COMISEF Fellows' Workshop on

Numerical Methods and Optimisation in Finance

Birkbeck, University of London
18–19 June 2009

last changes: 17 June 2009

The Workshop

The Workshop intends to give researchers, in particular PhD students, the opportunity to present and discuss current research projects and ideas on a range of topic areas concentrating on anything connected to computational and quantitative finance. This includes portfolio optimisation, option pricing, automated trading, and other related econometric and empirical studies.
Workshop attendance is free, everyone interested in the topics of the Workshop is welcome to join.

About COMISEF

COMISEF is a Marie Curie Research and Training Network, coordinated by Peter Winker from the University of Giessen, Germany. It comprises research teams from universities in Austria, Cyprus, Germany, Great Britain, Italy, Poland, and Switzerland, and Deutsche Bank in Germany as the industry partner.
The key objective for the network's research activities is to establish heuristic optimisation as an additional research paradigm in quantitative research in the fields covered by the network, including economics, statistics and finance. To this end, a clear formal analytical framework of performance and convergence of optimisation heuristics will be developed. New applications in economics and finance will demonstrate the versatility and power of the proposed paradigm.
For more information, visit `http://comisef.eu` and `http://comisef.wikidot.com`.

Organisation

Benoît Guilleminot, Enrico Schumann, Chris Sharpe.

Thanks and Acknowledgements

We thank Prof. Hélyette Geman of Birkbeck, University of London, who has allowed us to host the workshop at Birkbeck. Financial support from the EU Commission through MRTN-CT-2006-034270 COMISEF is gratefully acknowledged.

Schedule

The Workshop will take place at Birkbeck, Main Building, Malet Street, room B36.

Thursday

09:20–09:30	Welcome
09:30–10:00	An Introduction to Genetic Algorithms
10:00–11:00	Heuristic Strategies in Finance – An Overview
(break)	
11:30–12:30	Optimising Risk and Reward of Financial Portfolios with Threshold Accepting
12:30–13:00	An Application of Differential Evolution in Index Mutual Fund Replication
(break)	
14:00–15:00	[cancelled] Introduction to Option Pricing with the Fourier Transform
15:00–15:30	Option Pricing with Semidefinite Programming
(break)	
16:00–17:00	Programming Test Strategies and How to Test Optimisation Heuristic Implementations

Friday

10:00–10:30	Robust Optimization Applied to a Currency Portfolio
10:30–11:00	Robust Portfolio Optimization with Derivative Insurance Guarantees
10:30–11:30	Decomposition Scheme for Sparse Polynomial Optimization Problems and Application to Robust Portfolio Decisions
(break)	
12:00–12:30	An Automated Trading System based on Recurrent Reinforcement Learning
12:30–13:00	Financial Stability and Transmission of Credit Risk: A Multi-agent Computational Economics (ACE) Approach
(break)	
14:00–14:30	Bayesian Forecasting using an Extended Nelson–Siegel Model
14:30–15:30	Discussion
(break)	
16:00–17:00	Discussion

Presentations

An Introduction to Genetic Algorithms

Dr Mattheos 'Mantzos' Protopapas
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An introduction to Genetic Algorithms will be given in this lecture. Genetic Algorithms are amongst the most popular heuristic optimization algorithms, with many applications in Operations Research, Computer Science, Economics and Management. We will talk about what a Genetic Algorithm is, why chromosome and chromosome populations are useful, how solutions of mathematical problems may be encoded as chromosomes; then we will talk about how a genetic algorithm works: about chromosome fitness, and about the crossover and mutation operators. This lecture is to serve as a preliminary for following lectures which are about using Genetic Algorithms in Financial problems.

Background reading

[1] David E. Goldberg. *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley, 1989.

[2] John H. Holland. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence*. MIT Press, 1992.

Heuristic Strategies in Finance – An Overview

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I will present a survey on the application of heuristic techniques in the broad field of finance. Inspired by and named after nature's physical principles, heuristic algorithms have been extensively used to optimize complex financial problems, that traditional optimization techniques failed to capture. Due to their stochastic features and their ability to iteratively update candidate solutions, heuristics can explore the entire search space and approximate reliably the global optimum. This comprehensive overview reviews the main heuristic strategies and how they can be applied to the modern financial problems of robust estimation, model selection and clustering. I will emphasize more on describing Differential Evolution optimization technique. Further, I will analyze research papers published the last two decades, where alternative heuristics techniques were applied independently or complementarily to other intelligent techniques like Artificial Neural Networks or Support Vector Machines, to estimate the predictive variables or the parameters of the Kernel function, alternatively. Heuristic optimization techniques can provide reliable approximations and can be successfully applied to financial problems with great potentials.

Outline

1. Introduction
   - Describes the motive behind the use of heuristics optimization techniques
2. Heuristic Optimization Techniques
   - Briefly reports on heuristics and hybrid meta-heuristic methods and more extensively describes the Differential Evolution algorithm
3. Heuristics in Finance
   - Addresses the modern financial problems and analyzes how heuristics can be applied to approach and overcome these problems
4. Conclusion
   - The last part concludes and suggests further applications of heuristics to open financial questions

Background reading

Robust estimation

[1] Peter Winker, Marianna Lyra, and Chris Sharpe. Least Median of Squares Estimation by Optimization Heuristics with an Application to the CAPM and a Multi Factor Model. *Journal of Computational Management Science*, forthcoming, 2009.

Model selection

[1] Dietmar Maringer. *Portfolio Management with Heuristic Optimization*. Springer, 2005.

Clustering

[1] Thiemo Krink, Sandra Paterlini, and Andrea Resti. The Optimal Structure of PD Buckets. *Journal of Banking & Finance*, 32(10):2275–2286, 2008.

[2] Marianna Lyra, J. Paha, Sandra Paterlini, and Peter Winker. Optimization Heuristics for Determining Internal Rating Grading Scales. *Computational Statistics & Data Analysis*, forthcoming, 2009.

Optimising Risk and Reward of Financial Portfolios with Threshold Accepting

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Recent years have seen a proliferation of new risk and performance measures in investment management. These measures take into account stylised facts of financial time series like fat tails or asymmetric return distributions. In practice, these measures are mostly used for ex post performance evaluation, only rarely for explicit portfolio optimisation. One reason is that, other than in the case of classical mean–variance portfolio selection, the optimisation with these new risk measures is more difficult since the resulting problems are often not convex and can thus not be solved with standard methods. We describe a simple but effective optimisation technique called 'Threshold Accepting' which is versatile enough to be applied to different objective functions and constraints, essentially without restrictions on their functional form. This technique is capable of optimising portfolios under various recently proposed performance or (downside) risk measures, like Value-at-Risk, drawdown, Expected Shortfall, the Sortino ratio, or Omega, while not requiring any parametric assumptions for the data, ie, the technique works directly on the empirical distribution function of portfolio returns. We also discuss practical issues like parameter-setting, and the stochastics of the obtained solutions.

Background reading

[1] Gunter Dueck and Peter Winker. New concepts and algorithms for portfolio choice. *Applied Stochastic Models and Data Analysis*, 8(3):159–178, 1992.

[2] Manfred Gilli, Evis Këllezi, and Hilda Hysi. A data-driven optimization heuristic for downside risk minimization. *Journal of Risk*, 8(3):1–18, 2006.

[3] Manfred Gilli and Enrico Schumann. An Empirical Analysis of Alternative Portfolio Selection Criteria. *Swiss Finance Institute Research Paper No. 09-06*, 2009.

[4] Peter Winker. *Optimization Heuristics in Econometrics: Applications of Threshold Accepting*. Wiley, 2001.

Reference [3] is available from http://ssrn.com/abstract=1365167; a working paper version of [2] is also available from http://ssrn.com/abstract=910233.

An Application of Differential Evolution in Index Mutual Fund Replication

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This paper discusses the application of an index tracking technique to mutual fund replication problems. By using a tracking error (TE) minimization method and two rebalancing strategies (i.e. the calendar basis strategy and the tolerance triggered strategy), we develop a multi-period asset allocation model which tracks dynamically S&P 500 mutual funds. Two extensions of the TE optimization which consider an excess return measure and loss aversion behaviour are studied in order to explore their impact on replicated returns. In the optimization procedure, the selection of assets and the distribution of weights are carried out by employing an evolutionary method – differential evolution. According to the results of our experiment, the proposed model is found that successfully replicated the first and second moments of fund returns by using only five assets. Moreover, the TE optimization strategy under loss aversion with tolerance triggered rebalancing dominates other combinations studied regarding the tracking ability and cost efficiency.

Background reading

[1] J.E. Beasley, Nigel Meade, and T.-J. Chang. An evolutionary heuristic for the index tracking problem. *European Journal of Operational Research*, 148(3):621–643, 2003.

[2] Mark M. Carhart. On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1):57–82, March 1997.

[3] Manfred Gilli and Evis Këllezi. The Threshold Accepting Heuristic for Index Tracking. In P. Pardalos and V. K. Tsitsiringos, editors, *Financial Engineering, E-Commerce and Supply Chain*, Applied Optimization Series, pages 1–18. Kluwer Academic Publishers, Boston, 2002.

[4] Dietmar Maringer. Constrained Index Tracking under Loss Aversion Using Differential Evolution. In Anthony Brabazon and Michael O'Neill, editors, *Natural Computing in Computational Finance*. Springer, 2008.

[5] Nigel Meade and Gerald R. Salkin. Developing and maintaining an equity index fund. *Journal of the Operational Research Society*, 41:599–607, 1990.

[6] Richard Roll. A mean–variance analysis of tracking error. *Journal of Portfolio Management*, 18:13–22, 1992.

[7] William F. Sharpe. Mutual fund performance. *Journal of Business*, 39(1):119–138, January 1966.

[8] Rainer Storn and Kenneth Price. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11:341–359, 1997.

Introduction to Option Pricing with the Fourier Transform

[cancelled]

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Since the seminal Black and Scholes paper published in 1973, researchers and practitioners tried to go beyond this framework to include in their models important stylized facts of asset returns, such as jumps, stochastic volatility, excess kurtosis, leverage effects and so forth. When the model is not analytically tractable due to its complexity, numerical procedures (such as dynamic programming, monte carlo simulation, finite difference/elements) have been used. The Fourier transform techniques, which covers both analytical and numerical methods, have become popular and important in Finance, because it delivers pricing quickly while allowing for such complexities. Note that, the discrete Fourier transform (DFT) is a specific kind of Fourier transform and the fast Fourier transform (FFT) algorithm is an efficient way to compute it in practice. While in Engineering it has relevant interpretations, the Fourier transform is used in option theory for its convenient mathematical properties. Within this presentation, which is designed for an audience willing to get familiar with the subject, we first take a quick glance at the definition and most relevant properties of Fourier transform. Second, we briefly get an overview concerning the most useful stochastic processes in the Fourier Space, namely the Levy processes, and finally we investigate different approaches benefiting the Fourier transform properties to value different kind of options.

Background reading

[1] Alan L. Lewis. *Option Valuation under Stochastic Volatility: with Mathematica code*. Finance Press, 2000.

[2] Aleš Černý. Introduction to Fast Fourier Transform in Finance. *Journal of Derivatives*, 12(1):73–88, 2004.

Lewis's chapters 1 and 2 are available online from http://www.optioncity.net/pubs/Ch1Excerpt.pdf and http://www.optioncity.net/pubs/Ch2Excerpt.pdf.
Černý's article is available from http://ssrn.com/abstract=559416.

Option Pricing with Semidefinite Programming

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Recently, given the first few moments, tight upper and lower bounds of the no arbitrage prices can be obtained by solving semidefinite programming (SDP) or linear programming (LP) problems. In this paper, we compare SDP and LP formulations of the European-style options pricing problem and prefer SDP formulations due to the simplicity of moments constraints. We propose to employ the technique of change of numeraire when using SDP to bound the European-style call options. In fact, this problem can then be cast as a truncated Hausdorff moment problem which has necessary and sufficient moment conditions expressed by linear matrix inequalities (LMIs). With four moments information we show stable numerical results for bounding European call options and exchange options. Moreover, a hedging strategy is also identified by the dual formulation.

Outline

1 Problem description

2 SDP representations and approximations

3 Applications: options pricing with change of numeraire

4 Numerical results

Background reading

[1] Dimitris Bertsimas and Ioana Popescu. On the relation between option and stock prices: a convex optimization approach. *Operations Research*, 50(2):358–374, 2002.

[2] Jean B. Lasserre, Tomas Prieto-Rumeau, and Mihail Zervos. Pricing a Class of Exotic Options Via Moments and SDP Relaxations. *Mathematical Finance*, 16(3):469–494, 2006.

[3] Lieven Vandenberghe and Stephen Boyd. Semidefinite programming. *SIAM Review*, 38(1):49–95, 1996.

Programming test strategies and how to test optimisation heuristic implementations

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Testing is an essential part of computer programming, but all too often it is an afterthought to the main coding effort. Intensive bug fixing may only begin when a program fails to do what it is expected to do on its 'maiden voyage'. This may mean that a program produces quite unexpected results, or something a little more dramatic. Getting code to function correctly then becomes a labourious trial and error process. This waste of time and effort may be inconvenient, but there is something much more important at stake: if code hasn't been correctly and systematically tested, the credibility of results from experiments could also be called into question.
In this presentation I shall introduce some test methodology and explain how we ought to go about testing heuristic optimisation methods. I've take an Threshold Accepting applied to CAPM estimation to illustrate how to write experiment specification and select and devise appropriate test cases to validate that the code is working correctly.

Background reading

[1] William E. Howden. Functional Program Testing & Analysis. McGraw-Hill, 1987.

[2] Software and Testing, Carnegie Mellon University – `http://www.ece.cmu.edu/~koopman/des_s99/sw_testing/`.

[3] Threshold Accepting Algorithm – `http://comisef.wikidot.com/concept:thresholdaccepting`.

Robust Optimization Applied to a Currency Portfolio

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A currency investment strategy is presented, where the return on a portfolio of foreign currencies is maximized relative to any appreciation of the corresponding foreign exchange rates. Given the uncertainty in the estimation of the future currency values, we employ robust optimization techniques, to maximize the return on the portfolio for the worst case foreign exchange rate scenario. Currency portfolios differ from stock only portfolios in that a triangular relationship exists among foreign exchange rates, to avoid arbitrage. Although the inclusion of such a constraint in the model would lead to a non convex problem, we show that by choosing ellipsoidal uncertainty sets for the exchange rates relative to the base currency, and range uncertainty sets for the cross exchange rates, the problem may be simplified to a convex model and solved efficiently. Alongside robust optimization, an additional guarantee is explored by investing in currency options to cover the eventuality that foreign exchange rates materialize outside the specified uncertainty sets. Numerical results are given showing the relationship between the size of the uncertainty sets and the distribution of the investment among currencies and options. Results describing the complementary relationship between robust optimization and investment in currency options are also presented.

Outline

1 Introduction
  - Motivation & Aims
  - Notation

2 Robust Portfolio Optimization
  - Robust Counterpart

3 Hedging and Robust Optimization
  - Hedging the Currency Risk
  - The Robust Hedging Model

4 Numerical Results
  - Portfolio Composition
  - Simulated Backtesting

5 Conclusion/Discussion
  - Conclusion
  - Future Work

Background reading

[1] Aharon Ben-Tal and Arkadi Nemirovski. Robust Convex Optimization . *Mathematics of Operations Research*, 23(4):769–805, 1998.

[2] Sebastián Ceria and Robert A. Stubbs. Incorporating estimation errors into portfolio selection: Robust portfolio construction. *Journal of Asset Management*, 7:109–127, 2006.

[3] Cheol S. Eun and Bruce G. Resnick. Exchange Rate Uncertainty, Forward Contracts, and International Portfolio Selection. *Journal of Finance*, 43(1):197–215, 1988.

[4] Ian H. Giddy. Foreign exchange options. *Journal of Futures Markets*, 3(2):143–166, 1983.

Robust Portfolio Optimization with Derivative Insurance Guarantees

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Robust portfolio optimization finds the worst-case portfolio return given that the asset returns are realized within a prescribed uncertainty set. If the uncertainty set is not too large, the resulting portfolio performs well under normal market conditions. However, its performance may substantially degrade in the presence of market crashes, that is, if the asset returns materialize far outside of the uncertainty set. We propose a novel robust portfolio optimization model that provides additional strong performance guarantees for all possible realizations of the asset returns. This insurance is provided via optimally chosen derivatives on the assets in the portfolio. The resulting model constitutes a convex second-order cone program, which is amenable to efficient numerical solution procedures. We evaluate the model using simulated and empirical backtests and conclude that it can outperform standard robust portfolio optimization as well as classical mean–variance optimization.

Background reading

[1] Farid Alizadeh and Donald Goldfarb. Second-order cone programming. *Mathematical Programming*, 95(1):3–51, 2003.

[2] Aharon Ben-Tal and Arkadi Nemirovski. Robust Convex Optimization . *Mathematics of Operations Research*, 23(4):769–805, 1998.

[3] Sebastián Ceria and Robert A. Stubbs. Incorporating estimation errors into portfolio selection: Robust portfolio construction. *Journal of Asset Management*, 7:109–127, 2006.

[4] Lawrence G. McMillan. *Options as a Strategic Investment*. Prentice Hall, 1992.

[5] Karthik Natarajan, Dessislava Pachamanova, and Melvyn Sim. Constructing risk measures from uncertainty sets. *Operations Research*, forthcoming, 2009.

[6] Berç Rustem and Melendres Howe. *Algorithms for worst-case design and applications to risk management*. Princeton University Press, 2002.

[7] Steve Zymler, Berç Rustem, and Daniel Kuhn. Robust portfolio optimization with derivative insurance guarantees. Technical report, Imperial College London, 2009.

Reference [7] is available from http://www.optimization-online.org/.

Decomposition Scheme for Sparse Polynomial Optimization Problems and Application to Robust Portfolio Decisions

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We present a decomposition-based scheme for sparse Polynomial Optimization Problems (POPs). It has been shown that the optimal solution of a sparse POP, i.e. a POP with a structured sparsity, can be computed by solving a series of convergent semidefinite (SDP) relaxations (Lasserre 2006 and Waki et al. 2006). Moreover, the sparsity pattern underlying the POP is inherited into its (sparse) SDP relaxation. The decomposition method we propose admits as input a sparse POP but in reality applies to its sparse SDP relaxation. In particular, the SDP problem (relaxation) is decomposed into the *master* problem and the several *subproblems* depending on the inherited structure.

Our method is an extension of Benders decomposition for linear programs (Benders 1962) to Semidefinite Programming. We formulate the corresponding optimality and feasibility constraints by employing the Strong Duality Theorem and the Extended Farkas Lemma, respectively, for Semidefinite Programming (Alizadeh 1995). Our algorithm is divided into two phases. The first phase involves the method of partitioning the variables, thus we will usually refer to it as the pre-process phase. The second phase is the major body of the algorithm and involves the decomposition-based method for the sparse SDP relaxations.

As an application we address the robust, or worst-case, mean-variance-skewness-kurtosis portfolio optimization problem for discrete rival estimates of asset statistics. Although higher order moments, such as skewness and/or kurtosis, have been often considered in the deterministic portfolio selection problem as a remedy to non-normal return distributions (Athayde et al. 2004 and Jondeau et al. 2006), its robust counterpart remains still undiscovered despite uncertainty underlying the asset statistics estimates. We formulate the latter model which results in a sparse POP and we tackle it with our method. We present and discuss preliminary numerical results.

Outline

1 Introduction
  - Motivation
  - Contribution

2 Background Information
  - Semidefinite programming
  - Convergent sparse SDP relaxations

3 Theoretical development
  - Pre-process phase
  - Decomposition-based method

4 Application to robust portfolio optimization with skewness and kurtosis
  - Introduction & Notation
  - Formulation

5 Numerical Results
  - Benchmark Problems
  - Robust portfolio optimization with skewness and kurtosis

6 Discussion
  - Conclusion
  - Future Work

Background reading

[1] Farid Alizadeh. Interior Point Methods in Semidefinite Programming with Applications to Combinatorial Optimization. *SIAM Journal on Optimization*, 5(1):13–51, 1995.

[2] Gustavo M. de Athayde and Renato G. Flôres Jr. Finding a maximum skewness portfolio – a general solution to three-moments portfolio choice. *Journal of Economic Dynamics and Control*, 28(7):1335–1352, 2004.

[3] Jacques F. Benders. Partitioning procedures for solving mixed-variables programming problems. *Numerische Mathematik*, 4(1):238–252, 1962.

[4] Eric Jondeau and Michael Rockinger. Optimal Portfolio Allocation under Higher Moments. *European Financial Management*, 12(1):29–55, 2006.

[5] Jean B. Lasserre. Convergent SDP-Relaxations in Polynomial Optimization with Sparsity. *SIAM Journal on Optimization*, 17(3):822–843, 2006.

[6] Hayato Waki, Sunyoung Kim, Masakazu Kojima, and Masakazu Muramatsu. Sums of Squares and Semidefinite Program Relaxations for Polynomial Optimization Problems with Structured Sparsity. *SIAM Journal on Optimization*, 17(1):218–242, 2006.

An Automated Trading System based on Recurrent Reinforcement Learning

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The main purpose of this talk is to present part of our work on the design and implementation of an automated trading system based on recurrent reinforcement learning (RRL), an algorithm proposed by Moody and Wu (1997). The main features of the algorithm will be highlighted, and some preliminary results for a simplistic two-position RRL-trader, in a frictionless setting, will be presented. Moreover, potential improvements to the current algorithm, using heuristics and a regime-switching approach, will be discussed.

Background reading

[1] Richard S. Sutton and Andrew G. Barto. *An Introduction to Reinforcement Learning*. MIT Press, Cambridge, MA, 1998.

[2] John Moody and Lizhong Wu. Optimization of trading systems and portfolios. *Decision Technologies for Financial Engineering*, Y.Abu-Mostafa, A.N. Refenes, and A.S. Weigend, Eds. London: World Scientific, pp. 23–35, 1997.

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[4] Carl Gold. FX trading via recurrent reinforcement learning. *Proceedings of the IEEE International Conference on Computational Intelligence in Financial Engineering 2003*, 363–371, 2003.

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Financial Stability and Transmission of Credit Risk: A Multi-agent Computational Economics (ACE) Approach

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The talk's purpose is to present part of our work on developing a multi-agent based computational economics (ACE) framework that can articulate and demonstrate the interrelationships of the financial contagion with a view to aid policy analysis. Recent financial crisis has its roots in developments on CDS and subprime mortgage markets. We want to present a simple agent-based model of financial contagion that tries to grasp the phenomena of interconnectivity and interdependence of financial institutions (US banks) on Credit Default Swap (CDS) market and an impact of a default of one of the banks on the remaining market players.

Background reading

[1] Adam B. Ashcraft and Til Schuermann. Understanding the Securitization of Subprime Mortgage Credit. *Federal Reserve Bank of New York Staff Reports No. 318*, 2008.

[2] I. Onur Filiz, Xin Guo, Jason Morton, and Bernd Sturmfels. Graphical models for correlated defaults. *unpublished manuscript*, 2008.

[3] Jan Hatzius. Beyond Leveraged Losses: The Balance Sheet Effects of the Home Price Downturn. *Brookings Papers on Economic Activity*, 2008.

[4] Sheri Markose, Simone Giansante, Mateusz Gatkowski, and Ali Rais Shaghaghi. Too Interconnected to Fail: CDS Network of US Banks. *Paper presented at ESRC Money, Macro Finance Workshop, Brunel University, 21 May*, 2009.

Bayesian Forecasting using an Extended Nelson–Siegel Model

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To model the term structure of interest rates, we re-visits an extended Nelson–Siegel model (NS–SV model) based on the work of Hautsch and Ou (2008). This NS–SV model could not only capture the shifts in the yield curve by modelling the yield factors, but also model the volatility dynamics in these yield factors using stochastic volatilities. However, the estimations for this appealling NS–SV model in the literature was rather inefficient. In this paper, we propose an efficient algorithm, which was originally proposed by Kim et. al (1998) and Chib et.al (2002), to make simulation-based inference in the NS–SV model. Forecast capacities of the the NS–SV model and the original NS model are compared.

Background reading

[1] Carter, C.K. and Kohn, R. (1994). On Gibbs Sampling for State Space Models. Biometrika, 81(3), 541–53.

[2] Chib, S., Nardari, F. and Shephard, N. (2006). Analysis of high dimensional multivariate stochastic volatility models. Journal of Econometrics, 134(2), 341–71.

[3] Chib, S., Nardari, F. and Shephard, N. (2002/6). Markov chain Monte Carlo methods for stochastic volatility models. Journal of Econometrics, 108(2), 281–316.

[4] de Jong, P. and Shephard, N. (1995). The Simulation Smoother for Time Series Models. Biometrika, 82(2), 339–50.

[5] de Pooter, M.D., Ravazzolo, F. and van Dijk, D. Predicting the Term Structure of Interest Rates: Incorporating Parameter Uncertainty, Model Uncertainty and Macroeconomic Information. Tinbergen Institute Discussion Papers, 07-028/4.

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[10] Kim, S., Shephard, N. and Chib, S. (1998). Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models. The Review of Economic Studies, 65(3), 361–93.

[11] Koopman, S.J., Mallee, M.I.P. and van der Wel, M. Analyzing the Term Structure of Interest Rates using the Dynamic Nelson-Siegel Model with Time-Varying Parameters. Tinbergen Institute Discussion Papers, 07-095/4.

[12] Nikolaus Hautsch and Yangguoyi Ou (2008). Yield Curve Factors, Term Structure Volatility, and Bond Risk Premia. SFB649DP2008-053, Sonderforschungsbereich 649, Humboldt University, Berlin, Germany.

[13] Scruggs, J.T. and Nardari, F. (Forthcoming). Bayesian Analysis of Linear Factor Models with Latent Factors, Multivariate Stochastic Volatility, and APT Pricing Restrictions. Journal of Financial and Quantitative Analysis, .

[14] Zellner, A. (1971). An introduction to Bayesian inference in econometrics. New York ; Chichester: John Wiley.