# Master Thesis Topics Spring Semester 2020

## Topic 1: Measuring Tail Risk for Alternative Investments

Supervisor: Jan Bauer

Tail risk measures such as Value-at-Risk (VaR) or Expected Shotfall (ES) play an important role in financial risk management. The student introduces these tail risk measures and discusses non-parametric and parametric modelling frameworks.

In the empirical part, the student calculates VaR/ES using index return data for alternative asset classes (for example, hedged funds, real estate, commodities or cryptocurrencies). Risk figures for more conventional asset classes (stocks or bonds) should also be included in the analysis.

Depending on the preferences and previous knowledge, GARCH-based tail risk forecasts and/or VaR/ES-backtesting could be considered.

A programming tool should be used. We recommend Matlab (licenses provided).

**Starting literature:**

Albrecht, P., & Huggenberger, M. (2015). Finanzrisikomanagement. Schaefer Poeschel.

Alexander, C. (2009). Market Risk Analysis IV: Value-at-Risk Models. John Wiley & Sons.

Christoffersen, P. (2012). Elements of Financial Risk Management. Elsevier.

Hull, John. C. (2018). Risk Management and Financial Institutions. John Wiley & Sons.

# Topic 2: Multi-Asset Portfolio Selection with Heuristic Methods

Supervisor: Jan Bauer

A major problem with mean/variance portfolio optimization is that expected returns need to be estimated, which is a very difficult task. One way to deal with the associated estimation risk is to use heuristic techniques that do not require this estimate, such as equal weight-, minimum variance-, maximum diversification- or risk parity-investing. In this thesis, the performance of these heuristic techniques is evaluated in an out-of-sample study, where traditional mean/variance optimized portfolios serve as benchmarks.

The student should focus on risk parity, which has attracted a lot of attention ever since the global financial crisis due to its good performance figures. The aim of risk parity is to create portfolios that are well-diversified. Unlike in the classical Markowitz approach diversification is being measured via the portfolio constituent's contributions to portfolio risk. These contributions are equalized so that there are no concentrations in terms of risk contributions.

Depending on the preferences and previous knowledge of the student, extensions of risk parity could be considered. Furthermore, transaction costs could be taken into account.

A programming tool should be used. We recommend Matlab (licenses provided).

**Starting literature:**

Albrecht, P., & Maurer, R. (2016). Investment- und Risikomanagement: Modelle, Methoden, Anwendungen. Chapter 6.7.

Anderson, R. M., Bianchi, S. W., & Goldberg, L. R. (2012). Will My Risk Parity Strategy Outperform? Financial Analysts Journal, 68(6), 75–93.

Chaves, D., Hsu, J., Li, F., & Shakernia, O. (2011). Risk Parity Portfolio vs. Other Asset Allocation Heuristic Portfolios. The Journal of Investing, 20(1), 108–118.

Elton, E. J., Gruber, M. J., Brown, S. J., & Goetzmann, W. N. (2014). Modern Portfolio Theory and Investment Analysis.

Lee, W. (2011). Risk-Based Asset Allocation: A New Answer to an Old Question? The Journal of Portfolio Management.

Maillard, S., Roncalli, T., & Teïletche, J. (2010). The Properties of Equally Weighted Risk Contribution Portfolios. The Journal of Portfolio Management, 36(4), 60–70.

Roncalli, T. (2014). Introduction to Risk Parity and Risk Budgeting.

## Topic 3: Tail Risk and the Cross-Section of Expected Returns

Supervisor: Markus Huggenberger

Tail risk is a major concern for individual and institutional investors. Its effect on the aggregate market risk premium and its pricing in the cross-section of expected stock returns have therefore received considerable attention in the asset pricing literature.

Recently, Atilgan et al. (2020) document a negative relation between the left tail-risk of individual stocks as measured by their Value-at-Risk and future stock returns. The purpose of this thesis is to replicate this main finding and to test its robustness.

Besides controlling for standard characteristics and factors that are known to explain the cross-section of expected stock returns, the student should include simple non-parametric versions of the lower-tail-dependence measures used by Chabi-Yo et al. (2018) and van Oordt/Zhou (2016) as control variables.

Recommended Software: Matlab (licenses available)

Data Sources: CRSP and Compustat (maybe Datastream)

**Starting literature:**

Atilgan, Y., Bali, T. G., Demirtas, K. O., & Gunaydin, A. D. (2020). Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics*, *135*(3), 725–753.

Chabi-Yo, F., Ruenzi, S., & Weigert, F. (2018). Crash Sensitivity and the Cross Section of Expected Stock Returns. *Journal of Financial and Quantitative Analysis*, *53*(03), 1059–1100.

Kelly, B., & Jiang, H. (2014). Tail Risk and Asset Prices. *Review of Financial Studies*, *27*(10), 2841–2871.

van Oordt, M. R. C., & Zhou, C. (2016). Systematic Tail Risk. *Journal of Financial and Quantitative Analysis*, *51*(02), 685–705.

Bali, T. G., Engle, R. F., & Murray, S. (2016). *Empirical Asset Pricing*. Wiley.

Ang, A., Chen, J., & Xing, Y. (2006). Downside Risk. *Review of Financial Studies*, *19*(4), 1191–1239.

## Topic 4: Does ESG-Screening Reduce Tail Risk?

Supervisor: Markus Huggenberger

Environmental, social and governance (ESG) data are increasingly used for the construction of equity market indices. Compared to standard market capitalization-weighted indices, ESG-screened indices exclude or underweight companies with low ESG scores. As a recent example, "carbon-efficient'' stock market indices have been created that allow investors to reduce their exposure to companies with high levels of carbon emissions. Using such indices or exchange-traded funds (ETFs) on these indices, institutional and retail investors can easily include ESG criteria in their investment decisions.

The goal of this thesis is to assess the impact of ESG-screening on tail risk. On the one hand, ESG-screening can reduce the level of diversification and therefore increase the risk compared to a standard market-capitalization weighted index. On the other hand, ESG-screening can help to avoid large losses that are caused by the realization of ESG risks.

After reviewing methods for ESG-screening, this thesis should empirically investigate the tail risk of ESG-screened indices and the corresponding standard benchmarks for a selection of equity markets and screening methods.

Recommended Software: Matlab (licenses available), alternative statistical software packages can also be used.

Data sources: Datastream, MSCI ESG KLD

**Starting literature:**

Eccles, R. G., Verheyden, T., & Feiner, A. (2016). ESG for All? The Impact of ESG Screening on Return, Risk, and Diversification. *Journal of Applied Corporate Finance*, *28*(2), 47–55.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis. *The Journal of Finance*, *72*(4), 1785–1824.

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking and Finance*, *32*(9), 1723–1742.

Andersson, M., Bolton, P., & Samama, F. (2016). Hedging Climate Risk. *Financial Analysts Journal*, *72*(3), 13–32.

Hull, J. C. (2015). *Risk Management and Financial Institutions* (4th ed.). Hoboken: John Wiley & Sons.

## Topic 5: Machine Learning and the Cross-Section of Expected Returns

Supervisor: Markus Huggenberger

Machine Learning allows to handle high-dimensional data sets and to capture non-linear relationships. Recent applications in empirical asset pricing such as Gu et al. (2020) and Freyberger et al. (2020) exploit these advantages to predict risk premia.

The purpose of this thesis is to investigate the benefits of machine learning techniques for the forecasting of expected stock returns compared to standard linear regressions.

The thesis should review relevant machine learning methods and implement a selection of these methods to predict the risk premia of common stocks in the CRSP sample. Besides investigating the predictive power and economic gains that can potentially be realized with machine learning methods, the empirical results should be used to reassess the importance of well-known risk factors and characteristics.

Recommended Software: Matlab (licenses available)

Data sources: CRSP and Compustat

**Starting literature:**

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical Asset Pricing via Machine Learning. *The Review of Financial Studies*. Forthcoming.

Freyberger, J., Neuhierl, A., & Weber, M. (2020). Dissecting Characteristics Nonparametrically. *The Review of Financial Studies, Forthcoming*.

Bali, T. G., Engle, R. F., & Murray, S. (2016). *Empirical Asset Pricing*. Wiley.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning*. Springer.

## Topic 6: Risk-managed Industry Momentum

Supervisor: Lars Rickenberg

Jegadeesh/Titmann (1993) show that stocks that performed well in the past outperform stocks that performed poorly in the past. A momentum strategy that buys past winners and sells past losers produces high returns. Moskowitz/Grinblatt (1999) show that the momentum strategy can also be applied to industry portfolios.

Several studies show that the high returns of momentum investing are accompanied with occasionally periods of extremely low returns, e.g. more than −90% in two months. These momentum crashes have been examined by Barroso/Santa-Clara(2015) and Daniel/Moskowitz (2016) for the stock momentum strategy and by Grobys et. Al (2018) for the industry momentum strategy. Due to the high crash risk of momentum investing several approaches to manage momentum crashes have been developed in the literature. The main focus of this thesis should be to present two of these crash mitigation methods: volatility targeting (Barroso/Santa-Clara(2015), Daniel/Moskowitz (2016), Grobys et. Al (2018)) and volatility weighting (Du Plessis/Hallerbach (2016), Goyal/Jegadeesh (2018)). In particular, both approaches could also be combined as shown by Zakamulin (2016).

The purpose of this thesis is to investigate the risk and return of industry momentum and to assess the benefits of volatility targeting and volatility weighting applied to the industry momentum portfolio.

Recommended Software: Matlab (licenses available)

Data sources: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

**Starting literature:**

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116(1), 111-120.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.

Grobys, K., Ruotsalainen, J., Äijö, J. (2018). Risk-managed industry momentum and momentum crashes. *Quantitative Finance*, 1-19.

Moskowitz, T. J., Grinblatt, M. (1999). Do industries explain momentum?. *The Journal of Finance*, 54(4), 1249-1290.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. J*ournal of Financial Economics*, 122(2), 221-247.

Du Plessis, J., & Hallerbach, W. G. (2016). Volatility weighting applied to momentum strategies. *The Journal of Alternative Investments*, 19(3), 40-58.

Goyal, A., & Jegadeesh, N. (2018). Cross-sectional and time-series tests of return predictability: What is the difference?. *The Review of Financial Studies*, 31(5), 1784-1824.

Zakamulin, V. (2016). Optimal dynamic portfolio risk management. *The Journal of Portfolio Management*, 43(1), 85-99.