Applied Quantitative Finance
– Syllabus –

University of Zurich, Spring 2022

1 General Information

Instructors

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Seminar Description

This masters-level seminar covers current research in applied quantitative finance. The topics span new contributions in option pricing/hedging and variance/jump risk premia modelling, Ross recovery theorem and related research, as well as applications of machine learning techniques in quantitative finance.

The seminar serves as a continuation of the MSc Quant. Finance UZH/ETH course Financial Engineering.[1] The main goal is to gain insights into and to critically assess current research in quantitative finance. In particular, the seminar puts an emphasis on applied topics in financial engineering and work with financial data.

Readings

This syllabus includes a list of readings. Most of them can be downloaded from JSTOR or Sciencedirect or from SSRN. Additional materials will be available online.

[1] It is assumed that students have a good knowledge of mathematics, statistics, and financial theory. The seminar is recommended for advanced master students who have completed MSc Quant. Finance UZH/ETH course Financial Engineering.

Grading

The final grade will consist of three parts: (a) A seminar essay that students have to write in teams of three (60%), (b) In-class presentation of the results (30%), and (c) Discussion of another team's project (10%). Each essay should address one of the fundamental questions in applied quantitative finance. For each of these projects, we provide a key paper (recent research) that should serve as the main reference. The following rules apply:

1. Attendance on all three days is required.
2. Different teams are not allowed to work on the same project.
3. A 30 min presentation in class (with 15 min discussion) is mandatory.
4. A final report (not longer than 40 pages), including all files, i.e., LaTeX files, data files, and code (using a programming language of your choice), must be handed in on time. Swiss time!

Ideally, students should replicate, or try to replicate, the results of previous research. Potentially, previous research might be erroneous, results may not be robust, or findings have become outdated and new data brings new insights. In any case, writing replications with out-of-sample extensions is a perfect way to star working on research in a particular area.
Grading (scale: 1–6) will be based on originality of the discussion of the research question, quality of execution, and clarity of the written report and the presentation. The working language of the seminar is English.

Timeline

The table below provides an overview of the most important dates and activities during the seminar.

Date	**Time**	**Location**	**Description**
21 February 2022	16:15–18:00	Online (Zoom)	Introductory lecture
2 March 2022	until 18:00		Deadline for submission of topics
8 May 2022	until 22:00		Deadline for submission of projects (reports, code, etc.)
9 May 2022	until 22:00		Distribution of projects for discussions
16 May 2022	08:00–12:00	KOL-G-212	In-class presentations and discussions
17 May 2022	08:00–12:00	KOL-G-212	In-class presentations and discussions

Important Remark. When applying for a topic (deadline: 2 March 2022 at 6 p.m.), please keep in mind that first-come first-served principle applies. Therefore, to ensure a "second-best hedge", each team should submit 2–3 topics in the order of their preference. Nota bene: Students' own suggestions for potential topics will be considered as well—creativity is most welcomed in the AQF universe!

Good luck! :-)

Seminar Projects

This section provides the official list of topics that students can choose from for their seminar projects. We have classified them into two groups. Chapter I contains topics that represent recent advances in financial engineering using traditional techniques that are well-established in the literature. Chapter II puts an emphasis on machine learning techniques in the broader arena of quantitative finance. Machine learning is rapidly gaining traction across different scientific fields and disciplines, and our profession is not an exception. On the contrary, the research potential is enormous, and therefore it is important to build a solid knowledge base and explore new opportunities. Both chapters present students with interesting and relevant (read: hot!) research, and they have full freedom to decide on which journey to embark. Our task is to provide full support and assistance in the process, and to make sure that the final plan of research is feasible and can be completed within the pre-specified time frame.

Irrespectively of the selected topic, the projects should consist of the following steps:

- A literature review and detailed description of the research question,
- An overview of the theoretical framework and a discussion of the key results,
- An independent data collection and a summary in the report (including descriptive statistics and other relevant information),
- A description of the methods necessary for the execution of the empirical study,
- A replication and possible extensions of the empirical analysis conducted in the key reference paper (comparison with the findings of other research papers might be required for some projects),
- A critical analysis and discussion of the results,
- A conclusion and a suggestion for further research (with a short outline of the research plan, e.g., theoretical and empirical methods, data, etc.).

Although the general rules listed above apply, each project features specific requirements and challenges. Therefore, once the topics are distributed, a fine tuning of the list of tasks will be necessary to ensure that each team has enough resources to complete their respective projects successfully.

For any questions please contact Nikola via email. Additionally, during your work on the projects it might be necessary to organize meetings to discuss the open questions. Please do not hesitate to contact us—we would greatly appreciate if you could kindly let us know a few days in advance if you require a meeting.

Last but not least, students will be provided with direct access to the Wharton Research Data Services (WRDS). Additionally, there are Bloomberg terminals that can be accessed at the Department of Banking and Finance.

Chapter I: Financial Engineering Classics—Moving Forward

1. **Delta, vega, go!**

   Traders regularly compute hedge ratios in terms of the greeks, with the delta and vega being the most prominent examples. However, these quantities are unobservable and the method chosen for their calculation may have a strong (and possibly adverse) impact on the the effectiveness of hedging. Delta hedging has been extensively studied in academic literature. For example, the Practitioners' Black–Scholes model and the local volatility model are well-known delta-hedging approaches. Both methods treat the implied volatility of each option as a separate source of risk. However, they do not immunize hedging portfolio against the changes in the implied volatility. Therefore, many authors have tackled this problem from a fully parametric perspective, e.g., using a stochastic volatility model. Such an approach inevitably introduces a certain amount of model risk, which is amplified in the case of more complex strategies (e.g., delta–vega hedging). Model misspecification can be limited by applying a non-structural method. Recently, Barletta *et al.* (2019) proposed a novel non-structural approach—which leverages on the fact that an option price can be disentangled into a linear combination of risk-neutral moments—to explicitly compute delta and vega hedge ratios. In the empirical part of the study, they showed that non-structural delta–vega strategies provide an effective protection during stressed market periods.

   <u>Key Reference:</u>

   Barletta, A., Santucci de Magistris, P. and Sloth, D., 2019. It only takes a few moments to hedge. *Journal of Economic Dynamics and Control*, 100, 251–269.

   <u>Other References:</u>

   Barletta, A. and Nicolato, E., 2018. Orthogonal expansions for VIX options under affine jump diffusions. *Quantitative Finance*, 18(6), 951–967.

   Filipović, D., Mayerhofer, E. and Schneider., P., 2013. Density approximations for multivariate affine jump–diffusion processes. *Journal of Econometrics*, 176 (2), 93–111.

   Hull, J. and White, A., 2017. Optimal delta hedging for options. *Journal of Banking & Finance*, 82, 180–190.

   Schneider, P., 2015. Generalized risk premia. *Journal of Financial Economics*, 116(3), 487–504.

2. **Jumps for the short run**

   S&P 500 option contracts with weekly expiry (i.e., the so-called "weeklies") were relatively recently introduced by the Chicago Board Options Exchange (CBOE). Their share in the options market has been steadily rising over the past ten year—from below 8% in early 2011 to around 50% in mid-2015—therefore fundamentally reshaping the trading activities in different maturity profiles of the standardized CBOE option categories. The emergence of the weeklies represents a step towards market completion. By construction, these contracts have low time value, hence providing a cheaper alternative for delta hedging. In a recent study, Andersen, Fusari and Todorov (2017) addressed the question of why these contracts are particularly popular and proposed a new framework to investigate the information content of short-term options. They demonstrated that the relative prices of deep out-of-the-money (OTM) options are largely independent of the level of diffusive volatility, and instead reflect the characteristics of the risk-neutral jump process. On the other hand, short-dated at-the-money (ATM) options are strongly dependent on the current spot volatility. These findings imply that distinct option contract should be used to estimate different latent processes. By imposing only no-arbitrage and a set of weak parametric restrictions on the jump distribution, while remaining silent about the volatility and jump intensity, the paper builds a consistent seminonparametric procedure (labelled "structural calibration") that allows for inference of the spot characteristics of the risk-neutral distribution exclusively from all short-maturity options. The paper empirically investigates: (a) The shape of the jump distribution, (b) The time variation in diffusive and jump risk, and (c) Implied return variation measures.

Key Reference:

Andersen, T. G., Fusari, N. and Todorov, V., 2017. Short-term market risks implied by weekly options. *The Journal of Finance*, 72(3), 1335–1386.

Other References:

Andersen, T. G., Fusari, N. and Todorov, V., 2015. Parametric inference and dynamic state recovery from option panels. *Econometrica*, 83(3), 1081–1145.

Bollerslev, T. and Todorov, V., 2011. Estimation of jump tails. *Econometrica*, 79(6), 1727–1783.

Bollerslev, T. and Todorov, V., 2014. Time-varying jump tails. *Journal of Econometrics*, 183(2), 168–180.

Bollerslev, T., Todorov, V. and Xu, L., 2015. Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1), 113–134.

Jacod, J. and Protter, P., 2011. Discretization of processes (Vol. 67). *Springer Science & Business Media.*

3. **New shores: Vega–Gamma–Vanna–Volga**

Both practitioners and academics have been accustomed to use the Black–Scholes implied volatility surface (IVS) to represent the information in option contracts. However, this does not mean that they agree with the over-simplifying assumptions of that model. In fact, the Black–Scholes model is used merely as a transformation to enhance quote stability and to extract information that is easily understood and also comparable across different option markets. Additionally, many option pricing theories require specification of the instantaneous variance rate dynamics, whereas in practice this quantity is not directly observable. Only implied volatilities across a moneyness–maturity grid can be retrieved from market data. A direct implication of this gap between theory and practice is that quants have to re-calibrate their models frequently to match quoted option prices. This repetitive process is data intensive and in some situations presents a serious computational burden. Carr and Wu (2016) develop a new option pricing framework—called Vega–Gamma–Vanna–Volga (VGVV) model—that models the near-term dynamics of implied volatilities across different strikes and maturities, and derives no-arbitrage constraints directly on the shape of the IVS. As a consequence, the shape of the whole IVS is reduced to a simple algebraic constraint, i.e., a quadratic equation. In an empirical part, the paper demonstrated a rich set of results in the case of S&P 500 index options.

Key Reference:

Carr, P. and Wu, L., 2016. Analyzing volatility risk and risk premium in option contracts: A new theory. *Journal of Financial Economics*, 120(1), 1–20.

Other References:

Bakshi, G. and Kapadia, N., 2003a. Delta-hedged gains and the negative market volatility risk premium. *The Review of Financial Studies*, 16(2), 527–566.

Bakshi, G. and Kapadia, N., 2003b. Volatility risk premiums embedded in individual equity options: Some new insights. *The Journal of Derivatives*, 11(1), 45–54.

Hodges, H. M., 1996. Arbitrage bounds of the implied volatility strike and term structures of European-style options. *The Journal of Derivatives*, 3(4), 23–35.

4. **Is Janus the god of variance risk premia?**

   The market variance risk premium (VRP) is the compensation investors are willing to pay for assets that perform well when stock market volatility is high. Since it is embedded in the prices of various assets, it can be estimated either from equity portfolios (the equity VRP) or from index options (the option VRP). Recent studies show that there might be a potential mispricing between equity and option markets. Moreover, the role of financial intermediaries (broker-dealers) in determining index option prices is often discussed in this context. Barras and Malkhozov (2016) examined whether the two VRPs are equal. Their approach revolves around a formal statistical test that compares the linear projections of the equity and option VRP on a set of predictive variables which reflect different financial and economic information. Using the method of projections—instead of the VRPs themselves—allows for a direct comparison and economic interpretation of the conditional VRPs. The paper robustly rejects the null hypothesis that the variance risk has the same price in equity and option markets. Furthermore, it is shown that although market segmentation and margin requirements could partially explain the VRP difference, the strongest explanatory power lies with broker-dealer variables.

   Key Reference:

   Barras, L. and Malkhozov, A., 2016. Does variance risk have two prices? Evidence from the equity and option markets. *Journal of Financial Economics*, 121(1), 79–92.

   Other References:

   Adrian, T. and Shin, H. S., 2010. Liquidity and leverage. *Journal of Financial Intermediation*, 19(3), 418–437.

   Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X., 2006. The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259–299.

   Carr, P. and Wu, L., 2008. Variance risk premiums. *The Review of Financial Studies*, 22(3), 1311–1341.

   Garleanu, N., Pedersen, L. H. and Poteshman, A. M., 2008. Demand-based option pricing. *The Review of Financial Studies*, 22(10), 4259–4299.

5. **Two sides of the same coin: Vol and vol of vol**

   The volatility of the aggregate stock market is often measured by the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), which is computed on the basis of prices of options (with maturity of one month) written on the S&P 500 index. The VIX index varies substantially over time, hence introducing a significant source of risk for market participants. These fluctuations are measured by the volatility-of-volatility index (VVIX), which is defined as the risk-neutral expectation of the volatility of volatility in the financial markets (computed from the VIX options). The VVIX index also exhibits pronounced variation over time. Moreover, just like volatility, volatility-of-volatility features a negative market price of risk. Huang *et al.* (2019) investigated whether volatility of volatility represents a significant risk factor which affects the time-series and the cross-section of S&P 500 index and VIX options returns, above and beyond volatility risks. Building on the seminal paper by Bakshi and Kapadia (2003), the authors extend their approach by including a separate time-varying volatility-of-volatility risk factor. In an empirical study, using S&P 500 and VIX options data, it is shown that investors pay a premium to hedge against innovations in both volatility and volatility of volatility.

Key Reference:

Huang, D., Schlag, C., Shaliastovich, I. and Thimme, J., 2019. Volatility-of-volatility risk. *Journal of Financial and Quantitative Analysis*, 54(6), 2423–2452.

Other References:

Bakshi, G. and Kapadia, N., 2003. Delta-hedged gains and the negative market volatility risk premium. *The Review of Financial Studies*, 16(2), 527–566.

Grünthaler, T. and Hülsbusch, H., 2019. Tail risks and volatility-of-volatility. *Working paper*, Available at SSRN.

Jiang, G. J. and Tian, Y. S., 2005. The model-free implied volatility and its information content. *The Review of Financial Studies*, 18(4), 1305–1342.

Mencía, J. and Sentana, E., 2013. Valuation of VIX derivatives. *Journal of Financial Economics*, 108(2), 367–391.

Park, Y. H., 2015. Volatility-of-volatility and tail risk hedging returns. *Journal of Financial Markets*, pp.38–63.

6. **Scratching our heads about tails**

Both unconditional and conditional tail risks are notoriously difficult to estimate under the physical risk measure due to the lack of extreme return observations. On the other hand, in the risk-neutral world, tail risk is arguably easier to estimate since—at any point in time—market quotes of option prices are available over a moneyness–maturity grid. Therefore, an option-implied tail risk estimation procedure requires neither long time series nor large cross-sections of asset returns. The forward-looking nature of options makes risk-neutral estimates potentially more informative—and more granular given different maturity buckets—than their historical counterparts. O'Sullivan and Wang (2018) recently proposed a new model-free approach (labelled "effective spanning formula") to compute tail risk from option prices. The tails of the risk-neutral distribution are estimated using a non-parametric smoothing method, which is applied on the entire cross-section of option prices available for a fixed option maturity. The derived formula allows for a joint estimation of the unspanned tail probabilities and expectations. The accuracy of the proposed estimator is demonstrated in a simulation study. Finally, it is shown that the conditional expectation of the left tail scaled by its physical-measure counterpart significantly predicts S&P 500 returns (even above and beyond the variance risk premium).

Key Reference:

O'Sullivan, C. and Wang, Y., 2018. Nonparametric option implied tail risk and market returns. *Working paper*, Available at SSRN.

Other References:

Andersen, T. G., Fusari, N. and Todorov, V., 2015. Parametric inference and dynamic state recovery from option panels. *Econometrica*, 83(3), 1081–1145.

Bakshi, G., Kapadia, N., and Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, 16(1), 101–143.

Bollerslev, T., Todorov, V. and Xu, L., 2015. Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1), 113–134.

Hao, J., 2017. A model-free tail risk index and its return predictability. *Working paper*, Available at SSRN.

Kelly, B. and Jiang, H., 2014. Tail risk and asset prices. *The Review of Financial Studies*, 27(10), 2841–2871.

7. **A tale of recovery: Keep calm and carry on**

   One of the most interesting recent developments in financial economics is the Ross (2015)'s recovery theorem which enables—under certain conditions—a separation of the risk aversion from the natural probability distribution using option prices. More generally, the main idea behind the recovery is to provide insights about the conditional physical distribution in a model-free framework and with as few assumptions as possible, using only a cross section of asset prices. Several researchers have built on the original idea of Ross (2015), e.g., Borovička *et al.* (2016), Bakshi *et al.* (2018), Qin *et al.* (2018), Schneider and Trojani (2019), Audrino *et al.* (2019), and Jensen *et al.* (2019), among others. In a recent paper, Bakshi *et al.* (2019) introduced a discrete-time framework to compute the conditional expectation of return quantities under the physical probability measure from the set of spanning securities, i.e., the risk-free bonds, the underlying asset price, and the options on that asset. The numerical examples presented in the paper comprise calculation of wealth disaster and upside return probabilities, as well as conditional expected return and volatility.

   Key Reference:

   Bakshi, G., Gao Bakshi, X. and Xue, J., 2019. Recovery. *Working paper*, Available at SSRN.

   Other References:

   Audrino, F., Huitema, R. and Ludwig, M., 2019. An empirical implementation of the Ross recovery theorem as a prediction device. *Journal of Financial Econometrics*, 1–22.

   Bakshi, G., Chabi-Yo, F. and Gao, X., 2018. A recovery that we can trust? Deducing and testing the restrictions of the recovery theorem. *The Review of Financial Studies*, 31(2), 532–555.

   Borovička, J., Hansen, L. P. and Scheinkman, J. A., 2016. Misspecified recovery. *The Journal of Finance*, 71(6), 2493–2544.

   Jensen, C. S., Lando, D. and Pedersen, L. H., 2019. Generalized recovery. *Journal of Financial Economics*, 133(1), 154–174.

   Qin, L., Linetsky, V. and Nie, Y., 2018. Long forward probabilities, recovery, and the term structure of bond risk premiums. *The Review of Financial Studies*, 31(12), 4863–4883.

   Ross, S., 2015. The recovery theorem. *The Journal of Finance*, 70(2), 615–648.

8. **Examining options to get through the misty mountains cold**

   In a world full of uncertainty—be it socio-economic, geopolitical, or technological—economists, central bankers, wealth planners, and asset managers are keen to understand what is the effect of uncertainty shocks on the financial markets and the overall economy. One of the big open questions is if the impact of uncertainty is positive or negative over short and long horizons. Most academic papers approach this question by studying vector autoregression (VAR) systems under various modelling specifications. Dew-Becker *et al.* (2021) considered an alternative approach which hinges on information contained in the prices of securities traded in financial markets. In particular, they construct option portfolios to hedge uncertainty indices, e.g., an augmented version of Jurado *et al.* (2015)'s and Ludvigson *et al.* (2015)'s indices and Baker *et al.* (2016)'s Economic Policy Uncertainty (EPU) index. In a next step, the cost of hedging shocks to uncertainty and realized volatility is calculated for a number of financial assets and commodities. These results help to understand better the relative importance of good and bad uncertainty.

Key Reference:

Dew-Becker, I., Giglio, S., and Kelly, B. 2021. Hedging macroeconomic and financial uncertainty and volatility. *Journal of Financial Economics*, 142(1), 23–45.

Other References:

Baker, S. R., Bloom, N. and Davis, S. J., 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593–1636.

Bansal, R. and Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance*, 59(4), 1481–1509.

Berger, D., Dew-Becker, I. and Giglio, S., 2020. Uncertainty shocks as second-moment news shocks. *The Review of Economic Studies*, 87(1), 40–76.

Cremers, M., Halling, M. and Weinbaum, D., 2015. Aggregate jump and volatility risk in the cross-section of stock returns. *The Journal of Finance*, 70(2), 577–614.

Herskovic, B., Kelly, B., Lustig, H. and Van Nieuwerburgh, S., 2016. The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, 119(2), 249–283.

Jurado, K., Ludvigson, S. C. and Ng, S., 2015. Measuring uncertainty. *American Economic Review*, 105(3), 1177–1216.

Ludvigson, S. C., Ma, S., and Ng, S. 2021. Uncertainty and business cycles: exogenous impulse or endogenous response?. *American Economic Journal: Macroeconomics*, 13(4), 369–410.

9. **Laying out the options on the table: "American Dream" vs. "America First"**

Political uncertainty is one of the most pervasive forces in economic and financial developments, in particular over the last four years. The Brexit, European populism, US–China relations, raising nationalism in many countries, increasing number of state and non-state cyber conflicts, and other geopolitical rivalries are just some of the most recent examples. Political risks quickly spill over to the real and financial sectors. For an empirical finance researcher, one of the key challenges is to isolate the impact of political uncertainty on the overall economy and financial markets from other related factors, e.g., macroeconomic uncertainty. One approach is to focus on specific political events, e.g., national elections and global summits. Kostakis *et al.* (2019) studied the effects of political uncertainty surrounding the U.S. presidential elections on firm expected returns and risk, trading activity, and dispersion of investor beliefs. Using the information implied from liquid short-term option contracts, they measured the differential effect of political uncertainty across a pool of companies with diverse political characteristics. More specifically, they considered firm sensitivity to the economic policy uncertainty and political party affiliation, among other factors. The paper provides a rich set of results and insights, and lies at the junction between financial engineering and real-world applications which are extremely valuable for the financial industry.

Key Reference:

Kostakis, A., Gkionis, K. and Stathopoulos, K., 2019. Manifestations of political uncertainty around U.S. Presidential Elections: Cross-sectional evidence from the option market. *Working paper*, Available at SSRN.

Other References:

Akey, P. and Lewellen, S., 2017. Policy uncertainty, political capital, and firm risk-taking. *Working paper*, Available at SSRN.

Baker, S. R., Bloom, N. and Davis, S. J., 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593–1636.

Boutchkova, M., Doshi, H., Durnev, A. and Molchanov, A., 2012. Precarious politics and return volatility. *The Review of Financial Studies*, 25(4), 1111–1154.

Brogaard, J. and Detzel, A., 2015. The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1), 3–18.

Kelly, B., Pástor, L. and Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance*, 71(5), 2417–2480.

Martin, I. W. and Wagner, C., 2019. What is the Expected Return on a Stock?. *The Journal of Finance*, 74(4), 1887–1929.

Santa-Clara, P. and Valkanov, R., 2003. The presidential puzzle: Political cycles and the stock market. *The Journal of Finance*, 58(5), 1841–1872.

10. **Heraclitus of Ephesus was wrong: The way up is not the same as the way down**

Asymmetric behavior of volatility during risk-on and risk-off episodes in financial markets has attracted much attention in past ten years. Understanding the drivers of return fluctuations under different market conditions is critical for financing and investment activities of firms as well as individual and institutional investors. In a model-free setting, Bevilacqua *et al.* (2019) studied the determinants of positive and negative realized and implied volatilities (and volatility risk premia). Their key finding is that positive volatility is mostly affected by macroeconomic factors such as inflation and gross domestic product. On the other hand, negative volatilities are primarily driven by financial variables (e.g., the equity performance, credit and TED spreads, market sentiment) and economic policy uncertainty. Their results are confirmed also in two sub-samples: pre-crisis and post-crisis. However, the post-crisis period is characterized by a stronger shift to financial conditions as the most important volatility determinants. Last but not least, they conducted a battery of Granger causality tests at different frequencies for implied volatilities and volatility risk premia. These tests indicate that: (a) implied volatilities are able to predict future levels of economic activity, output growth, and inflation rate, and (b) volatility risk premia have some forecasting power for future levels of stock returns.

Key Reference:

Bevilacqua, M., Morelli, D. and Tunaru, R., 2019. The determinants of the model-free positive and negative volatilities. *Journal of International Money and Finance*, 92, 1–24.

Other References:

Bakshi, G., Kapadia, N. and Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, 16(1), 101–143.

Bekaert, G. and Hoerova, M., 2014. The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, 183(2), 181–192.

Diebold, F.X. and Yilmaz, K., 2008. Macroeconomic volatility and stock market volatility, worldwide. *NBER working paper*, Available at SSRN.

Fenou, B., Jahan-Parvar, M. R. and Okou, C., 2018. Downside variance risk premium. *Journal of Financial Econometrics*, 16(3), 341–383.

Kelly, B. and Jiang, H., 2014. Tail risk and asset prices. *The Review of Financial Studies*, 27(10), 2841–2871.

Kilic, M. and Shaliastovich, I., 2019. Good and bad variance premia and expected returns. *Management Science*, 65(6), 2522–2544.

Patton, A. J. and Sheppard, K., 2015. Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, 97(3), 683–697.

Paye, B.S., 2012. 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics*, 106(3), 527–546.

Chapter II: Machine Learning in Quantitative Finance

1. **Welcome to the machine**

One of the main goals of asset pricing is to understand differences in the expected returns across assets and to explain the behavior of the aggregate market risk premia. However, risk premia are very difficult to measure. They are computed as conditional expectation of a future realized excess return, hence it is critical to identify the most informative predictors. Over the past few decades, academics and practitioners have assembled a staggering number of potential predicting variables, ranging from single-stock characteristics to macroeconomic factors. Consequently, the set of potential model specifications is very large. This fact—coupled with high correlations among some of the predictors—makes the empirical asset pricing increasingly challenging field of research. Machine learning techniques offer potential remedy to these issues. First, they provide a disciplined and structured statistical approach to select the right model. Second, they venture into territories that have been uncharted by traditional empirical asset pricing by allowing for models that approximate complex non-linear relationships. Gu, Kelly and Xiu (2020) applied a battery of machine learning methods (e.g., linear regressions, generalized linear models with penalization, regression trees, and neural networks, among others) in the context of asset returns prediction using a large data set. They concluded that penalization and dimension reduction, together with non-linear methods, significantly improve predictions. Moreover, the economic gains from machine learning forecast are substantial.

<u>Key Reference:</u>

Gu, S., Kelly, B., and Xiu, D. 2020. Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), 2223–2273.

<u>Other References:</u>

Feng, G., Giglio, S., and Xiu, D. 2020. Taming the factor zoo: A test of new factors. *The Journal of Finance*, 75(3), 1327–1370.

Green, J., Hand, J.R. and Zhang, X.F., 2013. The supraview of return predictive signals. *Review of Accounting Studies*, 18(3), 692–730.

Harvey, C.R., Liu, Y. and Zhu, H., 2016. ... and the cross-section of expected returns. *The Review of Financial Studies*, 29(1), 5–68.

Hastie, T., Tibshirani, R. and Friedman, J., 2009. The elements of statistical learning: prediction, inference and data mining. *Springer-Verlag, New York.*

2. **Bonding to the machine**

One of the main goals of asset pricing is to understand differences in the expected returns across assets and to explain the behavior of the aggregate market risk premia. However, risk premia are very difficult to measure. They are computed as conditional expectation of a future realized excess return, hence it is critical to identify the most informative predictors. Over the past few decades, academics and practitioners have assembled a staggering number of potential predicting variables, ranging from single-stock characteristics to macroeconomic factors. Consequently, the set of potential model specifications is very large. This fact—coupled with high correlations among some of the predictors—makes the empirical asset pricing increasingly challenging field of research. Machine learning techniques offer potential remedy to these issues. First, they provide a disciplined and structured statistical approach to select the right model. Second, they venture into territories that have been uncharted by traditional empirical asset pricing by allowing for models that approximate complex non-linear relationships. Bianchi *et al.* (2021) applied a battery of machine learning methods (e.g., linear regressions, generalized linear models with penalization, regression trees, and neural networks, among others) in the context of bond risk premia prediction using a large data set. They concluded that penalization and dimension reduction, together with non-linear methods, significantly improve predictions. Moreover, the economic gains from machine learning forecast are substantial.

Key Reference:

Bianchi, D., Büchner, M., and Tamoni, A. 2021. Bond risk premiums with machine learning. *The Review of Financial Studies*, 34(2), 1046–1089.

Other References:

Cochrane, J. H. and Piazzesi, M., 2005. Bond risk premia. *American Economic Review*, 95(1), 138–160.

Gu, S., Kelly, B., and Xiu, D. 2020. Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), 2223–2273.

Feng, G., Polson, N., and Xu, J. 2019. Deep learning in asset pricing. *Statistics*, 1-33.

Hastie, T., Tibshirani, R. and Friedman, J., 2009. The elements of statistical learning: prediction, inference and data mining. *Springer-Verlag, New York*.

Ludvigson, S. C. and Ng, S., 2009. Macro factors in bond risk premia. *The Review of Financial Studies*, 22(12), 5027–5067.

McCracken, M. W. and Ng, S., 2016. FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4), 574–589.

3. **Taming the factor zoo**

Over the past five decades, literally thousands of papers have been published about factors that (allegedly) can explain the cross section and time series of expected returns. Such a proliferation of factors calls for systematic framework for model selection and evaluation of new asset pricing factors, above and beyond the extant factors that have been detected and researched in the past. Feng, Giglio and Xu (2020) proposed a model based on double-selection LASSO method select the best control model out of the large set of factors while explicitly taking into account model selection mistakes. Their empirical results indicate—among other things—that when the test is applied recursively over time only a small set of factors is selected. The main conclusion is that the double-selection LASSO method offers a structured and effective approach to selecting new factors.

Key Reference:

Feng, G., Giglio, S., and Xiu, D. 2020. Taming the factor zoo: A test of new factors. *The Journal of Finance*, 75(3), 1327–1370.

Other References:

Cochrane, J. H. 2011. Presidential address: Discount rates. *The Journal of finance*, 66(4), 1047–1108.

Harvey, C.R., Liu, Y. and Zhu, H., 2016. ... and the cross-section of expected returns. *The Review of Financial Studies*, 29(1), 5–68.

Harvey, C. R., and Liu, Y. 2021. Lucky factors. *Journal of Financial Economics*, 141(2), 413–435.

Belloni, A., Chernozhukov, V., and Hansen, C. 2014. Inference on treatment effects after selection among high-dimensional controls. *The Review of Economic Studies*, 81(2), 608–650.

Fama, E. F., and French, K. R. 2018. Choosing factors. *Journal of Financial Economics*, 128(2), 234–252.

Freyberger, J., Neuhierl, A., and Weber, M. 2020. Dissecting characteristics nonparametrically. *The Review of Financial Studies*, 33(5), 2326–2377.

4. **A machine maestro and her royal out-of-sample orchestra**

Forecasts of stock returns and equity indices are very important for asset allocation decisions. Although this topic has fascinated many academics and practitioners over past 60 years, it remains a challenging task to design a model that exhibits a lasting out-of-sample predictability. A number of econometric issues which complicate statistical inference and contribute to (often substantial) model uncertainty and parameter instability have been reported in the literature. However, several forecasting strategies have also been proposed to address these concerns, e.g., economically motivated model restrictions, combinations of forecasts, and regime shifts (for an overview, see Rapach and Zhou, 2013). In a recent paper, Jacobsen *et al.* (2019) consider an ensemble machine learning method that builds equity premium forecasts by combining different models, i.e., Bayesian model averaging (BMA), least absolute shrinkage and selection operator (LASSO), and weighted average least squares (WALS). More specifically, they introduce the method called adaptive bootstrap aggregation (in short AdaBagging) which is based on sequential sampling mechanism borrowed from AdaBoost. This algorithm is particularly successful—in terms of out-of-sample performance—in the periods of extreme market downturns. This results is a consequence of significantly reduced estimation error due to the ability of AdaBagging to maintain a high level of diversification across different forecasting strategies.

Key Reference:

Jacobsen, B., Jiang, F. and Zhang, H., 2020. Ensemble machine learning and stock return predictability. *Working paper.* Available at SSRN.

Other References:

Hastie, T., Tibshirani, R. and Friedman, J., 2009. The elements of statistical learning: prediction, inference and data mining. *Springer-Verlag, New York.*

Inoue, A. and Kilian, L., 2008. How useful is bagging in forecasting economic time series? A case study of US consumer price inflation. *Journal of the American Statistical Association*, 103(482), 511–522.

Rapach, D. E., Strauss, J. K. and Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *The Review of Financial Studies*, 23(2), 821–862.

Rapach, D. E. and Zhou, G., 2013. Forecasting stock returns. Published in Handbook of Economic Forecasting, Vol. 2, 328–383. *Elsevier.*

Rossi, A. G., 2018. Predicting stock market returns with machine learning. *Working paper.* Available at SSRN.

Welch, I. and Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, 21(4), 1455–1508.

5. **The inner workings of the exchange rate machinery**

Exchange rate forecastability is a topic that has been in the focus of economists and researchers over four decades. It is widely recognized that exchange rates are difficult to predict using economic models. Meese and Rogoff (1983)'s puzzle posits that out-of-sample forecasts of exchange rate models are not better than the random walk. A number of explanatory variables have been proposed in the literature, e.g., interest rate differentials, yield curve slope, monetary factors, industrial production, net foreign assets, foreign debt, risk and liquidity factors, and others. Currently, the consensus in the literature is that Taylor-rule and net foreign assets fundamentals provide the best out-of-sample predictions. Moreover, linear models seem to be the most successful ones (e.g., see Rossi, 2013). In a recent paper, Amat *et al.* (2018) employed machine learning methods and concluded that classical exchange rate models such as purchasing power parity (PPP), uncovered interest rate parity (UIRP), as well as Taylor-rule based models lead to improved forecasts in the fiat currency era—more specifically, in the period 1973–2014. Their approach is based on a comparison between classical ordinary least squares methods with exponentially weighted average strategy and sequential ridge regression (with discount factors). Overall, the paper provides some interesting insights into exchange rate forecastability, however it could be extended to many other machine learning methods.

Key Reference:

Amat, C., Michalski, T. and Stoltz, G., 2018. Fundamentals and exchange rate forecastability with simple machine learning methods. *Journal of International Money and Finance*, 88, 1–24.

Other References:

Cheung, Y. W., Chinn, M. D., Pascual, A. G. and Zhang, Y., 2019. Exchange rate prediction redux: new models, new data, new currencies. *Journal of International Money and Finance*, 95, 332–362.

Li, J., Tsiakas, I. and Wang, W., 2015. Predicting exchange rates out of sample: Can economic fundamentals beat the random walk?. *Journal of Financial Econometrics*, 13(2), 293–341.

Meese, R. A. and Rogoff, K., 1983. Empirical exchange rate models of the seventies: Do they fit out of sample?. *Journal of International Economics*, 14(1–2), 3–24.

Plakandaras, V., Papadimitriou, T. and Gogas, P., 2015. Forecasting daily and monthly exchange rates with machine learning techniques. *Journal of Forecasting*, 34(7), 560–573.

Rossi, B., 2013. Exchange rate predictability. *Journal of Economic Literature*, 51(4), 1063–1119.

6. **Down the slope and into a recession**

An inverted yield curve—a situation in which the yields on short-term Treasury bills (e.g., three-month) are above the yields on long-term Treasury notes (e.g., ten-year)—is often seen as an indicator of an upcoming recession. The reason for a build-up of such market sentiment is rooted in the fact that a yield curve inversion typically occurs in an environment in which investors do not have much confidence in the economy over short term. In a recession scenario, central banks are expected to lower target rates. As treasury bills follow closely target rates moves, investors would have to reinvest their funds at lower interest rates in short term, which—as a consequence—boosts demand for longer term fixed income instruments. Unsurprisingly, this topic constantly attracts attention of academics and practitioners. Gogas *et al.* (2015) investigated the forecasting ability of the yield curve in terms of the U.S. real GDP cycle within a machine learning framework. Their research revolves around an application of support vector machines (SVM) technique for classification. The results are promising—this method achieves a relatively high recession forecasting accuracy above that of classical methods such as probit and logit models.

Key Reference:

Gogas, P., Papadimitriou, T., Matthaiou, M. and Chrysanthidou, E., 2015. Yield curve and recession forecasting in a machine learning framework. *Computational Economics*, 45(4), 635–645.

Other References:

Ang, A., Piazzesi, M. and Wei, M., 2006. What does the yield curve tell us about GDP growth?. *Journal of Econometrics*, 131(1–2), 359–403.

Estrella, A., 2005. Why does the yield curve predict output and inflation?. *The Economic Journal*, 115(505), 722–744.

Gürkaynak, R. S., Sack, B. and Wright, J. H., 2007. The US Treasury yield curve: 1961 to the present. *Journal of Monetary Economics*, 54(8), 2291–2304.

Hodrick, R. J. and Prescott, E. C., 1997. Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 1–16.

Moneta, F., 2005. Does the yield spread predict recessions in the Euro area?. *International Finance*, 8(2), 263–301.

Nyberg, H., 2010. Dynamic probit models and financial variables in recession forecasting. *Journal of Forecasting*, 29(1–2), 215–230.

Plakandaras, V., Gogas, P., Papadimitriou, T. and Gupta, R., 2019. A re-evaluation of the term spread as a leading indicator. *International Review of Economics & Finance*, 64, 476–492.

7. The options rodeo

Options are non-linear derivative instruments that allow investors to tailor risk exposure in accordance with their preferences. By trading in option markets, investors are able to implement their views about the underlying security price and its volatility. Since the seminal paper of Black and Scholes (1973), hundreds of studies have been published about no-arbitrage option pricing models. On the other hand, studies about option returns are comparably scarce in the literature. Similarly to other financial securities, options should compensate investors with expected returns that reflect their systematic risk. Relatively short time to maturity and ever-changing moneyness, make it a very challenging task to capture option return dynamics using standard empirical asset pricing techniques such as factor models. A good reference for a comprehensive overview of the literature and a recent promising factor model for option returns is Büchner and Kelly (2022). Although this paper represents an excellent classical-approach benchmark, Ho and Hu (2018) presented an interesting competing approach. More specifically, they studied the least absolute shrinkage and selection operator (LASSO) for option return forecasting. Their results indicate that a model including a limited set of financial variables results in delta-neutral trading strategies with a high Sharpe ratio.

Key Reference:

Ho, S. W. and Hu, Y., 2018. Option return predictability, A machine-learning approach. *Working paper*, Available at SSRN.

Other References:

Black, F. and Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637–654.

Büchner, M., and Kelly, B. 2022. A factor model for option returns. *Journal of Financial Economics*, 143(3), 1140–1161.

Cao, J. and Han, B., 2013. Cross section of option returns and idiosyncratic stock volatility. *Journal of Financial Economics*, 108(1), 231–249.

Coval, J. D. and Shumway, T., 2001. Is sound just noise?. *The Journal of Finance*, 56(5), 1887–1910.

Feng, G., Giglio, S., and Xiu, D. 2020. Taming the factor zoo: A test of new factors. *The Journal of Finance*, 75(3), 1327–1370.

Goyal, A. and Saretto, A., 2009. Cross-section of option returns and volatility. *Journal of Financial Economics*, 94(2), 310–326.

Hastie, T., Tibshirani, R. and Friedman, J., 2009. The elements of statistical learning: prediction, inference and data mining. *Springer-Verlag, New York*.

8. **A deep ride on the implied volatility surface**

The implied volatility surface (IVS) changes over time. A number of authors have tried to address the questions of modelling of the IVS dynamics. Most notable approaches include principal components analysis (PCA) and Karhunen–Loève decomposition. On the other hand, it is well-established in the finance literature that both implied and realized volatilities are negatively correlated with the underlying asset's return (i.e., the leverage effect). Cao, Chen and Hull (2020) proposed an Artificial Neural Networks (ANN) approach to explore the relationship between the changes in implied volatilities (across a moneyness–maturity grid) of options on the S&P 500 and the daily returns of the underlying index. ANNs represent one of the foundational bedrocks of deep learning. They enable estimation of non-linear functions involving many parameters from big data sets. Empirically, Cao, Chen and Hull (2018) demonstrated that their three-feature ANN model (or the four-feature version that includes also VIX in the analysis) improves the expected implied volatility estimates relative to the classical financial engineering models that do not consider machine learning techniques.

Key Reference:

Cao, J., Chen, J., and Hull, J. 2020. A neural network approach to understanding implied volatility movements. *Quantitative Finance*, 20(9), 1405–1413.

Other References:

Cont, R. and Da Fonseca, J., 2002. Dynamics of implied volatility surfaces. *Quantitative Finance*, 2(1), 45–60.

Hull, J. and White, A., 2017. Optimal delta hedging for options. *Journal of Banking & Finance*, 82, 180–190.

Nian, K., Coleman, T.F. and Li, Y., 2018. Learning minimum variance discrete hedging directly from the market. *Quantitative Finance*, 18(7), 115–1128.

Telgarsky, M., 2016. Benefits of depth in neural networks, *JMLR: Workshop and Conference Proceedings*, 49, 1–23.

9. **Darth Hedger, beware of my new light SABR!**

Local volatility models represent a popular approach to managing smile and skew risk. They are self-consistent, arbitrage-free, and can perfectly match option prices observed in the market. However, these models predict wrong dynamics and smiles and skews, which has important repercussions on delta–vega hedging. The Stochastic Alpha–Beta–Rho (SABR) model was developed with the intention to resolve the aforementioned issues. It admits correlation between the underlying asset price and volatility, and can be solved approximately using singular perturbation techniques. Nevertheless, the SABR model has its limitations when applied across a wide parameter space and time domain, and it is rather inflexible in the wings of the implied volatility smile. A number of papers tried to address the deficiencies of the original SABR models, e.g., by implementing special integration and finite-difference approaches. Building on the Universal Approximation Theorem, McGhee (2020) applied an artificial neural network (ANN) to the SABR model, and demonstrated that even a network with a single hidden layer can improve model performance significantly. With a sufficiently large training set, ANNs can have a high degree of accuracy in only a fraction of the time taken for existing accurate schemes. In particular, the computational burden is about 10,000 lighter than in the case of finite-difference methods.

Key Reference:

McGhee, W. 2020. An artificial neural network representation of the SABR stochastic volatility model. *Journal of Computational Finance*, 25(2).

Other References:

Craig, I. J. and Sneyd, A. D., 1988. An alternating-direction implicit scheme for parabolic equations with mixed derivatives. *Computers & Mathematics with Applications*, 16(4), 341–350.

Hagan, P. S., Kumar, D., Lesniewski, A. S. and Woodward., D. E., 2002. Managing smile risk. *Wilmott Magazine*, 84–108.

McGhee, W., 2011. An efficient implementation of stochastic volatility by the method of conditional integration. *In ICBI Conference, Paris.*

10. **Value at risk, encoded**

Measuring, monitoring and forecasting risk is one of the key tasks of any risk management system. In particular, accurate forecasts of future volatility and tail risk over different investment horizons is critical for development of successful derivatives strategies (be it for hedging or speculation). To this end, up to date, numerous models have been developed and especially those that belong to the GARCH family of models. Such models aim to capture inherently non-linear nature of risk, e.g., asymmetric, fat-tailed distribution of returns that changes over time. From machine learning perspective, artificial neural networks (ANN) are particularly interesting candidate. Arian *et al.* (2020) considered variational autoencoders (VAE)—a type of generative ANNs—to estimate various quantiles of a return distribution using a non-parameteric model. Their findings indicate that the encoded VaR methodology is competitive with a number of classical VaR models.

Key Reference:

Arian, H., Moghimi, M., Tabatabaei, E., and Zamani, S. 2020. Encoded value-at-risk: A predictive machine for financial risk management. Available on arXiv.

Other References:

Engle, R. F., and Manganelli, S. 2004. CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics*, 22(4), 367–381.

McNeil, A. J., and Frey, R. 2000. Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. *Journal of Empirical Finance*, 7(3–4), 271–300.

Bauwens, L., Laurent, S., and Rombouts, J. V. 2006. Multivariate GARCH models: a survey. *Journal of Applied Econometrics*, 21(1), 79–109.

Kingma, D. P., and Welling, M. 2013. Auto-encoding variational bayes. Available on arXiv.