Ekaterina Seregina

ekaterina.seregina@email.ucr.edu • seregina.info • ekat92
900 University Avenue, Riverside, CA

Education

University of California, Riverside *Riverside, CA*
PhD in Economics *Sep 2016 – Jun 2021*

National Research University Higher School of Economics *Moscow, Russia*
MS Financial Economics *Sep 2014 – Jun 2016*
BS Economics *Sep 2010 – Jun 2014*

Research Area Financial Econometrics · Asset Management · Portfolio Optimization · Machine Learning

Research

[1]"Sparse Portfolio"*[Job Market Paper]*

[2]"Optimal Portfolio Using Factor Graphical Lasso" (*with TH Lee*)
Submitted to the Journal of Business & Economic Statistics

[3]"Learning from Forecast Errors: A New Approach to Forecast Combination" (*with TH Lee*)
Submitted to the International Journal of Forecasting

[4]"Time-Varying Factor Graphical Models"

[5]"Projected Factor Graphical Models"

Presentations

14th International Conference on Computational & Financial Econometrics (*Paper [1]*) *Dec 2020*
World Finance and Banking Symposium (*Paper [2]*) *Dec 2020*
European Winter Meeting of the Econometric Society (*Paper [2]*) *Dec 2020*
40th International Symposium on Forecasting (*Paper [3]*) *Oct 2020*
Department of Economics, UCR (*Paper [1]*) *Oct 2020*
Department of Finance, UCR (*Papers [1]-[2]*) *Jun 2020*

Teaching

University of California, Riverside
Instructor *Summer 2019, 2020*
Stock Market (35 students, Eval: 4.77/5) · Intermediate Macroeconomic Theory (40 students, Eval: 4.89/5)
Teaching Assistant *Sep 2017 – Jun 2021*
Econometrics (PhD) · Macroeconomics (PhD) · Stock Market · Statistics · Intermediate Macroeconomics

National Research University Higher School of Economics *Moscow, Russia*
Teaching Assistant *Sep 2015 – Jun 2016*
Corporate Finance · Financial Econometrics

Honors & Awards

2020 Dissertation Year Program Award, UC Riverside *Riverside, CA*
2019 Outstanding Teaching Assistant Award, UC Riverside *Riverside, CA*
2016 University of California Dean's Distinguished Fellowship *Riverside, CA*
2015 Research Grant from German Research Foundation (GR 4781/1-1) *Moscow, Russia*
2015 Presidential Grant for Support of Young Russian Scientists *Moscow, Russia*

Additional Information

Software R · Python · Matlab · SAS · STATA · MySQL · BigQuery · Bloomberg Terminal · Datastream · TEX
Membership AFA · FMA · SoFiE · AEA · ASA · IIF · AMS

References

Jang-Ting Guo	Jean Helwege	Tae-Hwy Lee (Chair)	Aman Ullah
Professor, UCR	Professor, UCR	Professor, UCR	Distinguished Professor, UCR
Department of Economics	Department of Finance	Department of Economics	Department of Economics
+1 951 827-1588	+1 951 827-4284	+1 951 827-1509	+1 951 827-1591
guojt@ucr.edu	jean.helwege@ucr.edu	tae.lee@ucr.edu	aman.ullah@ucr.edu

Paper Abstracts

SPARSE PORTFOLIO *[Job Market Paper]* *Sep 2020*

The classical approach to portfolio optimization is notorious for producing undesirable extreme long and short positions due to inaccurate estimation of asset weights that fluctuate substantially over time. Besides, its asset allocations are associated with non-negligible transaction costs, high turnover and large monitoring costs. To overcome these shortcomings, we develop a novel optimization approach which produces sparse wealth allocations by setting some weights to zero using a penalty function. The proposed statistical method proceeds in two steps: first, it uses an ℓ_1-penalty on the weight vector to select stocks, second, we apply de-biasing and post-lasso to obtain the optimal asset allocation weights. The main contribution is twofold: from the theoretical perspective, this paper establishes unbiasedness and consistency of the optimal sparse allocations in a high-dimensional setting, when the number of assets exceeds the sample size. We demonstrate the importance of the de-biasing step that has been overlooked in previous studies. From the empirical perspective, the application to the constituents of the S&P500 reveals that compared to the common strategy of holding all assets, our sparse portfolio strategy leads to lower risk, lower turnover, and higher out-of-sample Sharpe ratio. We illustrate that during several economic downturns including the dot-com bubble of 2000 and the financial crisis of 2007-09, our sparse de-biased estimator was the only model that produced positive cumulative excess return (CER) and did not exceed the target level of risk. In contrast, all non-sparse models produced negative CER and violated the risk constraint. This finding suggests that our de-biased sparse estimator exhibits desirable minimax properties: it minimizes the maximum risk level of a portfolio.

OPTIMAL PORTFOLIO USING FACTOR GRAPHICAL LASSO *[with Tae-Hwy Lee]* *Sep 2020*

This paper develops a framework for estimating a high-dimensional precision matrix which combines the benefits of exploring the factor structure of the stock returns and the sparsity of the precision matrix of the factor-adjusted returns. The proposed algorithm is called *Factor Graphical Lasso* (FGL). We study a high-dimensional portfolio allocation problem when the asset returns admit the approximate factor model. We demonstrate that FGL consistently estimates the optimal portfolio in high dimensions, even when the covariance matrix is ill-behaved. Our theoretical results and simulations demonstrate that the method is robust to heavy-tailed distributions. The empirical application uses daily and monthly data for the constituents of the S&P500 to demonstrate superior performance of FGL compared to the equal-weighted portfolio, index and some prominent precision and covariance-based estimators.

LEARNING FROM FORECAST ERRORS: A NEW APPROACH TO FORECAST COMBINATION *[with Tae-Hwy Lee]* *Sep 2020*

This paper studies forecast combination using the precision matrix estimation of forecast errors when the forecast errors admit the approximate factor model. This approach incorporates the facts that experts often use common sets of information and hence they tend to make common mistakes. This premise is evidenced in many empirical results. For example, the European Central Bank's Survey of Professional Forecasters (SPF) on Euro-area real GDP growth demonstrates that the professional forecasters tend to *jointly* understate or overstate GDP growth. Motivated by this type of stylized facts on forecast errors, we develop a novel framework which exploits the factor structure of forecast errors and the sparsity in the precision matrix of the idiosyncratic components of the forecast errors. An empirical application to forecasting macroeconomic time series in big data environment highlights the advantage of our approach in comparison with the existing methods of forecast combination.

TIME-VARYING FACTOR GRAPHICAL MODELS *Sep 2020*

When the portfolios are rebalanced each month and the number of assets is large, e.g. 500, we need to collect the monthly data for at least 42 years in order to make sure the sample covariance matrix is invertible. However, in addition to the data availability issues, longer time-series impose an assumption that the true covariance matrix does not change with time. We account for the time-varying nature of the covariance/precision matrices by using the data in two different frequencies: we estimate the lower frequency precision matrix using higher frequency returns. The proposed model is called the *Time-Varying Factor Graphical Model*. Using two frequencies is beneficial for portfolio allocation: an investor can extract the information from higher frequency observations and use it for updating portfolio weights less frequently leading to lower transactions costs.

PROJECTED FACTOR GRAPHICAL MODELS *Sep 2020*

We study the precision matrix estimation under the approximate factor model with unobserved factors for portfolio allocation. We propose a novel framework which allows the precision matrix to change with the state of covariates. Our estimator uses a factor model to estimate sparse idiosyncratic component, and applies the Debiased Graphical Lasso for the estimation of the precision matrix of the error terms. The proposed estimator is shown to be consistent and asymptotically normal. We also introduce the *measurable mispricing function* constructed as an orthogonal portfolio using the observable characteristics which allows us to use both common component and the mispricing function to form portfolio weights.