Applied Quantitative Finance
– Syllabus –

University of Zurich, Fall 2025

1 General Information

Instructors

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Seminar Description

This master's-level seminar provides a deep dive into contemporary research in applied quantitative finance, acting as a direct continuation of the MSc Quantitative Finance UZH/ETH course in Financial Engineering.[1] The seminar is designed to bridge the gap between foundational theory and cutting-edge practice.

The main goal is to develop a critical understanding of current research in the field. Upon completion, students will be able to analyze and interpret key academic papers, critically assess the assumptions and implications of advanced financial models, and apply modern quantitative techniques to real-world financial data. The curriculum will delve into several key areas, including the examination of novel models for advanced pricing and hedging of options and complex derivatives, as well as the in-depth modelling of variance and jump risk premia in asset returns. Furthermore, the course explores the application of modern, data-driven machine learning methods to problems in pricing, risk management, and algorithmic trading. Unifying these topics is a strong emphasis on empirical analysis, requiring students to implement and test these sophisticated models using financial datasets.

[1]Students are expected to possess a strong background in mathematics, statistics, and financial theory. Proficiency in conducting data analysis with a programming language such as Python, R, or Matlab is also essential. This seminar is designed for advanced master's students, and successful completion of the MSc Quantitative Finance UZH/ETH course in Financial Engineering is mandatory.

Readings

This syllabus includes a list of readings (see below). Most of them can be downloaded from JSTOR, Sciencedirect, SSRN, or ArXiv. Additional materials will be available online.

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 start working on research in a particular area.

Grades (scale 1-6) are based on the originality, quality, and clarity of the research, written report, and presentation. The seminar is conducted in English.

Timeline

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

Date	**Time**	**Location**	**Description**
15 September 2025	16:15–18:00	RAK-E-7	Introductory lecture
24 September 2025	until 23:59		Deadline for submission of topics
30 November 2025	until 23:59		Deadline for submission of projects (reports, code, etc.)
1 December 2025	until 23:59		Distribution of projects for discussions
8 December 2025	08:00–12:00	KOL-H-309	In-class presentations and discussions
9 December 2025	08:00–12:00	KOL-H-309	In-class presentations and discussions

Important Remark. Please submit your team's top 2–3 topic choices, ranked by preference, by Wednesday (EOD), 24 September 2025. Topics are assigned on a first-come, first-served basis, so providing multiple preferences is the best way to secure a project that you are excited about. We also encourage you to suggest your own research ideas—originality is highly appreciated in the AQF universe!

Good luck! :-)

Seminar Projects

The following section outlines the official topics for the seminar project, organized into two distinct categories. The first group, Chapter I, focuses on recent advances in financial engineering that build upon well-established quantitative techniques. The second, Chapter II, explores the growing application of machine learning in quantitative finance, a field with enormous research potential that is rapidly transforming the industry.

Both categories feature cutting-edge and highly relevant research questions, and students have complete freedom to choose the research path that best aligns with their interests. Our role is to provide dedicated support throughout the process, ensuring that each team develops a feasible research plan that can be successfully completed within the semester.

Irrespective of the selected topic, each project should include the following components:

- A comprehensive literature review and a precise formulation of the research question.
- An overview of the relevant theoretical framework and a discussion of key findings from the foundational literature.
- Independent data collection and descriptive analysis, including summary statistics and other relevant information.
- A detailed description of the empirical methodology used for the study.
- Replication of the analysis from the key reference paper, with possible extensions or comparisons to related research.
- A critical analysis and in-depth discussion of the empirical results.
- A conclusion summarizing the findings and providing suggestions for future research, including a brief outline of a potential research plan.

Although the above guidelines provide a general framework, each project has unique requirements. After the topics are assigned, we will work with each team to customize their specific tasks and deliverables, ensuring a clear and achievable plan for successful completion.

All inquiries should be directed to Nikola and Patrick via email. Should you require a meeting to discuss your research, please contact us with several days' notice to facilitate scheduling. We are available to help with any open questions during your project work.

Students will be provided with comprehensive data resources to support their research. This includes direct access to the Wharton Research Data Services (WRDS) and use of the Bloomberg terminals located at the Department of Banking and Finance. Additionally, access to high-frequency US market data (stocks, ETFs, futures, indicators, FX, and crypto at intervals from one minute to one hour) can be facilitated for specific projects.

Chapter I: Financial Engineering Classics—Moving Forward

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

   The construction of hedging strategies for derivative portfolios relies heavily on the "Greeks", with delta and vega being the primary inputs for hedge ratios. A fundamental challenge arises from the fact that these quantities are not directly observable. They must be estimated and the chosen model can critically impact the efficacy of the hedge. While delta hedging has been studied extensively, common methodologies like the Practitioners' Black-Scholes and local volatility models possess a notable shortcoming. Although they account for the volatility smile, they do not hedge against movements in the implied volatility structure. In response, a body of literature has explored fully parametric solutions, such as stochastic volatility models. Such an approach, however, inevitably introduces model risk due to the potential for misspecification. This risk becomes particularly acute for multi-factor strategies (e.g., delta–vega hedging). Consequently, non-structural methods have been proposed as a means to limit the impact of model misspecification. Barletta *et al.* (2019) proposed a novel non-structural methodology for hedging European options by leveraging a model-independent relationship between risk-neutral moments, the underlying futures price, and variance swaps. By decomposing option prices into a linear combination of risk-neutral moments using orthogonal polynomials, the paper derives explicit formulas for delta and vega hedge ratios. The study finds that while direct vega hedging using variance swaps is effective during market turmoil, it is less optimal in periods of low volatility, where alternative strategies, such as using at-the-money options, are more reliable.

   Key Reference:

   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.

   Other References:

   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. **Jumping to conclusions**

   Chen *et al.* (2025) introduce a novel approach to estimating jump risk measures from option data, focusing on the S&P 500 index. More specifically, they extend the Bakshi, Kapadia, and Madan (2003) framework to recover risk-neutral (semi-)moments and cumulants, enabling the extraction of jump risk characteristics such as positive and negative jump variations. The simulation results demonstrate that the proposed jump variation measures outperform existing methods in terms of accuracy under various jump process specifications (such as, e.g., those by Bollerslev, Todorov, and Xu 2015). Empirical analysis reveals that the negative jump variation measure is particularly effective in predicting short-term realized variance, while the jump variation premium significantly forecasts market excess returns, especially in the short term. The study also highlights the distinct impact of large jumps (LJ) on market predictions, showing that accounting for LJ improves both in-sample and out-of-sample forecasts. The paper further explores the predictive power of jump variation measures compared to existing indicators like the variance risk premium and Bollerslev, Todorov, and Xu (2015)'s left jump tail variation. The findings presented in the paper contribute to the literature by offering a more precise and comprehensive framework for analyzing jump risks, with implications for market volatility forecasting, return predictability, and investor behavior under tail risk.

Key Reference:

Chen, Q., Han, Y., Huang, Y., and Jiang, G. J. 2025. Jump risk implicit in options market. *Journal of Financial Econometrics*, 23(2), nbaf002.

Other References:

Andersen, T. G., Li, Y., Todorov, V., and Zhou, B. 2023. Volatility measurement with pockets of extreme return persistence. *Journal of Econometrics*, 237(2), 105048.

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.

Carr, P., Geman, H., Madan, D. B., and Yor, M. 2002. The fine structure of asset returns: An empirical investigation. *The Journal of Business*, 75(2), 305–332.

Carr, P., and Madan, D. 2001. Optimal positioning in derivative securities. *Quantitative Finance*, 1, 19–37.

Da, R., and Xiu, D. 2021. When moving-average models meet high-frequency data: uniform inference on volatility. *Econometrica*, 89(6), 2787–2825.

Kou, S. G. (2002). A jump-diffusion model for option pricing. *Management Science*, 48(8), 1086–1101.

3. **The Heston chameleon**

The Heston model remains a cornerstone of quantitative finance, achieving widespread popularity as it was the first widely adopted stochastic volatility model that could realistically capture key market phenomena like the volatility smile. However, the model struggles with simultaneously fitting the entire implied volatility surface across all strikes and maturities with a single, static set of parameters, especially for short-dated options. Inspired by this shortcoming, Sun *et al.* (2024) introduces a novel term-structure-based correction to the classical Heston stochastic volatility model to address its limitations in accurately capturing the implied volatility (IV) surface of options across all maturities. More specifically, the authors propose a correction function which dynamically adjusts the volatility-of-volatility term based on the option's time to maturity. Using the perturbation method, the paper derives an analytical formula for IV under the corrected model, termed the Heston model with dynamic adjustment of expiration-based exponential growth (H–DA–EEG). Numerical experiments and empirical studies on historical option data demonstrate that the proposed model significantly improves IV forecasting accuracy compared to the classical Heston model and other advanced models like stochastic volatility models with jumps.

Key Reference:

Sun, Y., Gong, Y., Wang, X., and Liu, C. 2024. A novel term-structure-based Heston model for implied volatility surface. *International Journal of Computer Mathematics*, 101(6), 577–600.

Other References:

Chen, Y., Han, Q., and Niu, L. 2018. Forecasting the term structure of option implied volatility: The power of an adaptive method. *Journal of Empirical Finance*, 49, 157–177.

Forde, M., Gerhold, S., and Smith, B. 2021. Small-time, large-time, and asymptotics for the Rough Heston model. *Mathematical Finance*, 31(1), 203–241.

Heston, S. L., 1993. A closed-form solution for options with stochastic volatility with applications to bond and currency options. *The Review of Financial Studies*, 6(2), 327–343.

Sun, Y., Gong, Y., Wang, X., and Liu, C. 2024. A novel term-structure-based Heston model for implied volatility surface. *International Journal of Computer Mathematics*, 101(6), 577–600.

Takahashi, A. 1999. An asymptotic expansion approach to pricing financial contingent claims. *Asia-Pacific Financial Markets*, 6(2), 115–151.

4. **Fractionally better?**

Rough volatility models have surged in popularity among academics and quantitative practitioners due to their ability to replicate the empirically observed fractal-like behavior and high-frequency fluctuations of market volatility. These appealing model features translate into more accurate volatility forecasts and demonstrably improved performance in the pricing and hedging of complex derivatives, particularly those with short maturities. Abi Jaber and Li (2025) presents a comprehensive empirical study comparing the performance of rough, path-dependent, and Markovian volatility models in capturing SPX option price dynamics. Using daily SPX implied volatility surface data, the study challenges the widely held belief that rough volatility models outperform their counterparts. The findings reveal that rough volatility models, characterized by their non-semimartingale nature and fractional Brownian motion kernel, fail to consistently fit the global SPX volatility surface and ATM skew, particularly for short maturities (1 week to 3 months). Additionally, the paper questions the necessity of roughness in spot volatility processes, showing that realized volatility roughness can arise from estimation errors rather than the underlying model dynamics.

Key Reference:

Abi Jaber, E., and Li, S. 2025. Volatility models in practice: Rough, path-dependent, or Markovian? *Mathematical Finance*, 00, 1–22.

Other References:

Bayer, C., Friz, P., and Gatheral, J. 2016. Pricing under rough volatility. *Quantitative Finance*, 16(6), 887–904.

Fukasawa, M. 2021. Volatility has to be rough. *Quantitative Finance*, 21(1), 1–8.

Guyon, J., and Lekeufack, J. 2023. Volatility is (mostly) path-dependent. *Quantitative Finance*, 23(9), 1221–1258.

Rømer, S. E. 2022. Empirical analysis of rough and classical stochastic volatility models to the SPX and VIX markets. *Quantitative Finance*, 22(10), 1805–1838.

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. **Risk-neutral density, reimagined**

The seminal work of Breeden and Litzenberger (1978) revealed a profound insight that the complete risk-neutral probability distribution of an asset's future price can be recovered directly from the market prices of options. The model-free approach introduced in the paper has made it an immensely popular and vital tool for academics and practitioners to extract market-implied probabilities, analyze the volatility smile, and construct measures of market sentiment. Cui and Xu (2022) proposes an alternative, model-free representation of the risk-neutral density derived from market-observed option prices. By combining exact series representations of the Dirac Delta function with the Carr–Madan asset spanning formula, a closed-form result is derived to estimate risk-neutral densities that are smooth and do not require curve fitting or optimization. In this framework, the risk-neutral density is statically replicated by a portfolio of cash and options. Furthermore, the model implementation is demonstrated through simulation studies and empirical applications using S&P 500 index option data, showing its effectiveness in recovering risk-neutral densities and its potential for practical applications, such as pricing exotic derivatives and estimating local volatility functions in Dupire's model.

Key Reference:

Cui, Z., and Xu, Y. 2022. A new representation of the risk-neutral distribution and its applications. *Quantitative Finance*, 22(5), 817–834.

Other References:

Breeden, D. T. and Litzenberger, R. H., 1978. Prices of state-contingent claims implicit in option prices. *The Journal of Business*, 51(4), 621–651.

Carr, P., and Madan, D. 1998. Towards a theory of volatility trading. In *Volatility: New estimation techniques for pricing derivatives*, 29, 417–427.

Carr, P., and Madan, D. 1999. Option valuation using the fast Fourier transform. *Journal of Computational Finance*, 2(4), 61–73.

Heston, S. L., 1993. A closed-form solution for options with stochastic volatility with applications to bond and currency options. *The Review of Financial Studies*, 6(2), 327–343.

Wu, L., and Zhu, J. 2016. Simple robust hedging with nearby contracts. *Journal of Financial Econometrics*, 15(1), 1–35.

Yang, N., Chen, N., and Wan, X. 2019. A new delta expansion for multivariate diffusions via the Itô–Taylor expansion. *Journal of Econometrics*, 209(2), 256–288.

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.* (2023) 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, X., and Xue, J. 2023. Recovery with applications to forecasting equity disaster probability and testing the spanning hypothesis in the treasury market. *Journal of Financial and Quantitative Analysis*, 1–35.

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. **Seeking for a bear hug (beta version)**

The notion of downside risk (and downside beta) has been studied in literature for almost two decades. Many authors posit that time variation in left-tail risk is critical for understanding of asset return dynamics. Lu and Murray (2019) define the bear market risk as time variation of the ex-ante probability of future bear market states. A distinct feature of their approach is that the proposed bear market indicator—which is constructed as a model-free Arrow–Debreu portfolio from traded index options—does not depend on present realizations of downside market states and jumps. In an empirical study they showed that high-bear-beta stocks have low average returns, i.e., there is a negative cross-sectional relation between bear beta and expected stock returns. These results withstand the test of accounting for a number of risk and characteristic variables such as CAPM beta, Ang (2006)'s downside beta, the volatility index (VIX) beta, Cremers *et al.* (2015)'s volatility and jump betas, Harvey and Siddique (2000)'s coskewness, Chang *et al.* (2013)'s aggregate skewness beta, Kelly and Jiang (2014)'s tail beta, among others.

Key Reference:

Lu, Z. and Murray, S., 2019. Bear beta. *Journal of Financial Economics*, 131(3), 736–760.

Other References:

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

Breeden, D. T. and Litzenberger, R. H., 1978. Prices of state-contingent claims implicit in option prices. *The Journal of Business*, 51(4), 621–651.

Chang, B. Y., Christoffersen, P. and Jacobs, K., 2013. Market skewness risk and the cross section of stock returns. *Journal of Financial Economics*, 107(1), 46–68.

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.

Fama, E. F. and MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 81(3), 607–636.

Harvey, C. R. and Siddique, A., 2000. Conditional skewness in asset pricing tests. *The Journal of Finance*, 55(3), 1263–1295.

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

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.

11. **The real rate of confusion**

Understanding the link between financial market volatility and tangible economic outcomes is fundamental to ensuring long-term stability and growth. As uncertainty over the trajectory of interest rates can deter investment and stall hiring, rigorously examining this relationship is essential for creating more accurate economic forecasts and effective policy. Qadan *et al.* (2023) study the relationship between uncertainty about U.S. Treasury yields and key macroeconomic variables using a VIX-style measure of forward-looking volatility derived from options data. By constructing volatility indices for mid-term (7–10 years) and long-term (20+ years) Treasury yields, the authors demonstrate that increases in interest rate uncertainty predict negative macroeconomic outcomes, including declines in industrial production, retail trade, consumer and producer prices, and increases in unemployment. The study finds that uncertainty about mid-term Treasury yields is more informative about the future economy than long-term yields, explaining a larger fraction of the variation in industrial production and unemployment. Additionally, decomposing the VIX-style measure into components based on out-of-the-money call and put options reveals that put options provide slightly better insights into economic variations. The findings highlight the recessionary effects of interest rate uncertainty, which persist for up to two years, and emphasize its role as a forward-looking macroeconomic indicator. Finally, the authors underscores the importance of central banks and policymakers in mitigating interest rate uncertainty during economic shocks, such as the COVID-19 pandemic.

Key Reference:

Qadan, M., Shuval, K., and David, O. 2023. Uncertainty about interest rates and the real economy. *The North American Journal of Economics and Finance*, 68, 101978.

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.

Cremers, M., Fleckenstein, M., and Gandhi, P. 2021. Treasury yield implied volatility and real activity. *Journal of Financial Economics*, 140(2), 412–435.

Fu, X., Sandri, M., and Shackleton, M. B. 2016. Asymmetric effects of volatility risk on stock returns: Evidence from VIX and VIX futures. *Journal of Futures Markets*, 36(11), 1029–1056.

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12. **Moment-astic predictions**

The enduring quest to predict stock market returns has led researchers to look beyond traditional economic and financial factors. A powerful modern approach involves analyzing moment risk premia, which measure the compensation investors demand for bearing risks related to the shape of the return distribution, offering a forward-looking signal of market performance. Fan et al. (2022) investigate the predictive power of option-implied moment risk premia embedded in the conventional variance risk premium for stock market returns. Using data from the S&P 500 index and its options, the authors separate the second-moment from higher-moment risk premia. They find that second-moment risk premium predicts short-term market returns with positive coefficients, while the third-moment and fourth-moment risk premia predict medium-term returns with negative and positive coefficients, respectively. The findings are robust to various checks and demonstrate economic significance in asset allocation exercises. The paper contributes to the literature by showing that separating and jointly analyzing moment risk premia enhances market return predictability, offering valuable insights for strategic portfolio management.

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13. **The tell-tale tail: Putting a SKEW index to the test**

The SKEW index is a financial metric derived from S&P 500 option prices that measures the perceived risk of an extreme, unexpected decline (a "black swan" event) in the market. Its importance lies in providing a forward-looking gauge of investor fear regarding rare but high-impact market crashes, offering a different perspective on risk than more common volatility measures like the VIX. Bevilacqua and Tunaru (2021) explore the decomposition of the implied skewness index derived from U.S. equity index options into two components: positive skewness (SKEW$^+$) from call options and negative skewness (SKEW$^-$) from put options. The paper demonstrates that SKEW$^+$ reflects market sentiment and speculative activity, while SKEW$^-$ is closely tied to tail risk and extreme market downturns. By isolating SKEW$^-$, the study identifies it as a more reliable and forward-looking measure of tail risk, capable of predicting recessions, market downturns, and uncertainty indicators up to one year in advance. In particular, The findings suggest that the total SKEW index may be influenced by optimistic biases from call options, potentially underestimating tail risk. SKEW$^-$, on the other hand, provides a prudent measure of market fear and tail risk perception, offering complementary information to existing volatility measures like VIX. The study concludes that decomposing the implied skewness index enriches the information extracted from options markets, providing valuable insights for investors and policymakers in monitoring financial stability and anticipating economic crises.

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14. **Mirror, mirror on the wall, who's the VaR-est of them all?**

Value at Risk (VaR), defined as the conditional quantile of the profit-and-loss distribution over a predefined horizon, has stood as one of the most popular market risk measures for the past two decades. The aftermath of the Global Financial Crisis of 2008-09 served as a catalyst, spurring intense interest in robust risk measurement and management systems, a demand fueled by both stringent regulatory requirements and increased risk aversion. Consequently, the academic literature features thousands of studies on risk measures published over the last thirty years. While the predominant approach in these studies is to estimate risk using historical asset returns, a critical strand of research investigates a pivotal question: can forecasts based on forward-looking information, such as option-implied data, outperform traditional historical models? Molino and Sala (2021) explore the use of option market data to forecast monthly VaR and Conditional Value at Risk (CVaR), presenting four econometric approaches: kernel regression, smoothing spline, generalized extreme value, and first-order condition. Their empirical study compares these option-implied methods with four stock-based approaches—variance-covariance, historical simulation, kernel regression, and GJR–GARCH–FHS using extensive backtesting. Results show that option-implied VaR and CVaR consistently outperform or match stock-based measures, demonstrating robustness across different econometric techniques.

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15. **Satoshi's rollercoaster: Risk and reward in the crypto casino**

    In the evolving landscape of cryptocurrency markets, researchers and financial professionals are increasingly interested in understanding the risk characteristics and pricing dynamics of digital assets like Bitcoin. A key question in this emerging field is how Bitcoin's risk premia compare to traditional financial assets and how they behave across different market conditions. Almeida *et al.* (2024) focus on risk premia implied by Bitcoin returns and option prices from the Deribit trading platform. The study finds that Bitcoin exhibits much higher volatility and variance risk premium than the S&P 500. Using a novel clustering algorithm on Bitcoin option-implied risk-neutral densities, the study reveals that risk premia vary across two distinct volatility regimes, with low-volatility periods showing higher Bitcoin variance risk premium and greater contribution from positive returns, suggesting that Bitcoin investors are more concerned about variance and upside risk during calm market conditions.

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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.

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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.

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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.

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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, Lv and Qi (2022) consider an ensemble learning approach, "stacking", to refine and aggregate a variety of linear and nonlinear individual stock return prediction models. Intuitively, the stacking approach refers to an algorithm that fits a higher-level model upon a group of lower-level models to produce a refined prediction. In contrast to traditional models, which average predictions from multiple models, the stacking model can be represented by a complicated function. The authors find the stacking approach to outperform traditional models both in- and out-of-sample in predicting U.S. market excess return. Additionally, the out-of-sample performance of the stacking model is particularly good during extreme downside market movements.

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5. **A delicate machine touch: Cherry picking in the stock market**

   Machine learning is an increasingly important and controversial topic in quantitative finance. A lively debate persists as to whether machine learning techniques can be practical investment tools. Although machine learning algorithms can uncover subtle, contextual, and nonlinear relationships, overfitting poses a major challenge when one is trying to extract signals from noisy historical data. Rasekhschaffe and Jones (2019) explore applications of machine learning algorithms in stock selection, emphasizing their ability to uncover complex, nonlinear patterns that traditional statistical methods like ordinary least squares struggle to detect. The authors highlight the challenges of overfitting in financial data, which is characterized by low signal-to-noise ratios, and propose two key strategies to mitigate this risk: feature engineering and forecast combinations. Feature engineering involves structuring data to enhance signal clarity, while forecast combinations aggregate predictions from diverse algorithms and training windows to improve robustness. In the empirical part of the paper, a case study using AdaBoost, gradient boosted regression trees, neural networks, and support vector machines is presented. The results show that combining forecasts from multiple algorithms and training windows yields superior performance compared to individual models or traditional benchmarks. Furthermore, this study highlights the importance of dynamically adjusting factor exposures over time, which contributes to the success of machine learning strategies.

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6. **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.

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

An inverted yield curve, a situation where short-term government debt yields surpass those of long-term debt, is a widely recognized harbinger of an economic recession. This phenomenon reflects investor expectations of a deteriorating economy, anticipating that the central bank will soon lower interest rates to stimulate growth. Consequently, investors seek to lock in higher long-term yields before rates fall, driving up the price of long-term bonds and depressing their yields while short-term yields remain elevated. Given its strong predictive power, the yield curve remains a focal point of analysis for economists and market practitioners alike. Choi *et al.* (2023) explore whether the predictive ability of yield spreads for forecasting recessions can be improved by using machine learning to identify optimal maturity pairs and coefficients. Traditionally, the 10-year minus 3-month Treasury yield spread is widely used for this purpose, but its pair selection and coefficient constraints have not been formally tested. Using logistic regression with L1 regularization, the study analyzes nine bond yield maturities and evaluates the performance of the ML-selected pairs against the conventional spread. The study concludes that relaxing restrictions on maturity pairs and coefficients does not substantially improve recession prediction due to dominant estimation risk.

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8. **The options rodeo**

While parametric models, such as the Black–Scholes and Heston models, provide useful frameworks for option pricing, they are often misspecified and fail to fully capture the observed nonlinear dynamics of implied volatility surfaces. Almeida *et al.* (2023) introduce a novel two-step methodology to improve the accuracy of parametric option pricing models using feedforward neural networks. The approach first fits a parametric model to observed implied volatility surfaces and then trains a neural network on the model-implied pricing errors to correct for mispricing. Using a dataset of S&P 500 options, the authors test their method on several parametric models, including the Black–Scholes, Heston, ad-hoc Black–Scholes, and Carr and Wu models. The results show that the neural network-corrected models consistently outperform their original counterparts across various prediction exercises, including same-day interpolation and multi-day forecasting. The study also explores the application of neural networks in an option panel setting, where implied volatility surfaces are analyzed over time. By incorporating time-varying covariates such as the VIX index and measures of market jump risk, the neural networks effectively learn the dynamic misspecification of parametric models, further boosting predictive accuracy. The corrected models not only improve pricing performance but also better capture the nonlinear dynamics of implied volatility surfaces, including their level, term structure, skew, and skew term structure. The findings suggest that financial institutions can enhance their option pricing, hedging, and risk management practices by adopting this methodology.

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9. **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.

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10. **Artificial neural networks: An (American) option to consider**

Option pricing has attracted a lot of attention since Black and Scholes (1973) published their groundbreaking research. Dozens of ideas have been proposed since then, most influential and successful being (univariate and multivariate) stochastic volatility and jump–diffusion models for the risk-neutral dynamics of the underlying process. However, the overwhelming majority or results are directly applicable only for the pricing and calibration of European-style options, whereas majority of market-traded options are American-style. American options can be exercised at any time before (and including) the maturity, hence they are path-dependent and more difficult to price (i.e., computational costs are much higher) than their European counterparts. Nwankwo *et al.* (2024) propose a deep learning method for solving American options models with free boundary features, introducing the Landau transformation to extract the early exercise boundary. They construct an implicit dual solution framework consisting of a novel auxiliary function that incorporates feed-forward deep neural network output and mimics various boundary conditions, along with free boundary equations that approximate the early exercise boundary directly from the deep neural network output. The auxiliary function is designed to handle the unknown nature of boundary values by using approximate forms, while option Greeks are obtained from the derivatives of this function. Testing against existing numerical methods demonstrates that their proposed deep learning approach provides an efficient and viable alternative for pricing options with early exercise features.

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11. **A long story short: Using LSTMs to price options**

    Over the last decade, neural networks have become highly relevant for option pricing as they offer a powerful, data-driven approach that can learn these intricate patterns directly from market data. Pimentel *et al.* (2025) explore the use of a Long Short-Term Memory (LSTM) neural network for pricing European call options on the S&P 500 index. The LSTM model is benchmarked against traditional parametric models like Black–Scholes and Heston, as well as a simpler neural network, the Multilayer Perceptron. Results show that the LSTM model outperforms all benchmarks in pricing options with longer time to maturity across various moneyness levels. However, for options with shorter time to maturity, Black-Scholes and Heston models perform better. The paper also incorporates explainable artificial intelligence using SHapley Additive Explanations (SHAP) to analyze feature importance in the LSTM model. The study concludes that the LSTM model is well-suited for dynamic market conditions and offers a robust alternative to traditional models, particularly for options with longer maturities.

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12. **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.

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13. **Honey, I heard that random forests whisper about realized variance**

Volatility forecasts are important for both trading and hedging. Luong and Dokuchev (2018) consider forecasting of realised volatility for financial time series using the heterogeneous autoregressive model (HAR) and machine learning techniques. In particular, they first study an extended version of the existing HAR model which includes purified implied volatility. In the second step, they apply the random forests algorithm for the forecasting of the direction and the magnitude of the realised volatility. Using historical high frequency data, they demonstrate improvements of forecasting accuracy for the proposed model.

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14. **DeepVol or DeepVoodoo? Forecasting financial chaos with a dash of machine learning**

Volatility forecasts play a central role among equity risk measures. Besides traditional statistical models, modern forecasting techniques based on machine learning can be employed when treating volatility as a univariate, daily time-series. Moreno-Pino and Zohren (2024) introduce a DeepVol, a model based on Dilated Causal Convolutions that uses high-frequency data to forecast day-ahead volatility. This architecture allows the usage of a large receptive field that can handle lengthy sequences of data effectively without a significant increase in the number of parameters thanks to the use of dilated connections, yielding improved computational efficiency. Their findings suggest that dilated convolutional filters are effective in learning global features from high-frequency data.

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15. **The good, the bad, and the generated: Load up your GANs...**

Generative Adversarial Networks (GANs) represent a monumental leap in machine learning, as their unique two-network structure allows them to learn the deep, underlying patterns of a dataset without explicit instructions. Their primary importance lies in the ability to generate entirely new, yet highly realistic, synthetic data, addressing critical challenges like data scarcity, privacy, and the robust simulation of complex scenarios in fields ranging from finance to medicine. Liao *et al.* (2024) introduce the Conditional Sig-Wasserstein Generative Adversarial Network (SigCWGAN), a novel framework for generating synthetic time-series data while addressing the challenges of capturing temporal dependencies and high-dimensional data. The proposed method integrates Wasserstein GANs with the mathematical concept of path signatures, which provide a universal and efficient representation of time-series data. The authors validate the effectiveness of SigCWGAN on both synthetic and real-world datasets, demonstrating its superior performance in capturing temporal and feature dependencies, as well as its predictive accuracy compared to state-of-the-art models like TimeGAN, RCGAN, and GMMN.

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16. **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, 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. Buch *et al.* (2023) considered temporal variational autoencoders (TempVAE)—a type of generative ANNs—to estimate various quantiles of a return distribution using a non-parametric model. Their findings indicate that the encoded TempVaR methodology is competitive with a number of classical VaR models.

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17. **Decrypting crypto returns**

The popularity of cryptocurrencies has been on the rise over the last 7–8 years. As of September 2025, CoinMarketCap lists more than 9,400 cryptocurrencies with total market capitalization slightly over $4T. For many investors, one of the most important questions is if crypto returns are predictable in the short-term and what are the key drivers. Alessandretti *et al.* (2018) and Akyldirim *et al.* (2021) are examples of academic studies that tried to address this question using machine learning methods such as support vector machines, logistic regression, artificial neural networks, and random forests. Their findings indicate that machine learning algorithms exhibit decent performance and can beat standard benchmarks.

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