Topics in financial econometrics

NES Research Project Proposal for 2011-2012

May 12, 2011

Project leaders:
Stanislav Anatolyev, Professor, New Economic School http://www.nes.ru/∼sanatoly
Stanislav Khrapov, Assistant Professor, New Economic School http://khrapovs.web.unc.edu/

Students with interests in time series econometrics are invited to participate in this project. The research in spirit is empirical modeling using real financial data, sometimes with twists in econometric methodology. There is also room for students interested in econometric theory (see the last topic below). The target is producing high-quality research publishable in international journals, both more academic and more practical.

Below are some potential research directions, but the project may not be limited to these and may change its content depending on the tastes and strength of participating students.

1. The most well known and widely used measure of financial market volatility is constructed as a model-free measure using a large set of option prices. This measure is known as Chicago Board Options Exchange Volatility Index, or simply, VIX CBOE (2009). The mathematical justification is provided, among others, by Britten-Jones and Neuberger (2000). In essence, this index is a risk-neutral forecast of future market volatility over the next 30 days. The 30 days forecast interval is actually a limitation of the index. It is natural to assume that there are situation when a longer or a shorter forecast is of interest. With this in mind the following research questions arise. Is it possible to construct and justify analogous VIX index for a general forecast interval? Without taking into account the model misspecification issue it may be possible to construct a more efficient volatility forecast based on a parametric model. See also Sizova (2010).

2. Continuous time models of stochastic volatility are estimated, for example, using the Efficient Method of Moments (Chernov and Ghysels, 2000), or using the Generalized Method of Moments (Bollerslev and Zhou, 2002). One of very surprising side results of these papers are standard errors of parameter estimates. An interesting observation about them is

that they are too small to believe. The potential damaging implication of a downward bias in computation of standard errors is overconfidence in risk management based on continuous time model of stochastic volatility. The idea of this topic is to either rationalize these small standard errors or propose a correction in case the methodology is flawed.

3. It is well known that the market volatility is a highly persistent time series. Some argue that it even possesses the long memory property (Bollerslev and Mikkelsen, 1996). At the same time the estimation of stochastic volatility models relies on high frequency stock market data. Separation of highly persistent and fast stochastic components in volatility was very successful for risk pricing purposes (Adrian and Rosenberg, 2008). The natural extension is to start thinking in between two opposite frequency marks similar to Corsi (2009) who proposed a cascade model of volatility components. The possible avenue of research here is the pricing of medium frequency components and their power in predictability of returns.

4. There is a strand of literature parallel to the research on stochastic volatility modeling with continuous-time and discrete-time models. The modeling framework of Darolles et al. (2006) and Gourieroux and Jasiak (2006) is discrete-time but much more flexible than highly popular GARCH models. CAR model of Darolles et al. (2006) in contrast to local normality breaks the link between moments of different order. ARG model of Gourieroux and Jasiak (2006) as a specific parametric case allows for very simple estimation and simulation of time series. At the same time it remains to be checked if these models are a good fit for the data. If not, it seems to be a natural extension to introduce a multicomponent structure to these models.

5. Balduzzi et al. (1998)put forward a simple approach to identify the so called central tendency in the dynamics of short-term interest rates. This latent component has a nice economic interpretation and plays an important role in asset pricing as it is highly persistent. It is also known that almost any model of interest rates may be applied to stochastic volatility. Hence, the purpose of this project is to explore the possibility of identification of central tendency in volatility.

6. Bollerslev et al. (2011)among others show that the volatility risk premium is informative in predicting future stock market returns. Also, Driessen et al. (2009) show that non-constant correlation risk is priced on the market. The also show that the strategy based on correlation trade generates purely theoretical and practically infeasible high alpha. At the same time the question arises if the extracted information about stochastic correlations and corresponding premium may be useful in predicting future returns on aggregate market as well as on asset classes and individual assets.

7. The factor-based covariance model for stock returns accounting for micro-structure noise and non-synchronous trading observed in the data proves to be very powerful for realized covariance estimation. However, the existing factor-based models (see, e.g., Bannouh et al., 2010; Kyj et al., 2009) of intra-day covariance do not explicitly allow for noise. There also exists an extensive literature on the treatment of market micro-structure noise in realized variance estimation. One can try to extend some of those methods to the multi-dimensional case of covariance estimation. Choice of the factors can also be on the research agenda. One can start with a single market factor model as in Kyj et al. (2009) and extend it by including Fama-French and industry factors, as in Bannouh et al. (2010). Possibly, even some better performing factor framework can be discovered.

8. The aim of this project is to develop a methodology to estimates correlation across asset classes. A good starting point for this project can be a paper by Andersen et al. (2007) where the authors investigate how a simple cross asset class correlation matrix responds to macro economic news. This paper builds a simple correlation matrix among major stock futures, FX rates, fixed income indexes, but an interesting extension could be a large scale matrix covering individual stocks rather than stock indexes. This would imply one will need to apply either covariance matrix shrinkage methodology of Ledoit and Wolf (2002, 2003) or factor modeling or any other methodology to reduce dimensionality of the problem and be able to estimate a large scale matrix in a robust manner.

9. This project can be focused on research and development of a model to estimate correlation structure between stocks in a trading universe on frequencies of several seconds to 1 hour. One interesting research question is to develop and test a factor-based covariance model for stock returns accounting for microstructure noise and non-synchronous trading observed in the data. The factor-based framework proves to be very powerful for realized covariance estimation, especially in high-dimensional applications. However, the existing factor-based models (see, e.g., Kyj et al., 2009; Bannouh et al., 2010) of intra-day covariance do not explicitly allow for noise. The effect of market microstructure features on covariance estimates is documented, e.g., in Oomen (2010). There also exists an extensive literature on the treatment of market microstructure noise in realized variance estimation. The student can try to extend some of those methods to the multi-dimensional case of covariance estimation. Choice of the factors can also be on the research agenda.

10. The theory of estimation with many instruments is quickly advancing. There are interesting asymptotic results that are quite involved (Hansen et al., 2008). Most of this complexity is concentrated in the asymptotic variance terms that originate from error non-normality. It

is interesting to investigate this impact of non-normal errors in terms of numerical values of asymptotic variances and distortions arising from ignoring error non-normality.

References

Adrian, T. and Rosenberg, J. (2008). Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk. *The Journal of Finance*, 63(6):2997–3030.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73(2):251–277.

Balduzzi, P., Das, S. R., and Foresi, S. (1998). The Central Tendency: A Second Factor in Bond Yields. *Review of Economics and Statistics*, 80(1):62–72.

Bannouh, K., Martens, M., Oomen, R., and Dijk, D. V. (2010). Realized mixed-frequency factor models for vast dimensional covariance estimation. Erasmus University Rotterdam.

Bollerslev, T., Gibson, M., and Zhou, H. (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of Econometrics*, 160(1):235–245.

Bollerslev, T. and Mikkelsen, H. O. (1996). Modeling and pricing long memory in stock market volatility. *Journal of Econometrics*, 73(1):151–184.

Bollerslev, T. and Zhou, H. (2002). Estimating stochastic volatility diffusion using conditional moments of integrated volatility. *Journal of Econometrics*, 109:33 – 65.

Britten-Jones, M. and Neuberger, A. (2000). Option Prices, Implied Price Processes, and Stochastic Volatility. *The Journal of Finance*, 55(2):839–866.

CBOE (2009). The CBOE Volatility Index - VIX. CBOE.

Chernov, M. and Ghysels, E. (2000). A study towards a unified approach to the joint estimation of objective and risk neutral measures for the purpose of options valuation. *Journal of Financial Economics*, 56:407–458.

Corsi, F. (2009). A Simple Approximate Long-Memory Model of Realized Volatility. *Journal of Financial Econometrics*, 7(2):174–196.

Darolles, S., Gourieroux, C., and Jasiak, J. (2006). Structural Laplace Transform and Compound Autoregressive Models. *Journal of Time Series Analysis*, 27(4):477–503.

Driessen, J., Maenhout, P. J., and Vilkov, G. (2009). The Price of Correlation Risk: Evidence from Equity Options. *The Journal of Finance*, 64(3):1377–1406.

Gourieroux, C. and Jasiak, J. (2006). Autoregressive Gamma Processes. *Journal of Forecasting*, 25(2):129–152.

Hansen, C., Hausman, J., and Newey, W. (2008). Estimation With Many Instrumental Variables. *Journal of Business and Economic Statistics*, 26(4):398–422.

Kyj, L., Ostdiek, B., and Ensor, K. (2009). Covariance Estimation in Dynamic Portfolio Optimization: A Realized Single Factor Model. Humboldt-Universitat zu Berlin.

Ledoit, O. and Wolf, M. (2002). Some hypothesis tests for the covariance matrix when the dimension is large compared to the sample size. *The Annals of Statistics*, 30(4):1081–1102.

Ledoit, O. and Wolf, M. (2003). Improved estimation of the covariance matrix of stock returns with an application to portfolio selection. *Journal of Empirical Finance*, 10(5):603–621.

Oomen, R. (2010). High-dimensional covariance forecasting for short intra-day horizons. *Quantitative Finance*, 10(10):1173–1185.

Sizova, N. (2010). Integrated Variance Forecasting: Model-Based vs. Reduced-Form. forthcoming in the Journal of Econometrics.