-DCC models have captured occasional breaks via dummy variables (Cappiello et al., 2006) and threshold effects (Kwan et al., 2009). Constant correlation models with regime switching (Pelletier, 2006) and smooth transitions (Silvennoinen and Teräsvirta, 2009) have also been used. In contrast, Audrino and Corsi (2010) and Asai (2013) approximate long memory in correlation via the heterogeneous autoregressive (HAR) structure of Corsi (2009), Andersen et al. (2003) fit ARFIMA models to realised correlations, and Janus et al. (2014) estimate a LM-DCC model via an ARFIMA specification that employs a Student t copula. These LM correlation models are only applied in a bivariate setting (i.e a single pairwise correlation), and have not been generalised to a multivariate setting given that they cannot ensure positive definiteness.

This paper remains agnostic on whether correlations have long memory dependence or are short memory with occasional breaks. A long memory specification is employed because even if data has occasional breaks and is weakly dependent, a fractional model may be useful for forecasting (Diebold and Inoue, 2001). Long memory processes may be viewed as a convenient forecasting tool because they do not require forecasts of break points out of sample. This is important because ex-ante break point identification is difficult and failure to do so may be costly. Dacco and Satchell (1999) for example show that failure to forecast the regime may result in regime switching model forecasts having a higher mean square error than forecasts from a random walk.[1]

The third motivation is the shortcomings in the limited literature that extends fractionally integrated GARCH models to a multivariate setting. Teyssiere (1998) and Pafka and Matyas (2001) estimate a multivariate FIGARCH model via a diagonal specification similar to Bollerslev et al. (1988). There are no analytical PD conditions and the diagonal specification is generally only suitable for several assets. Chiriac and Voev (2011) combine long memory volatility models (FIGARCH) with the SM-DCC model of Engle (2002). Whilst the SM-DCC model can be used for a large number of assets and analytical conditions for PD easily imposed, the correlation dynamics exhibit near unit root behaviour and so the use of long memory in volatility but not in the correlations may be sub-optimal. Niguez and Rubia (2006) propose an orthogonal HYGARCH (Davidson, 2004) model which may be used for a large number of assets, however principal components are difficult to interpret.

The final motivation is the limitations in existing LM (or near LM) models when applied to realised covariance matrices (Chiriac and Voev, 2011; Bauer and Vorkink, 2011; Golosnoy et al., 2012; Lucas and Opschoor, 2017). These models lack the flexibility of the DCC structure and are less amenable to large scale system estimation. The VARFIMA model of Chiriac and Voev (2011) imposes an ARFIMA structure on all the Cholesky factors from the realised covariance matrix. Identification requires the complicated Eschelon form (Lütkepohl and Poskitt, 1996) or the final equations form, which imposes a scalar autoregressive polynomial. Bauer and Vorkink (2011) fit a HAR model with a latent factor structure to the matrix log transformation of the realised covariance matrix. Estimation requires a GMM procedure which may be problematic when the number of assets is large. The conditional autoregressive wishart (CAW) model (Golosnoy et al., 2012), approximates long memory via a high order VARMA process and is therefore heavily parameterised. Their five asset model for example has 116 parameters, and even the most restricted version has 41 parameters.

[1] The perceived equivalence between these two approaches has seen recent attention focus on tests for long memory versus structural change (Qu, 2011) as well as the development of models that capture both features (Baillie and Morana, 2009). Near unit roots may therefore be due to long memory and/or neglected structural breaks. A model with long memory and occasional breaks is left for further research.